University of Zurich[UZH]

Internet Use in Algorithmized Digital Societies:

Selected Implications of a Socially Stratified Practice

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Abstract

The internet, and algorithmic-selection applications that rely on the automated assignment of relevance to selected pieces of information in particular, have pervaded all domains of our everyday lives in digital societies. This thesis approaches internet use and its implications from a user-centered, social-sciences perspective, relying on a co-evolutionary conceptualization of digitization as a socio-technical adaptation process, which becomes apparent through the trinity of datafication, algorithmization, and platformization. In the context of these algorithmized digital societies, the first part of this thesis addresses internet use and the use of algorithmic-selection applications in particular from a longitudinal digital-inequality perspective. The results reveal a persisting social stratification of internet use over time, even in the highly connected Swiss society. Conceptualizing implications of this internet use as co-occurring risks and opportunities, the second part of this thesis answers the call for theoretically-founded empirical research on implications of internet use that takes into account the growing relevance of algorithmic selection. Digital overuse and privacy violations are among the risks studied. The impact of the embeddedness of algorithmic-selection applications in everyday life is addressed from an institutional-governance perspective and results are discussed in the broader context of digital well-being outcomes. This thesis applies an innovative mixed-methods approach and draws on qualitative interviews, repeated cross-sectional telephone interviews representative of the Swiss population as well as data from a combined online survey and internet-use tracking for a representative sample of Swiss internet users. The results provide evidence-based answers to a set of pressing questions concerning internet use and selected implications in algorithmized digital societies and lead to broader directions for the empirical investigation of digitization effects.

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1 Introduction

There is no doubting that virtually any mundane, everyday activity such as reading the news, talking to friends, or doing a weekly shop has been fundamentally transformed by the internet. Societal participation requires internet use, anytime and anywhere access to the internet through mobile devices is regarded as a given, and constant availability is a new social norm (Büchi et al., 2019). This internet use is—often unavoidably—shaped by algorithms, which are embedded in the vast majority of widespread online services in order to perform searches, choose and allocate recommendations, recognize patterns, and profile users (Kitchin, 2017; Latzer et al., 2016). The ubiquity of and growing dependence on the internet, which heavily relies on algorithms, is fundamentally transforming people's everyday lives.

Digitization as a trinity of datafication, algorithmization, and platformization (Latzer, 2021)

There is a plethora of approaches to conceptually grasp this digitization process that range from purely techno-deterministic to socio-deterministic understandings. The co-evolutionary approach applied in this thesis (Latzer, 2013, 2021) overcomes this dichotomy and studies digitization from a media-change perspective, through which it manifests itself as a trinity of datafication, algorithmization, and platformization: datafication produces seemingly endless amounts of digital traces on people, things, and places, creating a big-data representation of everyday life. Algorithmization allows internet companies to capitalize on this data. Through a restructuring of markets and business models combined with a commercialization of the social sphere, platformization creates the ideal conditions for a continuous stream of ever more far-reaching datafications and algorithmizations. This digital trinity is shaping social order in societies similarly to how religions or states do (Latzer, 2021).

Digital inequalities in digital societies

These co-evolving, socio-technological transformation processes are constitutive of what is often referred to as "information societies" (ITU, 2018) and more recently as "digital societies", which provide the context in which individuals navigate their everyday lives. How individuals engage with the internet is very varied—even in highly connected digital societies: the digital-inequality research framework (e.g., DiMaggio et al., 2004; Robinson et al., 2015; van Dijk, 2005), situated at the intersection of sociology and communication science, deals with social differences in internet access, use, skills, and outcomes. In this field, the mutual shaping of technological and societal developments becomes especially apparent (Schroeder & Ling, 2014; Witte & Mannon, 2010): differences in internet access, use, and skills can influence internet users' and non-users' life chances in terms of social contacts, the content they consume, or where they purchase things, which in turn can become predictors for how strongly people can profit from their internet use. Within digital societies, research on digital inequalities has slowed down, entailing the assumption that the problem has been fixed (Reisdorf et al., 2017). Particularly in contexts where the role of the internet is profound, there is a lack of research on how social inequalities in various internet-use related variables have evolved—yet this is a particularly pressing question from a societal perspective because the relative disadvantages of a shrinking minority likely increase in these contexts (van Dijk, 2020). Therefore, the first part of this thesis addresses inequalities in internet access and use as well as their evolution in Switzerland, a country with one of the highest internet access rates across the globe (95% in 2021; see ITU, 2017; Latzer et al., 2021). As part of this endeavor, this thesis also sheds light on the minority of internet non-users. Despite the increasing importance of algorithmic-selection applications in people's everyday routines, extant research on digital inequalities that takes this into account remains sparse. This thesis therefore also provides results on digital inequalities with up-to-date definitions of algorithmized internet use.

Implications of internet use on personal well-being

Internet use and merely "being" in a digital society has manifold implications for individuals and society. Initial hopefulness regarding the social opportunities and benefits of the internet was quickly substituted by "moral panics" (Cohen, 1972) about associated risks and harms. These concerns about how new technologies might negatively affect populations or specific groups (e.g., young people) are not new. Public and academic discourses tend to focus on the risks and potential harms of a particular technology in cycles: concerns are widely discussed until a newer version of a technology replaces the prior as the object of concern and leads to the restart of such a cycle (Orben, 2019a). With the diffusion of the internet came promises on how it would improve people's well-being in a myriad of ways (Amichai-Hamburger, 2009). Implications of internet use on well-being are therefore an apt way of assessing a technology's overall effects on individuals and societies. Engagement with this topic in the public, academic, and policy realm has been dominated by panics about adverse well-being outcomes of internet use, yet nuanced research on this topic is only just emerging. This thesis argues for the necessity of addressing co-occurring opportunities (e.g., easier access to information, facilitated interpersonal contacts) and risks (e.g., disinformation, hate speech) that can arise from being online (Blank & Lutz, 2018) when investigating implications of internet use on well-being. This thesis provides theoretical and empirical indications for how internet use is associated with overall personal well-being and specifically focuses on digital overuse and privacy violations as exemplary risks from being online in an environment that is increasingly datafied and characterized by an overabundance of information and communication options.

Implications of algorithmized internet use as algorithmic governance

While discussions on implications for well-being are still very much part of ongoing debates, the increasing dependence on algorithms online has prompted equally widespread warnings about related risks. Algorithms have come under public scrutiny for causing societal polarization (Pariser, 2012), being sexist and racist (Davis, 2021; Zou & Schiebinger, 2018), or manipulating consumers through targeted advertisements (Mahdawi, 2019). Such assumptions are widespread and have already permeated into public-policy discussions, yet we lack both conceptual clarity on what constitutes algorithms and valid empirical assessments of the "social power of algorithms" (Beer, 2017) or of their "relevance" (Gillespie, 2014). Assessing the social, economic, and political implications of algorithms embedded in online applications for everyday life is especially vital because although they are so widely employed, internet users tend to be largely unaware of their functioning and impact (Eslami et al., 2015; Pasquale, 2015; Seaver, 2018). This thesis addresses the implications of the increasing algorithmization by acknowledging that technology can become effective as an institution: this governance by algorithms, conceptualized as steering mechanisms that result in a wide variety of social, economic, or political effects on individuals or society (Just & Latzer, 2017), is constitutive of the transformation process of algorithmization. This thesis dedicates a separate section to the conceptual understanding and empirical assessment of the significance of this algorithmic governance for everyday life.

Altogether, this thesis aims at describing, explaining, and interpreting everyday internet use and its implications in the context of digital societies, which are being transformed by a trifold digitization process. Specifically, it focuses on the state and evolution of digital societies by tracing digital inequalities for the internet in general (1) and algorithmic-selection applications in particular (2). Using these findings as a baseline, an investigation of implications of internet use on subjective well-being with a specific focus on two risks associated with internet use, overuse and privacy violations, follows (3). Taking the increasing role of algorithms into account, this thesis lastly investigates implications of algorithmized internet use on everyday life and relies on the concept of algorithmic governance to grasp these steering mechanisms by specific software systems (4).

User perspectives on internet use and implications

Based on the co-evolutionary understanding of digitization this thesis follows, it rejects techno-deterministic ideas that extrapolate assessments of a technology's impact derived merely from its features (Dutton, 2013). Rather, internet users—while undoubtedly being shaped by the technology they are using—tend to use said technology in unintended or unanticipated ways, which has implications on an individual and societal level (Haddon, 2006). To fulfil the aforementioned research tasks, this dissertation takes an internet-user centered perspective. Pursuing this bottom-up approach allows to take users' characteristics, attitudes, actions, and feelings into account. This thesis places the internet user and individual at the center and investigates how they navigate their lives in an environment that is increasingly shaped through the ongoing digitization as a broader societal change. This user perspective rejects the notion of ignorant internet users—which was, for instance, the basis for initial research on online privacy that found a seemingly paradoxical relationship between high privacy concerns and a lack of privacy protection (e.g., Barnes, 2006; Norberg et al., 2007)—with an understanding of internet users who are able to exert agency (Bucher, 2017) and can apply an array of practices (Fraser & Kitchin, 2017) to deal with the panoptic practices of powerful platform companies (De Certeau, 1984) that engage in dataveillance (enabled through datafication) and attempt to influence individuals' behaviors through, inter alia, their employment of algorithms.

Contributions to research on digital inequalities, critical algorithm studies, and computational communication science

This thesis addresses questions related to digitization from a social-science research approach and is, more specifically, disciplinarily rooted in empirical communication science. The results broadly contribute to the interdisciplinary field of internet studies (Baym, 2005) and make the following specific contributions: First, this thesis contributes to digital-inequality research by providing hitherto lacking representative empirical results on the evolution of internet access and use divides in a digital society with high levels of internet diffusion. It thereby contributes to resolving theoretical disputes and provides evidence for a persistent and increasing social stratification of internet use. Further, this thesis establishes subjective well-being as a relevant outcome of digital inequalities and provides population-level results for this relationship. In terms of risks associated with internet use, indications for how digital inequalities translate to differences in dealing with privacy risks are presented.

Second, this thesis makes significant contributions to critical algorithm studies, a subfield of internet studies that is characterized as "critical literature on algorithms as social concerns" and aims at an encompassing assessment of the implications of algorithms (Social Media Collective, 2015). In particular, this thesis presents a measurement model for the significance of algorithmic governance for everyday life, provides operationalizations for its five dimensions (use, subjective significance, awareness, risk awareness, and coping practices), and executes a sound empirical analysis of the significance of algorithmic governance at the population level. These results allow an evidence-based assessment of the significance of algorithmic governance for everyday life, provide input for evaluations of related risks, and contribute validated measures (for instance for awareness of how algorithms embedded in widely used internet services function) for further studies in the field.

Third, this thesis also makes methodological contributions to research on internet use and implications: it establishes an innovative mixed-methods design consisting of qualitative interviews, an online survey, and internet-use tracking to empirically measure the significance of algorithmic governance for everyday life and discusses its value. This thesis is also characterized by a meticulous methodological design that follows the theoretical research questions and adheres to principles of open science where applicable. It therefore fits into an emerging generation of research that places a strong emphasis on reproducibility and transparency. At the same time, the empirical articles included in this cumulative thesis apply novel research methods and present how computational methods (tracking data in particular) can be used to advance the field of internet-use research. This thesis thereby fits into and contributes to the emerging research field of computational social or communication science.

Structure of this synopsis

The following Chapter 2 introduces theoretical considerations on how this thesis conceptualizes the ongoing digitization from a media-change perspective. It introduces key considerations from the digital-divide framework with a specific focus on the evolution of inequalities in internet access and use in general and in the use of algorithmic-selection applications in particular. It proceeds by introducing subjective well-being as an outcome of such inequalities and by conceptualizing effects of internet use on well-being as a result of co-occurring harms and benefits. Two examples for such harms (digital overuse and privacy violations) are covered in greater detail. The influence of automated algorithmic selections on everyday life is then approached from a governance perspective, defining algorithmic governance as institutional steering by technology. Chapter 3 discusses guiding principles for the empirical investigation of (algorithmized) internet use as well as implications and introduces an innovative mixed-methods design. Subsequently, empirical results on socially stratified (algorithmized) internet use are presented in Chapter 4. Results on selected implications of internet use in general are summarized in Chapter 5. Focusing on a specific type of internet services—namely algorithmic-selection applications—empirical insights into how algorithmic-selection applications govern different life domains are presented. Finally, Chapter 6 discusses the findings, derives theoretical and methodological conclusions, and offers directions for further research on the topics addressed. This synopsis closes with concluding remarks in Chapter 7.

2 Theoretical Considerations on Internet Use and Implications in Algorithmized Digital Societies

This chapter prefaces this cumulative thesis and introduces important theoretical foundations. First, a general introduction details what understanding of digitization this thesis follows, which provides the framework in which internet use and implications are studied. Second, the concept of information societies as the context in which internet users navigate their everyday lives is described, the digital-inequality framework is introduced, its relevance for studying socially stratified internet use is explained, and research gaps regarding the evolution of these inequalities are presented. The third section focuses on implications of internet use and introduces subjective well-being as an outcome of internet use, affected by digital inequalities as well as co-occurring harms and benefits. Special attention is paid to two examples for harms that can impair well-being and are particularly relevant in algorithmized digital societies—digital overuse and privacy violations. Placing special emphasis on the ongoing process of algorithmization, this chapter continues by introducing the concept of algorithmic selection as the underlying functionality of common internet services and discusses implications of these algorithmic-selection applications for everyday life conceptualized as governance by technology. Upon introduction of these theoretical considerations, this chapter lastly situates the articles included in this cumulative thesis in an integrated model for internet use and implications.

2.1 A Co-Evolutionary Understanding of Digitization and the Digital Trinity of Datafication, Algorithmization, and Platformization

Internet use and its implications can be understood in the broader context of the role of technology in society and the relationship between media change and social change. There are different perspectives on how technological and social change interrelate (e.g., rational choice, systems theory, constructivism; see Latzer, 2013). An ex-ante discussion of the theoretical understanding of media change one follows is vital because it has implications for the research questions, the definitions and operationalizations of key variables, the methodological designs, and also predetermines the scope of possible results.

Innovations as driving forces of media change

In line with Latzer (2013, p. 15), this thesis understands "media change as an innovation-driven, co-evolutionary process in a complex environment, using a combined innovation-co-evolution-complexity perspective". Within this understanding, innovations are conceptualized as the "nucleus" of change (Hall & Rosenberg, 2010; Latzer, 2013) and as the driving forces for the ongoing, profound transformation processes in society. Driving forces of media change include technological, economic, political, and cultural forces. To understand how these different kinds of innovations relate to each other, (co-)evolution, a meta-theory of change (Schneider, 2008) is a helpful concept (Latzer, 2009). According to Latzer (2013), while *evolution* can be characterized as design without a central designer (Dennett, 1996), *co-evolution*, also referred to as co-construction or confluence (Benkler, 2007), captures the concurrent process of designing and being designed. This co-evolution, understood as a durable relation between agents that influence each other's evolutionary paths, is marked by complex, adaptive, and non-linear system behavior. More concretely, this implies that various processes in politics, economics, technology, and society are driven by mutually selective adaptation. Importantly—and this is arguably the aspect most characteristic of this approach—a co-evolutionary perspective overcomes techno- or socio-deterministic understandings of digitization and implies that technology is not only understood as the input, but also the output of economies and social systems. In bridging socio- or techno-deterministic approaches, this co-evolutionary understanding accounts for users' ability to shape the services they are using. This "social shaping of technology" (Dutton, 2013, p. 4) is shared in science and technology studies, social construction of technology, and actor network theory (Castells, 2002). Complexity theories, which can be regarded as a modern version of evolutionary theory (V. Schneider & Levi-Faur, 2012), offer concepts to explain and integrate basic properties such as non-linearity, emergence, adaptation, and networks, which play a central role in media change (Latzer, 2013). Another characteristic of this conceptual approach to digitization is the high degree of coincidence in these developments. An example for such a coincidental event is the COVID-19 pandemic, to which the ITU (2021) attested a "connectivity boost" in terms of internet access.

Co-evolutionary understanding of digitization: mutual shaping of technology and society

Technology can be understood as a "structure, actor, or institution" (Latzer, 2013, p. 10). This directly translates into understanding implications of technology use as institutional governance or governance by technology. This notion provides the basic rationale for the conceptualization of implications of internet use in this thesis, but is especially relevant for capturing the role of algorithmic selection, a specific type of software within the internet infrastructure, and will therefore be introduced in greater detail in chapter 2.3.3.

Digitization pervades all domains of everyday life

The current phase of digitization was prompted through the mass diffusion of the internet at the end of the 20th century (Latzer, 2021). The internet can be viewed as an example for convergence in the communications sector since it questions and overhauls longstanding dichotomies (e.g., between the private and the public or between producers and consumers; see Latzer, 2021, p. 2). Especially with the spread of the so-called web 2.0, internet use surged and was increasingly characterized by mobile and app-based use, enabled through powerful platform companies. Characterizing for this second wave of digitization is that it no longer is limited to the communications sector only but pervades all sectors and life domains.

This digitization is made apparent from a media-change perspective through the trinity of *datafication*, *algorithmization*, and *platformization* (Latzer, 2021). These three socio-technological transformation processes stand in a co-evolutionary relationship with each other: datafication creates big data (a new set of assets), and thereby reproduces life domains. Algorithmization automates selection processes and assignments of relevance to this data in order to make economic, social, and political capital out of it. Platformization restructures markets and business models, commercializes the social sphere, and builds optimized forms of organization for more far-reaching societal datafications and algorithmizations. Societies characterized by these transformation processes provide the context in which internet users navigate their (digital) everyday lives. Each element of this trinity is described in greater detail hereafter.

2.1.1 Datafication

When internet users engage in a wide range of online activities, they leave a large amount of data traces. Internet users implicitly and explicitly constantly trade their data—or their "digital souls" Zuboff (2019)—for services such as search results, suggestions for potential dating partners, or personalized fitness tips. This data on personal background, location, online behaviors, enriched with meta-data, is used by corporate, political, state, and private actors who try to make economic, political, or social capital out of it (Latzer, 2021).

This datafication entails that even aspects of the world that were formerly regarded as unquantifiable are now rendered into data (Cukier & Mayer-Schönberger, 2014), which includes the implicit assumption that anything from social relationships to personal taste is quantifiable. This has, for instance, been described as the "datafication of intimacies", whereafter a "mathematical mind-set to dating" (De Ridder, 2021, p. 2) is embedded in widely used mobile apps aimed at finding love—arguably the epitome of a practice hitherto devoid of mathematical and computational operations.

Datafication as the main source of concerns about internet users' privacy

The notion of datafication is closely tied to and a necessary prerequisite for *dataveillance*, which captures the "automated, continuous, and unspecific collection, retention, and analysis of digital traces by state and corporate actors" (Büchi et al., 2021) and has also been described as the "monitoring of citizens on the basis of their online data" (van Dijck, 2014, p. 205). This is one of the key sources of concerns about impairments to individuals' privacy online, which will be addressed in greater depth below.

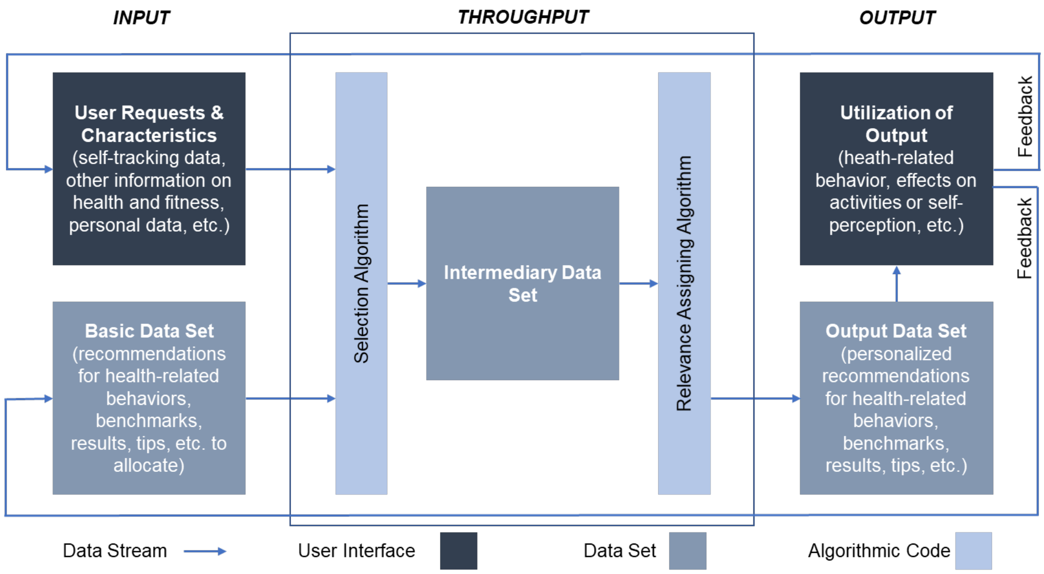
2.1.2 Algorithmization

Recognizing *algorithmization* as the second of the three key transformation processes of the ongoing digitization means acknowledging the important role that algorithmic-selection applications play as a key innovation in the broader, current internet infrastructure. There is a variety of terms that seeks to capture the increasing social relevance of algorithms on the internet, which have been described as “the new power brokers in society” (Diakopoulos, 2013, p. 2), including the society of algorithms (Burrell & Fourcade, 2021), the algorithmic age (Danaher et al., 2017), algocracy (Aneesh, 2009), or algorithmic culture (Striphas, 2015).

Input-throughput-output model of algorithmic selection

Since algorithmic selection is a key topic for a set of articles included in this thesis, a more in-depth deliberation on the concept is required. This thesis relies on the term algorithmic selection—a specific kind of selection—defined as the “automated assignment of relevance to selected pieces of information” (Latzer et al., 2016). The input-throughput-output model of algorithmic selection (Latzer et al., 2016), that builds on Gillespie’s (2014) understanding, is one way of explaining the basic functionality of algorithmic selection: a user request and available user characteristics—which typically take the form of big data enabled through datafication—prompt this process wherein information elements from a basic data set (input) are assigned relevance through automated statistical and computational operations (throughput). The resulting output can range from recommendations over rankings to specific search results (Latzer et al., 2016). This basic understanding can be applied to virtually any online service that applies algorithmic selection. Dörr (2016, p. 704) applied this model to algorithmic journalism. Article X elaborates how this algorithmic selection functions embedded in self-tracking applications for health and fitness (see Figure 1). Self-tracking for health and fitness is understood as a digital variant of self-surveillance and is typically based on input data from wearable devices and mobile applications.

Figure 1. Input–throughput–output model of algorithmic selection applied to self-tracking applications for health and fitness.



Source: Festic et al. (2021, p. 147), adapted from Latzer et al. (2016).

Based on their primary societal functions, i.e., the purpose they serve, algorithmic-selection applications can be categorized into different types (e.g., search, filtering, recommendation; see Latzer et al., 2014). These types are not conceptualized as mutually exclusive: in practice, most algorithmic-selection applications employ a range of different types of algorithmic selection and can therefore not be unambiguously assigned to one category. Upon engagement with the topics in this thesis, this has become very apparent. Still, this categorization illustrates how algorithmic-selection applications have comprehensively pervaded pivotal domains of everyday life (Latzer et al., 2016).

Functional typology of algorithmic-selection applications

Combining algorithmization with datafication, dominant internet services' goal is to capitalize on big data. The dominant strategy to do this is through a targeted influencing of individuals' behaviors (Latzer, 2021). Algorithmic-selection applications produce content that is tailored to internet users based on data on user behavior. This personalization of content ranges from customization in self-tracking applications (Bol et al., 2019) to political microtargeting (Kruikemeier et al., 2016). A defining characteristic of algorithmic-selection applications is their opacity (Kitchin, 2017), raising questions about their social power (Diakopoulos, 2015) and associated risks. These will be readdressed below.

Algorithmic selection produces personalized content and is opaque

2.1.3 Platformization

These algorithmic-selection applications that are embedded in users' everyday lives generally operate as platforms. Markets in all sectors are undergoing a profound platformization process, which provides conducive circumstances for the further advancement of the ongoing datafication and algorithmization. Underlying is the economic logic of multi-sided markets. For this thesis, this platformization is manifested in the fact that internet services in general and algorithmic-selection applications in particular are used as the unit of analysis.

It is important to understand that these three transformation processes are not independent from each other, nor have they come about by chance. Rather, they nurture each other: algorithmization only makes sense in a datafied environment where there is a trend toward control possibilities based on digital traces that accumulate automatically and in real-time of people and things, because of high connectivity, scalability, and ubiquity (see Latzer, 2021). From an internet-user perspective, considering these transformation processes also means considering the affordances of technologies, which are important when studying their use and implications. Affordances capture properties of technologies that enable and constrain the potential for action (Faraj & Azad, 2013). One example for affordances of a particular internet service is the limited number of characters allowed in a tweet (Jaidka et al., 2019). Trepte and colleagues (2020) have addressed how affordances of social networking sites influence people's self-disclosure and privacy concerns. For algorithmic-selection applications in particular, affordances can include the users' ability or inability to influence what is shown for instance in a news feed by hiding or liking content.

Illustrating datafication, algorithmization, and platformization using the example of self-tracking apps

To illustrate this trifold digitization process, the example of self-tracking applications for fitness or health provides a helpful example. Self-tracking for fitness and health is a practice that has been fundamentally *datafied*: tracking various vital and activity-related parameters on one's health status is increasing in popularity. These applications are generally characterized by the employment of algorithmic selection to derive personalized behavioral recommendations or provide condensed information about one's health. The output that is provided to users can range anywhere from alarms in certain stages of sleep to facilitate waking up to prompts for calming meditations in response to physiological measurements of increased stress levels. These benefits are generally provided to users in return for the personal fitness and health data at a cost of zero (Just, 2018). Self-tracking applications also provide an example for platforms that rely on multi-sided markets as they offer their services and user data both to users and to interested companies such as health insurance providers, employers, or even nation states (UnitedHealthcare, 2021). Insurance companies or employers want to capitalize on the data, and users want to receive the output results. These power structures can impose certain risks, especially since self-tracking applications typically rely on relatively sensitive input data.

Relying on this co-evolutionary understanding of digitization characterized by datafication, algorithmization, and platformization, this thesis contributes to the conceptual and empirical understanding of internet use and selected implications. The next section focuses on internet use. With a co-evolutionary understanding in mind, the necessity for the simultaneous investigation of media change and social change is apparent. Accordingly, studying internet use and implications is deeply intertwined with considerations on digital inequalities. This inequality perspective is introduced in the following chapter.

2.2 Social Stratification of Internet Use: Why an Inequality Perspective (Still) Matters

Digitization enabled the formation of information or digital societies

The previous chapter introduced the understanding of digitization that this thesis follows. Through this constant transformation process, societies have developed in which the role of the internet and algorithmic-selection applications is profound. Nation states as well as societal structures that transcend nation borders, which have undergone and continue to undergo these transformation processes, have been labelled as *information societies*[1]. More recently, this term

[1] The aptitude of these terms for capturing ongoing digitization transformations in societies is a matter of debate. As a concept, the notion of an information society has been contested and is normative. In the specific case of this thesis, the terminology is not of the utmost importance. What is relevant is that internet users navigate their lives embedded in societies that are highly connected and characterized by a strong dependence on ICTs for virtually all life domains.

has increasingly been replaced by the notion of *digital societies* serving as a blanket term for societies in which the internet is important for everyday functioning. The Internet Policy Review, a journal that routinely addresses internet use and implications, established a dedicated collection aimed at defining selected concepts of the digital society such as “datafication”, “privacy”, “filter bubble”, or “algorithmic governance” (Katzenbach & Bächle, 2019). They argue that while these terms “have become part of the vocabulary that is mobilized to make sense of the current rapid social and technological change”, a definition of the digital society that goes beyond listing key concepts of it remains lacking (Katzenbach & Bächle, 2019, p. 2). While the digital society provides a useful and widely acknowledged term for broadly capturing the ongoing digitization, the related concept of an information society is backed by a stronger theoretical basis and clear definition: the widespread diffusion of ICTs and a key role of information for a wide range of societal functions are the main defining characteristics of information societies (Feenberg, 2019; Floridi, 2009; Webster, 2014). The term is also relevant from a policy perspective since it is used, for instance, by the ITU to measure its ICT Development Index (IDI), which relies on three indicators: ICT infrastructure and access, ICT usage, and ICT skills (ITU, 2020). Thus, this thesis relies on the term “digital society” to broadly capture societies characterized by digitization processes, but relies on the information society for specific analyses that require an operationalization of clearly defined terms.

Digitization efforts on a global scale

From a democratic normative stance, these digitization processes have mostly been deemed desirable: becoming an information society—i.e., advancing the diffusion and adoption of the internet in a population—is the proclaimed political goal of many countries. A high diffusion of and strong dependence on ICTs is regarded as important for the prosperity and growth of societies (Castells, 2002). Using the relevance of digital ICTs for comparing nation states’ development status on a global scale has led to robust findings on inequalities for various indicators of information societies between countries: in 2021, according to the ITU (2021), 2.9 billion people have still never been online despite an alleged “COVID connectivity boost”. This lies in stark contrast to 95% of the Swiss population who were internet users in 2021 (Latzer et al., 2021). In Switzerland, the federal government’s *Digital Switzerland Strategy* strives to exploit the full potential of the ongoing digitization in different action areas such as education, infrastructure, political participation, and health (GDS, 2021). As part of this pursuit, one of their core objectives is to enable equal participation and strengthen the population’s ability to act autonomously online. Such an approach acknowledges that using the internet requires a new set of skills fundamental for realizing benefits and avoiding harms from online engagement. Also, lifelong learning and being able to transfer skills to newly emerging services is indispensable (ITU, 2018). The main hypothesis of traditional digital-inequality research is reflected in the notion of information societies as a normative target: skillful internet use is understood to be associated with benefits such as informed participation in democratic societies or facilitated political opinion formation (DiMaggio et al., 2004).

Approaching questions of the information society from a perspective that recognizes the co-evolutionary relationship between society and technology and their mutual shaping (Schroeder & Ling, 2014; Witte & Mannon, 2010) calls for an investigation of social dynamics in the adoption and use of the internet. The knowledge gap hypothesis (Tichenor et al., 1970) provides the basis for digital inequality research. It argues that as the information flow into social systems increases, its members differ in their acquisition of new knowledge depending on their social status. Higher social status, which traditionally already correlates with higher levels of educational attainment and knowledge, is sought to be predictive of acquiring information faster. This process ultimately leads to an ever-increasing knowledge gap over time. Applying this mechanism to internet use, popular internet services are believed to provide benefits to social groups who are already advantaged. Incentivizing internet use for them and allowing them to develop the respective skills to use these services leads to a continuous technological restructuring aimed at more ideally catering to their needs, while exacerbating the relative disadvantages of the excluded groups at the same time (Helsper, 2012).

Digital inequality research concerned with social differences in internet access, use, and outcomes

There is a rich body of qualitative and quantitative empirical literature that has repeatedly confirmed the cross-sectional relationship between social and digital inequalities, providing especially robust evidence that traditionally advantaged social groups are more likely to have access to the internet (first-level digital divide; see e.g., Helsper & Reisdorf, 2017), engage in differentiated types of skilled use, and have better internet skills (second-level digital divide; see e.g., Billon et al., 2020; Büchi et al., 2017; Hargittai, 2002), and gain more tangible benefits from their internet use (third-level digital divide; see e.g., van Deursen & Helsper, 2015). While these third-level divides that are concerned with outcomes or implications of internet use will be discussed in the following section, this chapter specifically deals with first- and second-level divides.

Research gap: how digital inequalities evolve over time

So far, it remains largely unknown how these digital inequalities evolve, although a longitudinal perspective is inherent to the knowledge gap hypothesis, which is foundational for digital-inequality research. For predictions on how digital inequalities evolve, concepts from traditional research on the diffusion of innovations are helpful: competing theoretical hypotheses for how digital inequalities evolve range from normalization, which points to the automatic resolution of inequalities over time, understanding the digital divide as more of a digital delay (Nguyen, 2012), to stratification, which implies a widening (i.e., individuals differ increasingly strongly in their online engagement) and deepening (i.e., the consequences from not engaging online increase) of divides over time (van Dijk,

2020) and points to the persistence or even increase of existing digital inequalities over time because the advantaged reap more benefits from their internet use (Hargittai & Hsieh, 2013). The stratification hypothesis is in line with the "innovativeness-needs paradox" (Rogers, 2003, p. 263), indicating that those in a social system who could benefit most from adopting an innovation do so later than advantaged groups, resulting in a wider socioeconomic gap due to the adoption of an innovation. This hypothesis corresponds with the conceptualization of information as a positional good (van Dijk & Hacker, 2003), understanding early access as a trigger for a plethora of advantages: personal and positional categorical inequalities affect the distribution of resources, which impacts access to the internet—a predictor of participation in society (van Dijk, 2017).

Research on digital inequalities especially relevant in digital societies

The evolution of digital inequalities is not only theoretically, but also empirically contested. Article I (Festic, Büchi, et al., 2021, pp. 335–340) includes a comprehensive review of existing empirical results on the evolution of digital inequalities. It reveals that the existing body of research presents inconsistent results and has shortcomings particularly in terms of up-to-date operationalizations of internet use. Extant research is also dominated by empirical studies from developing countries where internet diffusion is not as progressed as in digital societies like Switzerland, yet research on digital inequalities in such contexts is particularly pressing: in contexts where using the internet heavily for all different kinds of activities, where offline alternatives are increasingly costly or nonexistent, and where being constantly online and available is the norm, being part of an increasingly marginalized minority is likely to be connected to ever-increasing, compound disadvantages. The relative nature of digital inequalities captures this issue: how someone with a fixed scope of online engagement (e.g., in terms of using widespread services or having a certain level of internet skills) is positioned in a society is highly dependent on the role of the internet in their social context.

Therefore, the first set of articles included in this thesis addresses the state and evolution of information societies that have undergone digital transformation processes from a digital-inequality perspective and answers the following question:

Article I What are the usage patterns of the internet in the Swiss information society and how have they changed over time (2011–2019)?

Arguably, the most severe form of not participating in the information society and therefore potentially suffering disadvantages is being an internet non-user. There is relatively little research on this topic based on representative data, partially because this is a group that can be difficult to recruit for empirical research due to inability to collect data online, the small size of the group in information societies, and variables like age. Another reason for a lack of recent research on internet non-users is that the issue of digital inequalities, particularly concerning access divides, has been viewed as fixed in information societies. Van Deursen and van Dijk (2015) address this in their "multifaceted model of internet access" and argue that although the focus of policies and research on digital divides has shifted to divides in use and skills, considerations on motivational and material access stay important because they are required through all stages of internet appropriation. Article II contributes to this discussion and answers the following question:

Article II Who remains offline in the highly connected Swiss information society and why?

Digital inequalities likely amplified in algorithmized societies

It is arguably not only the heavy diffusion of the internet in digital societies that makes an analysis and resolution of digital inequalities more pressing, but also the changing affordances of the services used (Kadiyala, 2017). Emerging research has shown that the issue of digital inequalities is amplified through the growing reliance on algorithms for many decisions. Although these newly emerging digital inequalities may be less visible than those already established—it is arguably easier to see access or skills divides—research has shown that the increasing algorithmization affects people fundamentally, yet unequally (Gran et al., 2020). For instance, vulnerable population groups such as the poor or ethnic minorities tend to be exposed to more risks associated with the broad employment of algorithms for various decisions that have fundamental implications on their life chances (Eubanks, 2018). This thesis focuses on algorithms that are embedded in widely used internet services (i.e., algorithmic-selection applications). There is less research on the latter.

Given the changed usage habits of the internet paired with emerging evidence of biases in self-reported data on internet use (Jürgens et al., 2019), the need for updated assessments of very basic measures of internet use in algorithmized digital societies has amplified. Article III addresses the following question:

Article III How much time do people spend online, using widespread services and algorithmic-selection applications in particular?

Internet use that is subject to social inequalities has implications for people's everyday lives and individuals' ability to achieve benefits from their online engagement is also unequally distributed in societies. As has been noted above, digital inequalities do not only concern internet access and use, but also consequences. There is the least amount of research on such social inequalities in digital divide outcomes. This is relevant, however, because even if everyone used the internet, differences in achieving individually meaningful positive outcomes would remain as a social problem. The following subchapter addresses these implications of internet use.

2.3 Selected Implications of Internet Use

Uncontested that internet use offers opportunities

The ongoing digitization has manifold implications for individuals and society, which can take the form of opportunities or risks that can manifest in concrete benefits or harms. These implications capture how the ongoing digitization has fundamentally transformed social order in societies. On the one hand, the creation of social or economic values, reductions of complexity in everyday life, reductions of transaction costs as well as improvements in human decision-making can increase overall welfare. Consequently, participating in digital societies can be conceptualized as beneficial for personal well-being (Amichai-Hamburger, 2007, 2009; Lissitsa & Chachashvili-Bolotin, 2016). As has been described above, this optimistic narrative presented the starting point for research on digital divides; its relatively recent expansion of the framework to including outcomes revealed that reaping benefits from internet use is unequally distributed in digital societies (see Chapter 2.2).

Stronger focus in extant research on risks of internet use

In addition, more attention has been placed on risks of internet use that can impair welfare and personal well-being. Manipulation, distorted perceptions of reality, discrimination, overdependence on technology, market abuse, loss of cognitive abilities, and restrictions on freedom of communication and privacy are among those risks (Latzer, 2021; Latzer et al., 2016).

Uses and gratifications approach to conceptualize co-occurring risks and opportunities of internet use

Blank and Lutz (2018) draw on the uses and gratifications paradigm (Katz et al., 1973) to conceptualize harms and benefits of internet use because, in contrast to more traditional media, the internet facilitates a plethora of different uses in the same digital environment and internet use is generally characterized through active choices for content. The uses and gratifications approach fits into this dissertation because it takes a user perspective on media effects and proposes that people use different media (content) to satisfy their varying needs. This active role that the user is assigned fits into the approach taken here where users can exert agency when they engage in online activities. The basic assumption is that people have specific needs that they are seeking to satisfy through their internet use by reaping benefits, and this will also expose them to potential harms. “Risk is a harm that has not yet happened, harm is a risk that has been realised [sic]” (5Rights Foundation, 2020). In that vein, benefits of internet use in general and the use of algorithmic-selection applications in particular are understood as opportunities that have been realized. For instance, the potential for buying a train ticket for a reduced price online presents an opportunity offered by internet use, actually saving the money is a benefit; potentially receiving tailored recommendations for series is an opportunity of using algorithmic-selection applications for entertainment, actually receiving them and consequently watching a movie that is aligned with one’s personal preferences is a benefit.

A crucial but, under-researched addition here is the analysis of differential consequences of internet use (Van Deursen & Helsper, 2018). Thus far, outcomes of Internet use have particularly been studied in terms of tangible, manifest outcomes in social, political, institutional, educational, or economic domains like finding a job or making friends online (Blank & Lutz, 2018; A. J. A. M. van Deursen & Helsper, 2015; Van Deursen & Helsper, 2018). On an individual level, personal well-being is a relevant indicator of digitization effects. The next section establishes subjective well-being as an additional and relevant digital divide outcome and discusses internet-use related predictors. Understanding these implications of internet use from an inequality perspective is especially relevant given the "compoundness and sequentiality of digital inequality" (van Deursen et al., 2017): having certain internet skills increases the likelihood of having other skills, and obtaining certain benefits is linked to obtaining others. Further, individuals who are able to achieve higher (offline) returns from their online engagement can use this increased economic, cultural, or social capital to increase their internet skills, which can affect opportunities from internet use in the future. These kinds of feedback effects amplify the relevance of investigating digital inequalities.

Understanding implications of internet use as digital inequality outcomes

2.3.1 Implications of Internet Use on Subjective Well-Being

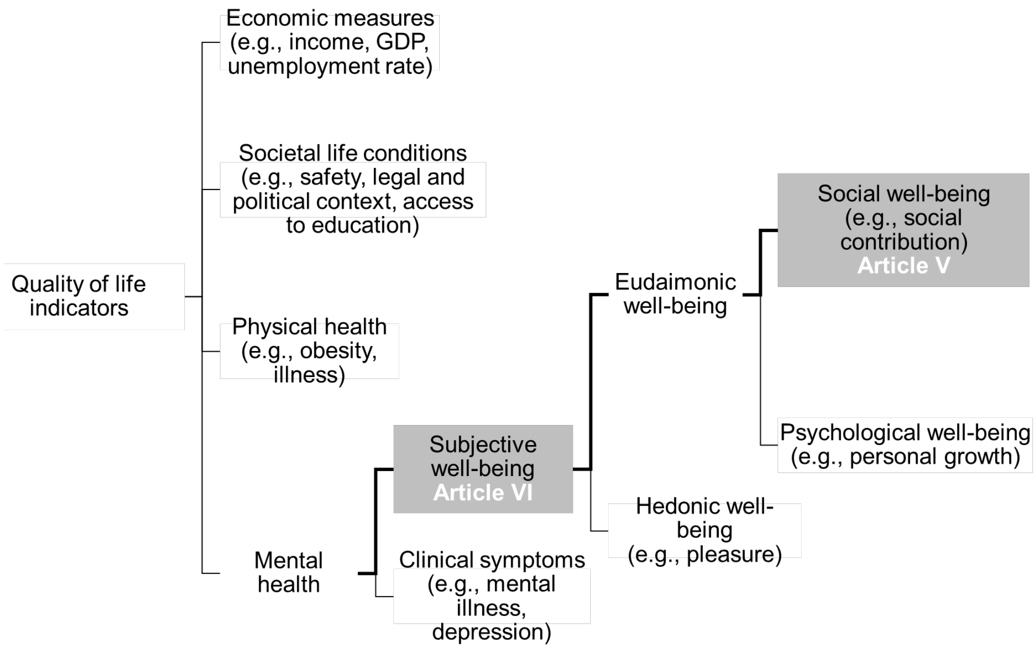
The association of internet use and personal well-being has been a matter of a heated public and academic debate. The public and academic interest in the relationship between media use in a broader sense and personal well-being is not new. While this research tradition is rooted in and a natural development of research on harmful media effects through violent contents or TV, the focus has shifted more toward mostly potentially harmful implications of social-media use such as hate speech, cyberbullying, or distorted perceptions of body image. There is also a strong emphasis on younger people in this research tradition, mostly presenting them as the group most vulnerable to these risks.

2.3.1.1 Subjective Well-Being as Individuals' Appraisal of Quality of Life

Subjective well-being as an indicator for quality of life

Before addressing the relationship between internet use and well-being, some deliberations on the concept of *well-being* and the associated research traditions are necessary. There is a plethora of indicators for quality of life (see Figure 2). Earlier operationalizations generally relied on objective and externally perceptible criteria such as economic measures or societal life conditions. Keyes and Shapiro (2004), among others, criticized that such approaches only ever measure the quality of life of a small societal group and noted that inferring an individual's quality of life from such macro-level conditions harbors inaccuracies. At the same time, there was an increasing consensus on the importance of mental health. Consequently, the research tradition surrounding subjective well-being, which can be defined as "an evaluation or declaration that individuals make about the quality of their lives" (C. L. M. Keyes, 2014, p. 1), emerged in the late 1950s and was aimed at monitoring social change and improving social policies. Since subjective well-being was explicitly conceptualized as a relevant object or basis for public policies, it is an apt indicator for quality of life when assessing intended an unintended societal consequences of the wide spread of the internet. The defining characteristic of measures of subjective well-being is not that they are self-reported—income, political context, or whether someone suffers from a physical illness can equally be measured through surveys—but that they refrain from setting universally valid benchmarks. Rather, subjective well-being relies on individuals' own appraisals of their quality of life.

Figure 2. Well-being as a quality of life indicator: situating Articles V and VI.



Source: own, adapted from Büchi et al. (2018).

Hedonic and eudaimonic well-being are based on differing assumptions about the good life

Within research on subjective well-being, two dominant research strains can be distinguished that differ based on their underlying philosophical assumptions. These two traditions are "founded on distinct views of human nature and of what constitutes a good society" (Ryan & Deci, 2001, p. 143). *Hedonic or emotional well-being* is generally concerned with measures of life satisfaction in different areas of life and focuses on a balance of positive and negative affect as well as pleasure and happiness in life (Bradburn, 1969; Diener, 1984; Diener et al., 1999). Based on this notion, well-being is understood as and measured through the *absence* of negative aspects such as anxiety or depression.

In parallel with the increased emphasis on "positive psychology" (Seligman & Csikszentmihalyi, 2000), research on subjective well-being also increasingly considered positive aspects of well-being: then-emerging conceptualizations of *eudaimonic well-being* placed a stronger emphasis on positive functioning based on the realization that those who do not suffer from a mental illness do not automatically report high subjective well-being (C. L. M. Keyes & Shapiro, 2004). Referring to Artistotle's *eudaimonia,* proponents of the eudaimonic strain of subjective well-being noted that equating happiness with well-being involves the illegitimate normative differentiation between right and wrong needs. Aristotle's idea of human well-being is based on the assumption that the pursuit of self-realization is the destiny of humans and therefore constitutive of their well-being. Accordingly, the eudaimonic strain of subjective well-being focuses on factors such as personal expressiveness, leading a meaningful life, personal growth, self-acceptance, and the desire to fulfill one's destiny in life (Jahoda, 1958; Ryan & Deci, 2001; Waterman, 1993).

Eudaimonic well-being: self-realization as a key indicator for quality of life

To account for the social or societal component of subjective well-being, Keyes (1998) established the concept of social well-being within the strain on eudaimonic well-being, defined as "the appraisal of one's circumstance and functioning in society" (C. L. M. Keyes, 1998, p. 122). This concept is founded in the finding that there is a strong relationship between a societal "need to belong" (Baumeister & Leary, 1995) and the physical and mental health of an individual and accounts for the social nature of humans who satisfy their needs primarily by fulfilling their societal roles (Townsend, 1987). Social well-being is an indicator for quality of life that places individuals' perceptions of the quality of their relationships with other people, communities, and society as a whole at the center (C. L. M. Keyes, 1998). It is important to note that social well-being is the personal experience of a lack in social contacts and belonging, and thereby equates to perceived social isolation (Cotten et al., 2013) whereas social isolation, for instance, is conceptualized as the objective lack in contact with other people. While the two are likely related, they are not the same. Keyes' (1998, p. 122) social well-being scale includes five dimensions, which are understood as social challenges that constitute possible roots of social well-being. This concept of social well-being was used for Article V.

Social well-being as the appraisal of one's functioning in society (Article V)

While there is no academic consensus on the terminology around the concept of social well-being, the importance of including social components to measures of well-being is uncontested. This is reflected in the fact that scales, which attempt to measure individual's quality of life, include similar dimensions to Keyes' social-well-being concept (C. L. M. Keyes, 1998). It is important to note that eudaimonic and hedonic understandings of subjective well-being are not viewed as opposing or mutually exclusive concepts. Rather, they are complementary psychological functions and the pursuit of both goes hand in hand (Huta, 2015). Keyes (2002) describes the combination of these two components as "flourishing". Accordingly, measures like Diener's (2009) flourishing scale, Diener's and Keyes' (2014) mental health continuum, or the Warwick-Edinburgh Mental Well-Being Scale (R. Tennant et al., 2007) have arisen, which aim at a more encompassing assessment of subjective well-being and do not differ between well-being dimensions, but view it as a one-dimensional concept. Article VI

Subjective well-being as an individual's assessment of their quality of life (Article VI)

relies on the Warwick-Edinburgh Mental Well-Being Scale as a measure for subjective well-being.

2.3.1.2 Subjective Well-Being and Internet Use

In extant literature, the relationship between well-being and internet use is highly contested and results range from positive (Bekalu et al., 2019) to negative effects (Dienlin & Johannes, 2020). In a recent meta-review, Meier and Reinecke (2021) found a weak negative association between social media use and mental health, but conclude that it strongly depends on the operationalization of both variables in question.

It is important to note that effects of internet use on well-being are highly varied. The following section introduces one approach and disentangles this complex matter by focusing on specific types of internet use and specific definitions of well-being. Internet use is highly multifaceted in terms of services, devices, contexts, and purposes of use. Both internet use as an independent variable as well as quality of life as the dependent variable need to be disaggregated to obtain a more fine-grained understanding of the associations between the two.

2.3.1.3 Digital Inequalities as a Predictor of Subjective Well-Being

Subjective well-being as a digital inequality outcome

Personal well-being can be viewed as an outcome of internet use and thereby fits well into the discussion on digital inequalities. When assessing implications of internet use on well-being, a necessary first step in conjunction with the considerations presented above is to assess how digital inequalities affect subjective well-being:

Article V How is social well-being affected by digital inequalities?

2.3.2 Risks and Harms of Internet Use

Internet use and well-being: a net effect of co-occurring harms and benefits

Since the emergence of early studies that postulated strong effects of internet use on well-being, a consensus seems to have evolved in this research tradition that using the internet more and for a wider range of purposes implies the simultaneous exposure to risks and opportunities. Co-occurring risks and benefits culminate in an overall net effect on well-being. “Using mobile media can be both detrimental and beneficial for well-being. Thus, explaining *how* and *when* they elicit such effects is of crucial importance” (F. M. Schneider et al., 2021). The “mobile connectivity paradox” (Vanden Abeele, 2021) captures that being constantly connected can increase people’s autonomy in their everyday lives because it enables them to “perform their social roles, manage their social networks and access personalized information and services anywhere, anytime” (Vanden Abeele, 2021, p. 934). At the same time, this very experience can impair people’s autonomy “when mobile technologies exert […] control over thoughts and behaviors” (Vanden Abeele, 2021, p. 934).

Research in the broader field of internet studies has addressed various risks of internet use in everyday life (e.g., privacy violations or displacement of offline social interaction, see Liu et al., 2019; Waldman, 2013). Some of these risks are explicitly tied to the algorithmic functioning of online applications. These are discussed in chapter 2.3.3. Among those risks that have received the most attention and that do not require the employment of algorithmic selection are digital overuse and privacy violations.

2.3.2.1 Digital Overuse

Effects on personal well-being are often discussed in conjunction with digital overuse as a result of the increasingly pervasive, personalized, and mobile nature of the internet. At a first glance, the main hypothesis of research on digital overuse stands diametrically opposed to the predominant narrative of digital-inequality research; while the latter has generally assumed that more internet use is better (see Chapter 2.2)—and therefore not using the internet or certain services is understood as a disadvantage—the underlying notion of research on digital overuse has mainly been that more internet use leads to adverse outcomes, for instance on personal well-being. Accordingly, this discussion accounts for the fact that while a certain amount of internet use presents a social requirement in digital societies, the overabundance of online contents and services can be an impairment to individuals' well-being (Gui et al., 2017). News reports on internet overuse, generally focusing on social media or smartphones, often propose negative effects on individuals' mental health (e.g., Booth, 2019; Cornish, 2017; Klass, 2019). Initial concepts that emerged to capture this are problematic internet use (Caplan, 2002) and internet or smartphone addiction (Brand et al., 2014). These early accounts understood the phenomenon as clinically defined, pathological, and concerning minorities. More recently, excessive use of the internet and potential effects were also addressed by neuroscientific (He et al., 2017) and public-health research, and linked to productivity losses in the workplace due to perceptions of information overload (Karr-Wisniewski & Lu, 2010), or exhaustion and mental strain due to technostress (Salo et al., 2017).

Perceived digital overuse: a subjective and relative measure

Concepts like problematic internet use or internet addiction rely on an exogenously set threshold of how much internet use is considered "unproblematic" or not indicative of an addiction (Kardefelt-Winther et al., 2017). In contrast to early accounts of excessive internet use, perceived digital overuse is conceptualized as an emerging social phenomenon (Gui & Büchi, 2019) and is a subjective and relative measure. It takes into account the changed context in which internet users navigate their lives, a "permanently online, permanently connected" world (Vorderer et al., 2017). The concept of screen time, which is an example for an exogenously fixed level of internet use, has been widely discussed in this field. It did not correlate with adolescents' well-being (Orben & Przybylski, 2019). This is one reason why perceived digital overuse is conceptualized as a subjective measure that is studied in relation to subjective well-being. Additionally, the results of Article V motivated this decision to base the measurement of perceived digital overuse in individual experiences (see Chapter 5.1).

Digital trinity of datafication, algorithmization, and platformization as triggers for digital overuse

The emergence of this concern can be tied to the algorithmization of the internet: according to developers of recommending systems in the US, keeping internet users hooked is a proclaimed goal achieved by implementing "captivating algorithms" (Seaver, 2018) into all kinds of online services. In social systems characterized by the attention economy, this is especially true for mobile technologies (Eyal, 2014; Williams, 2018). The internet that everyday internet users engage with is characterized by personalized advertisements, tailored news, or social media news feeds curated with the intention to make users scroll infinitely (Willson, 2017). These services, often accessed through mobile devices, have deeply permeated into users' everyday lives. In the case of social media, for instance, the importance of the process of platformization becomes very apparent: by making news feeds as interesting as possible for the respective users, the platform attempts at increasing the users' engagement with the contents and therefore also their exposure to advertisements, which in turn increases the platforms' appeal to advertisers and increases their profits. Gathering, storing, and analyzing a large amount of personal data is a necessary prerequisite for the personalization of news feeds.

Perceived digital overuse as a harm of internet use that can impair well-being

Digital overuse is included in this thesis as a specific harm of internet use that can impair subjective well-being. Adapted from Gui and Büchi (2019) and Gui et al. (2017), Article VI defines perceived digital overuse as "the positive difference between the extents of practiced and desired Internet use, that is, the perceived excess of time allocated to internet use in absolute, relative, and synchronistic terms" (Büchi et al., 2019, p. 2). The three dimensions in which digital overuse manifests itself are the following: feeling like too much time is spent online (*absolute*), believing that the time allocated to internet use displaces available time for other valued activities (*relative*), or perceiving a cognitive overload because one is trying to do too many things at the same time online (*synchronistic*). The perception of digital overuse is an assessment of one's internet use in total, across all devices, life domains, and usage situations. As such, it is an "abstracted consequence of the interplay between specific usage patterns and technology push" (Büchi et al., 2019, p. 2).

Coping skills and social digital pressure as covariates

Article VI conceptualizes perceived digital overuse in association with subjective well-being and empirically tests this relationship. The model also takes into account a specific type of skills aimed at coping with the overabundance of digital contents and managing potential impairments to well-being resulting from internet use. Additionally, we took into account the social context in which people navigated their internet use, specifically the pressure to function digitally, because this likely increases the need for coping skills as well as the likelihood of digital overuse.

Empirically addressing how common perceived digital internet use is in the general population and how it is related to individuals' general subjective well-being is crucial given the abundance of information and communication options in digital societies:

Article VI To what extent do internet users self-report digital overuse and how is that perception related to subjective well-being?

2.3.2.2 Privacy Violations

Privacy violations as another prominently discussed risk of internet use

Privacy violations are among the risks studied most intensively in relation to internet use in everyday life. Especially with the ongoing datafication of people's everyday lives came concerns about implications of these unprecedented infringements on people's privacy. The interdisciplinary literature on online privacy deals with the implications of dataveillance embedded in widespread services people use day-to-day.

Early research on the topic mostly evolved around the term "privacy paradox", finding very weak or non-existent relationships between privacy concerns and privacy protection behaviors. This seemingly paradoxical lack of engaging in protective behavior despite being aware of privacy risks or concerned about them was interpreted as naïve behavior by internet users. The explanation for the empirical finding that people do not necessarily protect their privacy online has been replaced more recently by a calculus logic, indicating that internet users consciously weigh the risks and opportunities of engaging in certain online activities against each other and base their behavior on the result of this calculation (Baruh et al., 2017).

One path through which invasions to internet users' privacy is likely to be impaired is *chilling effects*, which refer to the self-inhibition of legitimate or even desired behaviors such as searching the internet for sensitive information or expressing one's opinion online (Büchi et al., 2021). Chilling effects are distinguished by the mundaneness of digital behaviors that are affected by very vague ideas about popular dataveillance practices and potential harms or repercussions.

As has been described above, literature on digital inequalities assumes that inequalities in internet access and use can affect the extent to which individuals reap benefits from their internet use or, in turn, are exposed to risks. Differences in dealing with risks to one's online privacy have not been sufficiently addressed. In terms of behavioral responses to perceived privacy risks or impairments online, extant research focuses more heavily on inhibited disclosure (e.g., sharing less personal information online) as a mechanism to cope with these risks. However, another relevant piece to this puzzle is privacy protection behavior that internet users actively engage in.

Article IV How is privacy self-protection behavior affected by digital inequalities?

2.3.3 Implications of Algorithmized Internet Use on Everyday Life as Algorithmic Governance

As introduced in chapter 2.1, algorithmization is one of the key transformation processes characterizing the ongoing digitization. Therefore, algorithmic-selection applications as a specific type of internet service characterized by the employment of algorithmic selection warrant specific attention. Algorithmic-selection applications have become deeply embedded in a multitude of mundane everyday practices. The increasing diffusion of this type of internet service raises questions about how to understand and measure its implications.

2.3.3.1 Understanding Algorithmic Governance

Governance by algorithms

Algorithmization not only captures the increasing role of algorithmic-selection applications, but also refers to algorithmic, individual reality constructions (Berger & Luckmann, 1967; Couldry & Hepp, 2016). Algorithmic selection also affects how people behave in their everyday lives (Just & Latzer, 2017). This influence on internet users' everyday behavior can be conceptualized as governance by technology in general, and governance by algorithms in particular (Just & Latzer, 2017). Governance by algorithms addresses a type of steering through software and captures "the economic and social effects of algorithms on individuals and the society, that is, on all the opportunities and risks involved" (Latzer & Just, 2020, p. 2). Accordingly, it also includes opportunities (e.g., efficiency gains, tailoring of content to meet customer needs) and risks (e.g., discrimination, biases, manipulation) involved in using algorithmic-selection applications (Latzer et al., 2016).

The governance term refers to "institutional steering" (Kenis & Schneider, 1996) and captures both horizontal and vertical extensions of traditional notions of government (Engel, 2001). The notion of algorithmic governance is related to Yeung's (2018) algorithmic regulation and extensions to this framework (Eyert et al., 2022), but goes beyond it since it includes not only intentional, but also unintentional effects of algorithmic selection (Latzer & Festic, 2019).

This notion of algorithmic governance understands technology (or specifically algorithms) as institutional structures "constraining and facilitating communicative behaviors and preferences" (Napoli, 2013, p. 7). In line with neo-institutionalist arguments, algorithmic selection can therefore be understood as a set of norms and rules that govern behaviors by simultaneously enabling and limiting room for action (Napoli, 2014). This corresponds with Katzenbach's (2012) argument that the design of a technology not only impacts social behavior by impacting the room for action, but it is also impactful on how new technologies evolve and how they are used. These approaches fit well into a co-evolutionary understanding of the interplay between media change and social change because they acknowledge that the adoption and diffusion of a technology is not predetermined according to a technological logic, but rather highly contested in political and social terms (Katzenbach, 2012).

The impact that algorithmic selection has on people's behavior is partially comparable to the effect of nudges, a term rooted in behavioral economics and psychology; changes to the choice architecture, i.e., the context in which people make decisions, can significantly change how people behave even if no options were forbidden and the economic incentives were not meaningfully altered (Thaler & Sunstein, 2009). By affecting people's behaviors in their everyday lives, algorithmic governance consequently leads to a changed social order that fundamentally differs from traditional constructions through media on a societal level (Just & Latzer, 2017).

Research gaps in extant empirical studies on algorithmic governance

Existing research on the role of algorithms for everyday life has been mostly based on theoretical considerations and empirical results are only beginning to emerge. There is a research gap regarding comprehensive and systematic empirical investigations, with existing research taking a narrower perspective in terms of focusing on specific algorithmic-selection applications in isolation and investigating the significance of algorithmic selection without taking user perceptions into account (Latzer & Festic, 2019). The lack of representative data that would allow generalizable statements at the population level further substantiates the need for a comprehensive empirical assessment in this field.

2.3.3.2. Measuring Algorithmic Governance

Article VII introduces a measurement model for the significance of algorithmic governance in everyday life consisting of five variables and thereby answers the following question:

Article VII How can algorithmic governance be conceptualized and empirically measured?

Five variables measure the significance of algorithmic governance for everyday life from a user perspective

Determining how significantly algorithmic-selection applications govern everyday life first requires an assessment of their **use** (1) in terms of extent and frequency. We further suggest to measure how much **subjective significance**[2] (2) people assign to these algorithmic-selection applications for their everyday functioning in different life domains. Adding subjective significance to the measurement model also means that we take into account users' perceptions and acquire an additional measure to weight extant findings on use times. Certain applications might be very influential despite being used for short amounts of time, for instance, and vice versa. Jointly, these first two dimensions enable us to assess the weight that algorithmic-selection applications carry, particularly compared to their online and offline counterparts. This follows the rationale that the everyday practices that have been transformed by the growing importance

[2] In Article IX, subjective relevance was used as a synonym for subjective significance.

of algorithmic selection (e.g., purchasing products, gathering health information) are not exclusive to the internet. Therefore, online and offline alternatives must be taken into account when assessing the significance of algorithmic selection for these everyday activities. This approach allows us to understand the significance of algorithmic selection in the broader context of individuals' everyday practices.

Awareness of algorithmic selection as a key variable in determining the significance of algorithmic governance

Especially since the opacity of algorithmic-selection applications is the leading source of many concerns about the impact of algorithmic-selection applications, it is crucial to understand the level of **awareness** (3) users have of the algorithmic functioning of the internet services they use. In this context, a research tradition on algorithm skills or algorithmic literacy has emerged (see Oeldorf-Hirsch & Neubaum, 2021 for an overview). Awareness of the underlying modes of algorithmic operation is a prerequisite for a realistic risk assessment. Paired with individuals' ability to interact with algorithmic-selection applications in a conscious and critical way, awareness can be seen as an emerging "digital strength" (Gran et al., 2020).

Consequently, **awareness of risks** (4) is the next variable in the model. The risks associated with the broad employment of algorithmic selection are rooted in the finding that algorithms can never be neutral, but carry social meaning and are therefore likely to be subject to biases (Gillespie, 2014). Latzer et al. (2016) derived a list of social risks from cost-benefit calculations as well as normative considerations that ranges from threats to privacy and surveillance over manipulation and diminishing variety in content to fear of repercussions and deception. These risks are often induced by the personalization of content that is contingent on categorizations that are opaque and nontransparent. Algorithmic selection is the technology that enables such practices that induce these risks. Other risks of using algorithmic-selection applications have been linked to social inequalities: For instance, for oximeters (at-home machines that measure the oxygen saturation in someone's blood), which are paramount in determining covid-positive patients who need hospital care, it has been shown that they are less accurate for people with darker skin (Davis, 2021). Examples for risks that have been associated with using algorithmic self-tracking applications for health and fitness include, but are not limited to, poor scientific quality of the applications (Mercurio et al., 2020), inaccurate measurements, scientifically unfounded fitness recommendations that are not suitable for a specific user (Depper & Howe, 2017), and an inability of current legislation to adequately address the handling of personal data (Marelli et al., 2020). Consequently, different governance options such as self-help protection behaviors by users are likely to play an important role in coping with the risks associated with algorithmic-selection applications for health self-tracking (Ireland, 2020).

The last dimension is therefore concerned with **practices** (5) that users can apply to cope with these perceived risks. These practices stand opposed against platform companies' strategies and are therefore a means for internet users to exert agency and regain autonomy over their personal data online, an activity otherwise described as "slow computing" (Fraser & Kitchin, 2017). This is related to notions of resilience against data grabbing infrastructures.

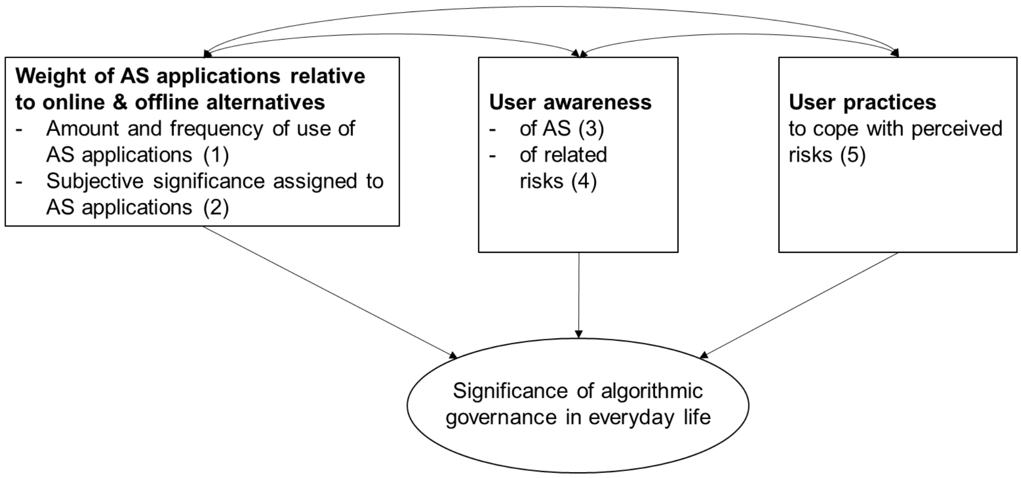
Coping practices as users' ability to deal with perceived risks

To understand the concept of coping practices, De Certeau's (1984) distinction of strategies and tactics is helpful: in accordance with the basic ontological conception of a calculable and measurable world that underlies users' and companies' trust in algorithmic selection (Latzer, 2021), algorithmic-selection applications apply panoptic practices: they monitor, measure, and control internet user data and transform users into types. These practices enable platforms to classify their users on the basis of their habitus that reflects various aspects of their social disposition. This is the mechanism through which algorithmic-selection applications co-govern their users' realities through the mirroring of their social disposition that can take the form of recommendations, search results, scorings, or ads. Coping practices are the direct counterpart tactics of these strategies that platforms or the companies behind them apply. They are directed at the risks that internet users are exposed to because they are using algorithmic-selection application, which makes them subjected to the various data collection and analysis strategies.

Research on the implications of algorithms has been dominated by a techno-centric view, ascribing algorithms human-like agency. A co-evolutionary understanding of social and media change that allows for the social shaping of technology has to take into account users' behaviors and interactions with algorithmic-selection applications for an encompassing and realistic assessment of the societal implications of their use.

Altogether, this model makes the following claim: As a starting point, algorithmic governance is considered to be neutral. A high significance of algorithmic governance can, however, entail risks, leading to an increased governing potential of algorithmic-selection applications. For algorithmic governance to be assessed as significant for everyday life —and this may be accompanied by fears of associated harms—algorithmic-selection applications have to be widely used in the first place (1), a substantial substitution of online and offline counterparts by algorithmic-selection applications is required (2), there needs to be some unawareness among internet users about both the functioning of these applications (3) as well as associated risks (4), and coping practices need to be applied rarely (5). As the arrows in Figure 3 illustrate, these five variables are conceptualized as covarying dimensions that jointly measure the significance of algorithmic governance for everyday life.

Figure 3. Theoretical model of variables measuring the significance of algorithmic governance in everyday life.



Source: own, adapted from Latzer & Festic (2019, p. 9).

Chapter 3 details the proposed empirical framework to empirically measure the significance of algorithmic governance in everyday life in accordance with this theoretical model.

Algorithmic-selection applications are deeply embedded in everyday life

One key reason why algorithms are often assigned high social power and are associated with risks is because they are so deeply embedded in all domains of everyday life. Everyday life has been studied in different disciplines and with different theoretical approaches (see e.g., Adler et al., 1987; De Certeau, 1984; Schütz, 1960). There is no agreed-upon definition of everyday life, but relationships with others that are enacted through internalized habits and routines have been mentioned as one defining characteristic (Sztompka, 2008). Assessing the role of technology, or algorithmic-selection applications in particular, requires a conceptualization of everyday life that goes beyond human relationships. To understand how social interactions and media technologies shape how people perceive the (social) world, theories of the social (Berger & Luckmann, 1967) or mediated (Couldry & Hepp, 2016) construction of reality are helpful (Just & Latzer, 2017; Latzer & Festic, 2019): the starting point is that social interactions combined with reciprocal typification and habitualized actions gradually construct the social world (Berger & Luckmann, 1967). In the social world that is constructed through this process, habitualized actions "provide orientation, make it possible to predict the actions of others, and reduce uncertainty" (Latzer & Festic, 2019, p. 2). This results in a sense that in societies, there is knowledge of the world in common (Schütz & Luckmann, 2003) and there is no questioning of the shared understanding of habitualized practices in everyday life that are increasingly shaped by algorithmic selection.

For an operationalizable categorization of everyday life, this thesis follows a practice-related approach (Pink, 2012): leaning on results from a confirmatory factor analysis based on common online activities in Switzerland (Büchi et al., 2015), five life domains are distinguished: information, entertainment, health, commercial transactions, and socializing. These five life domains are understood to reflect pivotal areas of everyday practice.

The colored shading in Table 1 displays the main dimensions addressed in the respective articles, but they are not a complete representation of the research questions (all articles also included analyses based on personal background). The guiding research questions for all articles are introduced below.

Table 1. Situating Articles III, VIII, IX, and X in the matrix of life domains and variables measuring the significance of algorithmic governance in everyday life.

<table>
<tr><th></th><th>Information</th><th>Entertainment</th><th>Health</th><th>Commercial Transactions</th><th>Socializing</th></tr>
<tr><td>Use of AS applications</td><td colspan="5">Article III</td></tr>
<tr><td>Subjective significance assigned to AS applications</td><td colspan="5">Article IX</td></tr>
<tr><td>User awareness of AS</td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>User awareness of related risks</td><td></td><td></td><td rowspan="2">Article X</td><td></td><td></td></tr>
<tr><td>User practices to cope with risks</td><td>Article VIII</td><td></td><td></td><td></td></tr>
</table>

Source: own.

Article VIII How does the significance of algorithmic governance compare between five domains of everyday life?

Article IX What subjective significance do Internet users assign to algorithmic-selection applications relative to online and offline alternatives and how does it compare across life domains and social groups?

Article X How aware are Swiss self-trackers of the risks associated with the applications they use and how do they cope with them? How is risk awareness related to the employment of coping practices[3] among Swiss internet users?

Four articles included in this cumulative thesis provide contributions to the empirical assessment of the significance of algorithmic governance in everyday life. While Article III and Article IX address one specific dimension of the significance of algorithmic selection for everyday life (use and subjective significance, respectively) comparatively for all life domains, Article X focuses on one life

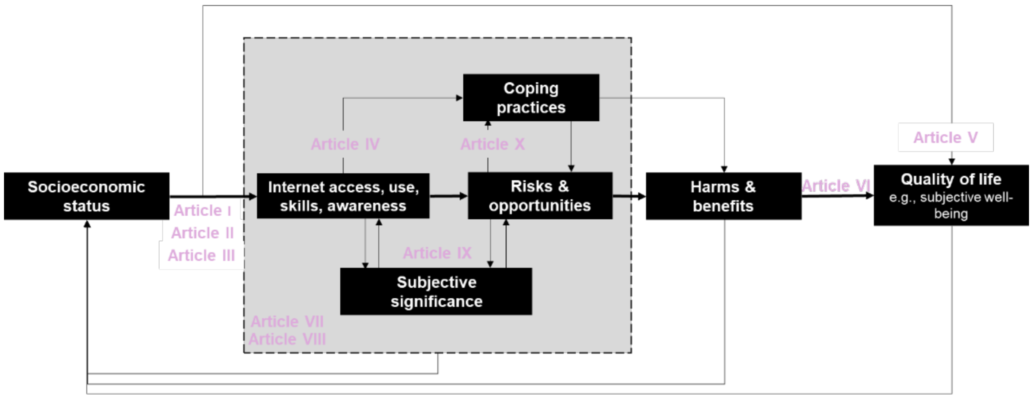
[3] In Article X, coping practices are referred to as coping strategies. For reasons of consistency, only the term “coping practices” is used in this synopsis.

domain (i.e., health) and investigates two specific dimensions of the measurement model, risk awareness and coping practices, as well as their association with each other. Article VIII provides an encompassing empirical assessment of the phenomenon of the significance of algorithmic selection for everyday life and therefore includes all five dimensions and all life domains. Table 3 details which methods these contributions draw on to address the respective combinations of life domains and variables of the measurement model.

2.4 Situating the Articles in a Generalized Model for Socially Stratified Internet Use and Selected Implications

Combining all these theoretical considerations presented in this chapter, Figure 4 depicts how the different contributions of this thesis relate to each other.

Figure 4. A generalized model for socially stratified internet use and selected implications: situating the articles included in this cumulative thesis.



Source: own.

Note. The grey rectangle encloses all variables that jointly measure the significance of algorithmic governance for everyday life (see Chapter 2.3.3.1).

Individuals' socioeconomic status, understood relatively to the society in which they live, has a direct relationship with internet access, use, and outcomes, as has been well-established by research in the digital-inequality framework. Articles I, II, and III contribute to the empirical assessment of such digital inequalities in terms of internet access (Article II) and use (Article I), with Article III placing a specific focus on algorithmic-selection applications. Article V is concerned with how such digital inequalities affect a specific outcome of internet use, namely subjective well-being.

The model assumes that internet use in all its facets simultaneously exposes internet users to both opportunities and risks (see Chapter 2.3). Both awareness of risks and exposure to risks do not automatically lead to harms. While a wide range of variables is conceivable as moderators or mediators for this relationship (e.g., coincidence), this thesis places specific emphasis on coping practices that users can apply to deal with the risks they perceive (Article IV, Article

X). This is in line with the understanding of active internet users who are able to exert agency. In terms of implications of internet use, this thesis has a specific focus on risks and harms. However, the same mechanism is conceivable for opportunities and benefits: as has been shown in research on digital-divide outcomes, the mere exposure to opportunities (conceptualized as potential benefits) from using the internet does not automatically translate into reaping benefits. Rather, people differ in this ability. Following this conceptualization, perceived digital overuse is a harm because internet users report being affected by it, not only concerned about its potential occurrence (Article VI).

The dashed rectangle encloses the five variables that jointly measure the significance of algorithmic governance as introduced above. The articles that contribute to the conceptual and empirical understanding of algorithmic governance (Articles VII–X) contribute to different parts of this rectangle (as presented in Table 1).

Well-being as an outcome variable

With algorithmized internet use deeply embedded in everyday lives, all of these variables ultimately affect well-being and quality of life as a meta topic (Staats, 2021). Algorithmic governance can therefore be seen as one way in which a specific technology impacts individuals in their everyday lives, which can ultimately be associated with well-being outcomes. Chapter 2.3.2 introduced an institutional-governance perspective on implications of using algorithmic-selection applications. This understanding can be expanded to all internet services.

This model offers an updated theoretical perspective to grasp the mutual dependencies of the internet and social life, that is, it explains well-being not as a function of technology itself, but of its ensuing individual and social harms (e.g., overuse, privacy violations, manipulation based on digital traces) and benefits (e.g., relevant information, online social capital, economic efficiency) (Büchi et al., 2019). This model takes this into account and situates the broader discussion of internet use and implications in the context of algorithmized digital societies in the debate on digital well-being, addressing how internet users' quality of life relates to the ongoing transformation processes of digitization. The model also accounts for the co-evolutionary relationship between social and media change: differences in all variables included in the model (broad conceptions of internet use, awareness of and exposure to risks/harms and opportunities/benefits, well-being outcomes, etc.) feed back into individuals' social status and affect how they navigate their lives in digital societies.

It must be noted that this is a simplified depiction of the relations between the included concepts to illustrate the contributions of this thesis. Since this thesis investigates internet use and selected implications from a user perspective, the model presented above focuses on the level of internet users. However, these mechanisms at the micro level have implications for broader societal processes and are in turn affected by the societal context in which internet users navigate their everyday lives. Specifically, algorithmic governance is conceptualized as a driving force of changes to social order in societies (Just & Latzer, 2017).

Figure 4 is a generalized depiction of key concepts and their relationships that form the basis for this thesis. In the following, this thesis will zoom into different boxes, arrows, and combinations thereof and contribute to more specific questions in the broader context of internet use and implications. Table 2 summarizes the specific contributions of the ten articles included in this cumulative thesis in light of the proposed model.

After this introduction on key theoretical concepts that are relevant for the different articles included in this cumulative thesis, the following chapter shifts the focus toward the empirical investigation of the ongoing media change since the methodological approaches and empirical results are a central contribution of this thesis.

Table 2. Overview of article contributions.

Article #	Research Interest in Light of Thesis Topics	Guiding Research Question	Main Contributions
I	Socially stratified internet use: evolution of access and use divides	What are the usage patterns of the internet in the Swiss information society and how have they changed over time (2011–2019)?	Longitudinal, representative results on persistent digital inequalities (access, use types, skills) in the Swiss information society 2011–2019, indications for exacerbation of digital inequalities over time, widening digital divides particularly for groups of higher age
II	Socially stratified internet use: evolution of access divides with a focus on internet non-users	Who remains offline in the Swiss information society (2011–2019) and why?	Longitudinal, representative results on persistent digital inequalities in internet access, results on reasons for internet non-use in the Swiss information society 2011–2019, discussion of compound disadvantages for internet non-users as an increasingly marginalized minority
III	Socially stratified use of algorithmic-selection applications: use divides addressed with a novel method of data collection (tracking internet use)	How much time do people spend online and using widespread algorithmic-selection applications?	Digital inequalities prevalent for user shares of and time spent on algorithmic-selection applications, substantial differences between self-reported and tracked time spent online, considerations on readdressing basic internet-use questions with internet-use tracking data
IV	Implications of socially stratified internet use: inequalities in protection behavior from risks to privacy online	How is privacy self-protection behavior affected by digital inequalities?	Testing the association of social status and internet-related variables (use, skills, privacy attitudes & breaches) with online privacy protection, digital inequalities in privacy protection prevalent, higher age as strongest predictor of less privacy protection
V	Implications of socially stratified internet use: digital inequalities and social well-being	How is social well-being affected by digital inequalities?	Representative evidence: perceptions of digital belongingness and digital potential (internet skills) are directly resp. indirectly associated with higher social well-being, digital participation (amount of internet use) not related to social well-being
VI	Implications of socially stratified internet use: harm of perceived digital overuse and subjective well-being	To what extent do internet users self-report digital overuse and how is that perception related to subjective well-being?	Empirical test of the concept of perceived digital overuse, modeling of negative association of perceived digital overuse with subjective well-being including context variables (social digital pressure, digital coping skills)

VII	Implications of the use of algorithmic-selection applications: conceptual considerations, measurement model, and mixed-methods approach for the significance of algorithmic governance for everyday life	How can algorithmic governance be conceptualized and empirically measured?	Nuanced conceptualizing of algorithmic governance, suggesting a measurement model consisting of five variables and a mixed-methods approach to empirically address the significance of algorithmic governance for everyday life
VIII	Implications of the use of algorithmic-selection applications: qualitative, explorative investigation of the significance of algorithmic governance for five life domains	How does the significance of algorithmic governance compare between five domains of everyday life?	Qualitative results for the five dimensions of the significance of algorithmic governance for everyday life, substantial differences between life domains (e.g., lower risk awareness for entertainment or commercial transactions than for social and political orientation)
IX	Implications of the use of algorithmic-selection applications: significance internet users assign to them as one dimension of the measurement model for the significance of algorithmic governance for everyday life	What subjective significance do internet users assign to algorithmic-selection applications relative to online and offline alternatives and how does this compare across life domains and social groups?	Representative evidence on generally low significance that internet users assign to algorithmic-selection applications compared to personal well-being and offline contacts, differences between social groups: younger internet users and those who spend more time online assign higher significance to algorithmic-selection applications
X	Implications of the use of algorithmic-selection applications for fitness and health self-tracking: focus on the association between risk awareness and coping practices as two dimensions of the measurement model for the significance of algorithmic governance for everyday life	How aware are Swiss self-trackers of the risks associated with the applications they use and how do they cope with these risks?	Representative evidence for low risk awareness and rare application of coping practices among Swiss internet users, low association between risk awareness and coping practices paired with high willingness to share personal data with insurance companies indicate presence of a calculus effect (weighing harms and benefits)

Note. An overview of article information is available in the appendix (A1).

Source: own.

3 Empirically Investigating Internet Use and Implications in Algorithmized Digital Societies

The ongoing transformation processes in digital societies not only have theoretical implications, but also affect how we can and should empirically measure socially stratified internet use and its implications. All articles included in this cumulative thesis are either empirical articles based on original data or are concerned with how to measure a concept (i.e., algorithmic governance) best empirically. Before the methodological designs the empirical articles rely on are presented, this chapter begins with a methodological preamble and introduces considerations on the choice of a suitable methodological design resulting from the author's engagement with internet use and implications from an empirical communication-science perspective.

3.1 Employing a User Perspective to Investigate Internet Use and Implications

User perspective on internet use and implications

In general, all methodological designs and empirical parts of this dissertation have in common that they rely on a user perspective: rather than, for instance, talking to programmers or investigating content, this dissertation is interested in internet use and related concepts from a user perspective (self-reported or not). For subjective well-being and perceived digital overuse, for instance, a user perspective is the straightforward choice and suits the methodological design. In the latter case, this is because while people may find it hard to assess their actual time spent online, they are the experts when it comes to whether they believe that they spend too much time online (Büchi et al., 2019).

Especially in the field of critical algorithm studies, researchers have also increasingly called for investigations from user-centered approaches: while it is uncontested that algorithms are affected by the context in which they are programmed (see e.g., Geiger, 2014), they are equally a function of their users' encounters and use, which shapes them (Eyert et al., 2022; Gillespie, 2014). Accordingly, a realistic assessment of the social power of algorithms requires an understanding of how people "make sense of algorithms, and how these experiences, in turn, not only shape the expectations users have towards [sic] computational systems, but also help shape the algorithms themselves" (Bucher, 2017, p. 33). Investigating algorithms from a user perspective also equates that we investigate them as one part of a broader "socio-technical assemblages" (Kitchin, 2017) consisting of technical (e.g., software) as well as human (e.g., uses) components (Willson, 2017) because algorithms are merely "meaningless machines" (Gillespie, 2014) unless these computational procedures are applied to real-world data (Sandvig et al., 2014). This circumstance is considered in research that takes the socio-technical context of algorithmic selection into account, viewing algorithms as situated artefacts and generative processes embedded in a complex ecosystem (Beer, 2017; Willson, 2017).

Kitchin (2017) lists specific epistemological and practical challenges when researching algorithms (pp. 20–22): algorithms are often characterized as *black boxes* since their inner workings are opaque and the codes on which they operate are not accessible to researchers or the public. Even if the code were accessible to the public, having access to the code of a single algorithm is not very helpful: the services that are so widespread today and are subject to these concerns are based on an entire system of algorithms, which is often not even entirely transparent to their programmers (see also Kitchin, 2017; Seaver, 2013). This is another reason why investigating algorithmized internet use from a user perspective is a necessary addition to the field.

Algorithmic-selection applications as units of analysis

Articles V and VI relied on a broad definition of using "the internet" to establish the association between internet use and well-being. This is suitable because the internet services people use are varied. For the articles focusing specifically on algorithms, the unit of analysis were algorithmic-selection applications, which are internet services that rely on some kind of algorithmic selection. This choice fits well into the user perspective that underlies these articles because algorithmic-selection applications are concrete manifestations of algorithmic governance that users interact with during their everyday internet use and by means of which they experience implications. This is especially important given the black-box nature of algorithms (Kitchin, 2017; Pasquale, 2015): as has been discussed earlier, their inner workings are often opaque and user awareness of the algorithmic functionalities of the services they use is generally low (see e.g., Eslami et al., 2015). Using algorithmic-selection applications as concrete examples when discussing use and implications with users is a helpful solution that circumvents the problem of assumedly low and unequally distributed awareness.

3.2 Choosing the Suitable Methodological Approach

All articles included in this thesis adhered to the rationale that the methodological approach should be explicitly addressed and made dependent on the research interest one pursues. Having substantiated the decision for addressing internet use and implications from a user perspective, this section establishes what needs to be considered when deciding on a methodological approach and details how these principles informed the methodological design of the articles included in this cumulative thesis.

3.2.1 Qualitative, Quantitative, and Mixed-Methods Approaches

According to Creswell (2003, p. 3), when deciding between the three dominant frameworks in the social sciences—qualitative, quantitative, and mixed-methods approaches—there are three elements to initially consider: the *philosophical assumptions* about what constitutes knowledge claims, the general procedures of research called *strategies of inquiry*[4], and the detailed procedures of data collection, analysis, and writing referred to as *methods*. This section will proceed by addressing these three elements and thereby justifying the choice of the research framework employed by the articles included in this cumulative thesis.

Postpositivist knowledge claims underlie quantitative research

For this thesis, two different types of *philosophical assumptions* about knowledge claims are relevant: postpositivist and socially constructed knowledge claims. Postpositivist knowledge claims are generally embedded in quantitative empirical research. They are reflective of a deterministic philosophy, which assumes that causes probably determine outcomes. Accordingly, studying a topic with underlying postpositivist assumptions entails addressing causes and outcomes. This approach corresponds with the traditional scientific method, which starts by deducting hypotheses from a theory, proceeds to collect data that either supports or rejects these hypotheses, and adjusts the theoretical assumptions based on the empirical findings before resuming empirical investigations (Creswell, 2003). This process is necessarily reductionistic because broader social phenomena are reduced to smaller, discrete ideas that can be empirically tested. Accordingly, developing numeric scales to measure behaviors are a standard approach for research following postpositivist knowledge claims.

Socially constructed knowledge claims underlie qualitative research

In contrast, *socially constructed knowledge claims* assume that individuals develop a subjective understanding of the world and make meaning of their experiences, which can be directed toward objects or things. Importantly, these meanings are subjective and therefore varied, which implies that researchers should not narrow these meanings into a limited number of categories but rather acknowledge and be open to the complexity of different views. For research, this means that asking broad questions and understanding how people construct meaning is important. Such knowledge claims favor open-ended questions that allow respondents to narrate their experiences in their everyday lives. The subjective meanings that individuals develop are formed through social and historic contexts, interpersonal interactions (see: *social* constructivism), as well as historical and cultural norms in the context of which people navigate their lives (Creswell, 2003).

Strategies of inquiry differ for quantitative and qualitative research

Additionally to these assumptions about knowledge claims, which a researcher brings to the choice of a research design, *strategies of inquiry* or methodologies are to be determined at a more applied level (Creswell, 2003). Quantitative strategies of inquiry involve, for instance, structural equation models or regression models that consist of multiple causal paths. The overall strength of multiple variables explaining one or more outcome variables is the key interest here. Qualitative strategies, and phenomenological research in particular, attempt to

[4] The term “methodology” is used as a synonym for strategies of inquiry hereafter.

understand a social phenomenon in terms of human experiences that participants describe (Creswell, 2003). While quantitative research based on positivist assumptions aim at *explaining* how and why certain things happen, qualitative research rooted in socially constructed knowledge claims aims at *understanding* how and why they happen.

In terms of the actual *methods* used, for studies from a user perspective, quantitative approaches can, for instance, rely on survey or tracking, while interviews or focus groups are typical for qualitative approaches.

Mixed-methods approach overcomes limitations of quantitative and qualitative approaches

Taking all these three elements into consideration, both qualitative and quantitative approaches have inherent limitations. Qualitative research is more open to (theoretical) changes that occur during the stages of data collection and analysis. Quantitative research often fails to uncover what meaning humans attach to social phenomena. Mixed-methods approaches overcome this dichotomy of quantitative and qualitative research by acknowledging that every method entails specific inherent biases and limitations. To preface the following section, it is important to note that these philosophical assumptions and resultant choices for the methodology and applied methods are not mutually exclusive. Rather, the same topic can—and should—be approached by different frameworks because they allow for answering slightly different questions from different angles. Employing a combination of different methods allows to fill the blind spots of these different methods (Creswell, 2003, p. 15). What is typical for mixed-methods approaches is a "sequential procedure" (Greene et al., 1989) where the findings from one method inform the next. A usual way to do this is to begin with qualitative, exploratory research and follow up with a larger, quantitative sample to be able to generalize the results. Such an approach, combining qualitative and quantitative research, allows for an encompassing understanding of the object of study. More subtly, employing a mixed-methods research design also entails making a conscious effort to include qualitative and quantitative literature when reviewing extant research on a topic and engaging in collaborations with scholars who apply different methodologies than oneself. While all articles in this thesis adhere to this principle, Article X presents an example for an article that explicitly included qualitative research on self-tracking for health and was written in collaboration with a co-author who applies qualitative methods.

Mixing tracking with survey data to mitigate self-report biases, but tracking data is not "ground truth" either

As has been noted above, a distinguished advantage of mixed-methods approaches is that they allow to overcome specific biases of certain singular methods. This is not only true on the level of different approaches (i.e., quantitative vs. qualitative), but also when referring to specific methods applied: one bias of quantitative survey data that is often discussed in research on internet use and its implications is distorted self-reports. Relying on a comparison of self-reported survey data and some kind of tracking (e.g., log data, mobile experience sampling), a myriad of emerging studies has provided evidence for deviations depending on the method of data collection: for instance, users overestimate how much time they spend on Facebook, but underestimate how often they access the platform (Ernala et al., 2020). It has been shown that users overestimate how much time they spend online (Araujo et al., 2017) and that the correlation between self-reported and tracked amount of internet use is low (Scharkow, 2016). Another study revealed that the time spent on Facebook, WhatsApp, and YouTube was consistently overestimated compared to in-situ experience sampling results (Naab et al., 2019). Such biases have not only been documented for self-reported behaviors, but also, for instance, for the frequency of exposure to like-minded content (Dvir-Gvirsman et al., 2016), for the frequency of sharing content on Facebook (Guess et al., 2019), and for news exposure in general (Vraga & Tully, 2020). While it is intuitive that self-reporting internet use or the use of specific services is error-prone for different reasons (e.g., difficulty remembering, social desirability), it is very important to note that tracked internet use should not be understood as a more objective method of measurement either. Jürgens et al.(2019), for instance, identified sampling, selection, and response biases that are specific to tracking data and conclude that "tracking data should not by default be considered an unbiased source of 'true' media exposure" (p. 612). Additionally, especially when addressing questions on internet use and implications from an inequality-perspective, personal-background variables are important. Inferring such variables like age or gender from big data gathered from user behavior is likely error-prone. The need for survey data in combination with tracking data is amplified when user perceptions (e.g., on risks) or their knowledge matters. Altogether, this provides good reason for the combination of survey and tracking data.

Quantitative approaches to empirically address digital inequalities, digital well-being, and privacy protection on a population level

Articles I, II, III, IV, V, and VI rely on quantitative approaches and survey data (complemented by tracking data for Article III). These articles have in common that there was a sound theoretical foundation that allowed us to derive hypotheses and test them empirically: the rich body of literature on digital inequalities (for instance the existing measurement scales for internet skills) provided the necessary theoretical input for Articles I, II, and III. This, combined with extant research on online privacy and theories explaining how people protect their privacy online (e.g., privacy paradox, privacy calculus) also allowed the quantitative assessment of privacy protection behavior in Article IV. Extant research on personal well-being provided the required basis for the hypotheses on the associations between internet use and well-being, as well as for the measurement of concepts such as subjective well-being, social well-being, or perceived digital overuse (Articles V and VI). Further, all these articles have in common that they aim at assessing internet use and implications at the nation-level and provide generalizable results. This requires a quantitative approach.

Articles VII, VIII, IX and X, which study algorithmized internet use, draw on a mixed-methods design consisting of qualitative interviews, a quantitative online survey, and quantitative tracking of internet use following a sequential procedure. To illustrate the interplay of these different methods and show how they jointly contribute to the empirical understanding of algorithmic governance by addressing varying questions, Table 3 depicts the expected contributions of each method to every dimension of the measurement model for the significance of algorithmic governance in everyday life. The colored shading illustrates which variable(s) measuring the significance of algorithmic governance for everyday life each article addresses (*row*) and on which part of the method mix it relies (*column*). While this reveals the main focus of each of the articles, it is not an exhaustive representation of all research questions addressed in the article.

Mixed-methods approach to assess the significance of algorithmic governance for everyday life

3.2.2 A Note on Representativeness

Choosing between qualitative and quantitative approaches in empirical communication science often entails associating oneself with a specific subfield and community. One key allegation that more quantitatively-oriented scholars tend to make against qualitative research is its supposed inability to provide generalizable results because samples are composed randomly. There are two arguments to counter this widespread notion that illustrate why qualitative and quantitative research should not be viewed as two opposites wherein the former is condemned as an inferior, less systematic version of the latter.

First, contrary to common belief, selecting samples for qualitative studies can and should happen systematically and in adherence to certain guidelines. With the research interest in mind, a sample with maximum variation in certain independent variables was the goal for the qualitative interviews included in this cumulative thesis. Since the qualitative interviews were explorative and served the goal of mapping the field and providing input for the quantitative survey, we aimed to achieve maximum variation in the sample regarding age, gender, education, and amount of internet use. For this sample, we used the statistically nonrepresentative stratified sampling technique (Trost, 1986): based on theoretical deliberations (e.g., on relevant variables in the field of digital inequality), we chose the following independent variables: age, gender, and education. These variables were combined into a property space, resulting in 30 cells, which is within the ideal range of the “sufficient and manageable” amount (Trost, 1986, p. 55). In this case, no cells are logically empty because all combinations of the three variables of interest are possible. Through the recruitment process, the cells were filled iteratively. Though “the sample will not be representative in a statistical sense, [it] will guarantee a variation along some of the independent variables” (Trost, 1986, p. 55). Some cells happened to be empirically empty, however.

Statistically nonrepresentative stratified sampling technique (Trost, 1986) to ensure maximum variation in qualitative samples

Table 3. Contributions of the three components of the mixed-methods design to the empirical assessment of the significance of algorithmic governance in everyday life.

	Qualitative interviews with internet users	Quantitative survey with internet users	Quantitative tracking of individual internet use
Use of AS applications	Not primarily relevant, gather context data on circumstances of use	Determine frequency of use of offline alternatives	Determine frequency of use of AS applications (and online alternatives)
Subjective significance assigned to AS applications	Find reasons why AS applications are (not) significant in comparison to online and offline alternatives and for different life domains	Quantify significance of AS applications, online and offline alternatives for domains of everyday life in different social groups	Not primarily relevant
User awareness of AS	Determine interviewees' understanding of AS applications, use results for developing a survey measure for awareness	Quantitatively determine distribution of awareness of AS at population level	Not primarily relevant
User awareness of related risks	Expand existing list of risks; understand context to explain, interpret, and contextualize survey data on risk awareness	Quantify awareness of risks associated with AS applications at population level	Not primarily relevant
User practices to cope with risks	Find practices that users apply to cope with risks associated with the use of AS applications	Quantitatively determine frequency of use of coping practices	Not primarily relevant

Note. "AS" = algorithmic selection.

Source: own, adapted from Latzer & Festic (2019).

Article III

Article VIII

Article IX

Article X

In contrast to a quantitative approach aimed at composing a representative sample (representative as in quotas that correspond with the population shares of certain groups)[5], this process ensures maximum variations. Table 4 is a simplified depiction of the property space for purposes of illustrating this method of sampling for qualitative interviews.

Table 4. Property space for the qualitative interview sample.

Age	18–25						…						>55					
Education	low		med		high		…		…		…		low		med		high	
Gender	f	m	f	m	f	m	…	…	…	…	…	…	f	m	f	m	f	m

Source: own.

In total, the property space results in 5 (age groups) x 3 (education levels) x 2 (genders) = 30 cells. Applying this method, the sample for the qualitative interviews was compiled iteratively. Often, qualitative research does not include sufficient information on sample composition, recruitment, and data analysis. This brief excurse illustrates how qualitative methodological designs can adhere to open-science and reproducibility standards.

Representativeness of «representative» quantitative samples must be discussed

Second, quantitative data is not as objective of a measurement method as is often assumed and this also applies to sample composition. Many studies rely on convenience samples because conducting research with representative samples is costly. Such convenience samples are, however, arguably not better equipped to making statements about the prevalence of a phenomenon in a social group. Further, it is important to note that representativity needs to be addressed for quantitative studies that claim relying on a representative sample. While a sample may be balanced for a set of sociodemographic variables, checking how bi- and multivariate combinations of these basic variables in the data correspond to the distribution in the population is necessary. Further, we need to check for biases in certain samples, for instance by comparing tracking samples to the general population. Shaw and Hargittai (2021) compared “representative” samples of Amazon Mechanical Turk workers with a sample recruited from the general internet-user population in the US and revealed that the two samples significantly differed in the participants’ social media use and experiences in contributing own online content. For the articles included in this cumulative thesis, Article III discusses how the tracking sample differs from the survey sample in terms of sociodemographic variables.

[5] Following such an approach, a possible outcome is that the quotas are met (e.g., about 50% females, 50% males), but there is no mechanism to avoid a biased sample where, for instance, all 18-25-year-olds are female or all participants with a high level of educational attainment are male.

3.2.3 On the Importance of Transparent Research

Paradigm shift towards reproducibility and open science

The emergence of black-box services employing algorithms, novel computational methods, and emerging questions on representativeness have, among other things, prompted discussions on transparent research. The reproducibility crisis in psychological empirical research has provided an example for a discipline undergoing a fundamental shift and communication science is beginning to follow suit (Open Science Collaboration, 2015). Especially in research on internet use and mental health, which has resulted in sensationalist and dystopic headlines, it is vital to be very precise about what empirical research can and can not achieve. Not only effects on digital well-being, but also research on the implications of the growing importance of algorithms has been dominated by sensationalist assumptions. As an academic community, we need to be precise about what conclusions we draw and when evidence can provide indications for a causal effect and when it can not. The current development appears to be the beginning of a much-needed paradigm shift, which Orben (2019b) has described as follows: “if science had generations, mine would not be defined by war or Woodstock, but by reproducibility and open science”.

Besides theoretical and methodological advances in the field, one way to overcome this problem is by making as much of the empirical research process as possible publicly available and freely accessible. Empirical data can only ever be a partial and incomplete depiction of reality and, due to the different decisions that researchers have to make when conducting a research project, is always somehow biased or has embedded assumptions. Therefore, the push for open science should be taken seriously when discussing topics similar to the one addressed in this thesis. Therefore, this thesis and the included articles aim at following open-science principles.

Transparent research with personal data

One option to make the empirical process more public is to share the respective datasets on dedicated online repositories. When dealing with empirical research that draws on personal data, the benefits of openly sharing data have to be carefully weighed against the potential cost of infringing on participants’ privacy. For this thesis in particular, this means that tracking data can only be shared in an aggregated form or pseudonyms are used in lieu of the respondents’ real names when reporting the qualitative interviews. All empirical analyses and results (when applicable) are available on the Open Science Framework (OSF), which is an online repository that allows researchers to share empirical data, empirical results, syntax files used for data analysis, and any other materials that may be important for ensuring transparency and reproducibility of the empirical research process. This is both for the anonymous peer-review process as well as for the long-term availability of empirical data once an article is published. The links to the OSF projects are available in the respective articles.

In terms of the publication process of research output, publishing in open-access outlets is in line with goals like enabling replicability and maximizing transparency in research. Of the ten articles included in this cumulative dissertation, eight were published in an open-access format. Additionally to publishing in open-access journals, there are more far-reaching initiatives to increase transparency such as unblinding the peer-review process and making reviewer comments as well as authors' responses during the review process openly available (see e.g., J. P. Tennant et al., 2016).

Taking all these general principles into consideration, the following section addresses the methodological designs of the articles included in this thesis.

3.3 Methodology of the Empirical Articles in this Thesis

The empirical articles included in this cumulative thesis draw on different datasets from two overarching projects, which are introduced in the following sections.

3.3.1 World Internet Project: Survey Data

The World Internet Project is an international partnership of research institutions that assesses different internet-related measures[6]. The Media Change & Innovation Division at the Department of Communication and Media Research of the University of Zurich is the Swiss country partner and has conducted biannual surveys on internet use in Switzerland since 2011. The empirical analyses in the following articles are based on the World Internet Project – Switzerland (WIP-CH[7]) survey data: Article I (WIP-CH 2011–2019), Article II (WIP-CH 2011–2019), Article IV (WIP-CH 2015), Article V (WIP-CH 2017), and Article VI (WIP-CH 2019).

WIP-CH: representative, repeated cross-sectional telephone interviews with internet users and non-users

Data Collection: The data were collected through computer-assisted telephone interviews. This mode ensured that the samples also included internet non-users, which is vital for answering questions about the diffusion patterns of the internet and those who remain offline. An independent market research company conducted the interviews exclusively by landline in 2011 and 2013. For the subsequent survey periods, a fifth to a quarter of the respondents were reached through mobile phones (2015: 21%, 2017: 21%, 2019: 25%). This adaptation of the data collection mode ensures high data quality and takes into account the increasing importance of mobile phones and the simultaneously decreasing importance of landline telephones in Switzerland (Bundesamt für Statistik, 2021). A set of questions in the survey has remained unchanged in wording since the first survey period, ensuring the possibility for comparisons over time to track the evolution of various indicators of internet use. In this thesis, this was especially relevant for Articles I and II, which apply a longitudinal perspective.

[6] https://www.worldinternetproject.com/
[7] https://mediachange.ch/research/wip-ch-2019/

Sample: Repeated cross-sectional surveys were conducted for representative (regarding age, gender, employment status, and Swiss language region) samples of the Swiss population aged 14 and over. Some key characteristics for the samples are summarized in Table 5:

Table 5. Representative, repeated cross-sectional WIP-CH survey samples.

Year	*N* total	Max. margin of error	Share of internet users	Share of mobile internet users
2011	1,104	±2.95%	77%	20%
2013	1,114	±2.94%	85%	39%
2015	1,121	±2.93%	88%	63%
2017	1,120	±2.93%	90%	72%
2019	1,122	±2.93%	92%	80%

Source: own, adapted from Festic et al. (2021).

Measures: All WIP-CH surveys included a set of questions on internet use, on various online activities, on internet skills, on internet-related attitudes as well as a section on personal background relevant for investigating the internet-use related variables from an inequality perspective. Additionally, the survey included thematic modules that varied between the survey periods, namely privacy concerns and protection behavior (Article IV), social well-being (Article V), as well as subjective well-being, and perceived digital overuse (Article VI).

Table 6. Data analysis strategies for the articles based on WIP-CH survey data.

Article # and focus	**Data analysis strategies**
Article I *evolution of access and use divides*	Multivariate regression analyses to test the association of demographic and socioeconomic variables, internet skills and experience, and mobile internet use with different use variables Models estimated with the *glm* function (Rdocumentation.org, 2020) using binomial logit regressions for binary dependent variables (internet use, mobile internet use, internet skills) and gaussian identity regressions for ordinal dependent variables (internet skills mean score, internet use types)
Article II *evolution of access divides*	Multiple binary logistic regression analyses with *lavaan* (Rosseel, 2012) to determine and compare the influence of socio-demographic and socioeconomic characteristics on the probability of being an internet non-user Descriptive statistics to complement the findings with self-reported reasons for non-use and intention to use the internet as well as inclusion in the information society
Article IV *inequalities in privacy protection*	Path modeling using the *lavaan* package (Rosseel, 2012) with robust maximum likelihood estimation Saturated version of the model, i.e., all exogenous variables predicted all mediators and the outcome, and all mediators predicted the outcome, and alternative model where non-significant paths were removed in favor of model parsimony

Article V *internet use and social well-being*	Multivariate regression analysis to test the association of internet use vs. non-use with social well-being Confirmatory factor analysis (CFA) to test the measurement models of the latent variables Structural equation modeling to address the question of how internet-related variables are associated with social well-being Analyses performed using *lavaan* (Rosseel, 2012)
Article VI *digital overuse and subjective well-being*	Descriptive statistics Confirmatory factor analysis (CFA) to test the measurement models of the latent variables Regression and moderation analyses including control variables and structural equation modeling to retest the nomological network of latent variables in *lavaan* (Rosseel, 2012) with unweighted least squares estimation and polychoric correlations due to the ordinal measurement of the items (Forero et al., 2009)

Source: own.

Regression-based analyses of the WIP-CH survey data

Data Analysis: All analyses based on the WIP-CH survey data were conducted in *R*. Multiple imputation of missing values using predictive mean matching with the *mice* package was performed. Models were assessed using conventional cutoffs from literature on confirmatory factor analyses and structural equation modeling (Hu & Bentler, 1999; Schermelleh-Engel et al., 2003). Table 6 details which specific methods of analysis were applied in the articles.

Additionally to these articles answering questions on various aspects related to internet use in general, another set of articles included in this thesis specifically addressed algorithmic-selection applications. The empirical basis for these articles is introduced in the following section.

3.3.2 The Significance of Algorithmic Selection for Everyday Life in Switzerland: Mixed-Methods Data

This project[8], funded by the Swiss National Science Foundation, aimed at the systematic empirical assessment of the significance of algorithmic selection for everyday life and particularly addressed the case of Switzerland. The project relied on a mixed-methods design. The following sections introduce details on the three complementary methodological approaches—qualitative interviews, an online survey, and internet-user tracking—and detail how they contributed to different articles included in this thesis.

Qualitative interviews

The first part of the method mix consisted of a set of qualitative interviews with Swiss internet users. While the interviews served the purpose of providing input for the development of survey questions and answer scales—and are therefore implicitly the basis for all articles relying on the survey data—Article VIII is explicitly based on the qualitative interviews.

[8] https://mediachange.ch/research/algosig/

Data Collection: Prior to the interviews, we informed the participants about the study's funding, provided a statement of informed consent, and informed the participants of their right to withdraw their answers. A team of three researchers conducted the interviews between May and July 2018 and the average duration was one hour. We closely collaborated during the recruitment phase, the development of the interview guides, and the actual interview process to ensure maximum inter-interviewer reliability. We conducted all interviews face-to-face in the same room, relying on a similarly structured interview guide. The interviews were conducted in German, which is the mother tongue of all interviewees and interviewers. The interviewees received a small pecuniary incentive.

Qualitative face-to-face interviews with internet users as first step in method mix

Sample: Sociodemographic characteristics of the sample are summarized in Table 7 below.

Table 7. Qualitative interview sample characteristics.

	Total Sample		Life Domains			
			Information	Recreation[9]	Comm. Trans.	Socializing
	Number (*N* = 58)	Percentage of Sample	Number (*N* = 15)	Number (*N* = 14)	Number (*N* = 14)	Number (*N* = 15)
Gender						
Female	31	53%	7	9	7	8
Male	27	47%	8	5	7	7
Age group						
18–25	11	19%	2	4	3	2
26–35	16	28%	6	1	5	4
36–45	10	17%	2	3	2	3
46–55	7	12%	3	0	0	4
55+	14	25%	2	6	4	2
Education level						
Low	13	22%	4	3	4	2
Medium	22	38%	5	5	5	7
High	23	40%	6	6	5	6

Note. The education categories correspond to the following completed degrees: Low: primary / secondary school; medium: vocational training; high: college.

Source: own, adapted from Festic (2020).

Measures: The interview guides for each life domain contained identical questions on all five dimensions of the measurement model for the significance of algorithmic governance (use, subjective significance, awareness, risk

[9] For the qualitative interviews, the life domains "entertainment" and "fitness and health" were combined in this broader category.

awareness, coping practices; see Figure 3) as well as a few specific questions for each life domain. For investigating the subjective significance assigned to algorithmic-selection applications, we applied a sorting technique (Hasebrink & Hepp, 2017): the interviewees were asked to name and rank non-algorithmic online applications, online applications that rely on algorithmic selection, and offline functional equivalents according to their significance for different life domains. This specifically provided input for the survey questions used for Article IX.

Data Analysis: Each interview was audiotaped and transcribed, and the text files were shared among the team of three researchers to enable iterative coding. The five variables that measure the significance algorithmic governance for everyday life served as the primary guidance for the coding procedure. Since the interviews aimed at revealing hitherto unknown aspects, particularly with regard to the comparison between the life domains, and due to the explorative nature of the study, a thematic coding approach was applied (Gibbs, 2008). Based on the tradition of social phenomenology, we added codes both inductively from the data and deductively from previous theoretical considerations (Fereday & Muir-Cochrane, 2006). During the coding procedure, the research team met regularly to re-evaluate and extend the codebook. Using the qualitative data analysis software MAXQDA, excerpts from the interviews were assigned to the codes. Although there were codes that were specific to certain life domains, the research team aimed at keeping the codebook applicable for all life domains to enable comparisons.

Online survey

Articles IX and X are mainly based on the online survey data that were collected subsequently to the qualitative interviews.

Representative online survey on the significance of algorithmic selection

Data Collection: The data was collected through a representative online survey of Swiss internet users (N = 1,202) aged 16 and over by gender, age, language region, household size, and employment status. The independent market-research company LINK Institute collected the data between 27 November 2018 and 23 January 2019 in three languages (German, French, and Italian). The participants first participated in internet-use tracking (introduced below) and received a link to this online survey at the end of the tracking. We obtained informed consent from all participants of the survey and tracking, and the University of Zurich's ethics review board approved the research design. On average, the survey lasted 30 minutes.

Sample: The LINK Institute recruited the participants from an existing internet panel (LINK Internet panel). The participants received a pecuniary incentive for participating. The initial sample of 1,202 respondents was representative by age, gender, region, household size, and employment status for Swiss internet users aged 16 and over. The response rate was 76%.

Measures: The main sections of the survey were derived from the measurement model presented in Article VII: amount and frequency of use of algorithmic-selection applications (Article III), subjective significance assigned to algorithmic-selection applications (Article IX), user awareness of algorithmic selection as well as awareness of related risks and practices to cope with them (Article X). The survey further included various questions on internet use and attitudes toward the internet in general and algorithms in particular as well as questions on personal background.

Data Analysis: The data was analyzed with the lavaan package in *R* (Rosseel, 2012). The specific data analysis strategies applied for the articles are presented in table 8:

Table 8. Data analysis strategies for the articles based on survey data from the project "The Significance of Algorithmic Selection for Everyday Life: The Case of Switzerland".

Article IX *Subjective significance of algorithmic-selection applications in social groups*	Descriptive statistics Standardized linear regression to test the association between personal background and internet use with the subjective significance assigned to algorithmic-selection applications in different life domains
Article X *Risk awareness and coping practices among self-trackers*	Descriptive statistics Path model to test the relationship between risk awareness and coping practices with freely estimated covariances between the items for risk awareness and coping practices

Source: own.

Internet use tracking

Internet-use tracking and online survey for the same representative sample of Swiss internet users

Data Collection: As described above, the participants were already part of an existing mobile internet-use tracking panel. This panel is actively recruited, which reduces the likelihood of internet users with lower privacy concerns self-selecting themselves into the sample. Since this project aimed at tracking internet use on mobile as well as on desktop/laptop devices, the participants received installation instructions for an existing passive-metering software by Wakoopa for their desktop/laptop devices at the beginning of the field phase. Relying on this software, the tracking data was collected between November 2018 and January 2019.

Sample: Compared to the survey sample, the tracking sample slightly overrepresents internet users aged around 40 and somewhat underrepresents those aged 70 and over. The tracking data was preprocessed before analysis: we excluded site visits with 0 seconds of usage times because these are likely automatic redirects, we excluded participants who were tracked for fewer than thirty days, and extreme outliers. This resulted in a sample of $N_{participants}$ = 923 and $N_{tracked\ events}$ = 13,252,235.

Measures: The collected variables were the URL of a visited webpage (desktop and mobile) or name of a used app (mobile only), duration and time of the visit, device, and operating system used. To illustrate, Tables 9 and 10 depict the structure of the tracking data for desktop/laptop and mobile devices. The data entries were slightly altered to ensure the participants' privacy.

Table 9. Excerpt from tracking data for a desktop device for one participant.

ID	URL	Time	Duration
32359	srf.ch/meteo/europa	04.10.2018 11:10	49
32359	bluewin.ch/de/index.html	04.10.2018 11:12	3
32359	google.ch/search?q=die+zeit&rlz=1C1CHBF_ deCH812CH812&oq=die+zeit&aqs=chrome.. 69i57j0l5.2541j0j4&sourceid=chrome&ie=UTF-8	04.10.2018 11:12	4
32359	zeit.de/index	04.10.2018 11:12	80

Source: own.

Table 10. Excerpt from tracking data for mobile devices for different participants.

ID	App	Time	Duration	Connection	OS	Device
66757	YouTube	07.10.2018 18:09	11	wifi	android	smartphone
61758	Solitaire	07.10.2018 18:39	5	wifi	ios	tablet
67473	WhatsApp Messenger	07.10.2018 18:49	99	3G	android	smartphone
11857	Fitbit	07.10.2018 18:54	5	3G	ios	smartphone

Source: own.

Data Analysis: Analysis of the tracking data for Articles III and X relied on descriptive statistics in *R* and particularly on mean score comparisons between different social groups for Article III.

After describing the applied methodological frameworks, the following sections present the empirical results on socially stratified internet use and selected implications, considering internet services in general and with a specific focus on algorithmic-selection applications.

4 Empirical Results on Socially Stratified Internet Use

This chapter presents the empirical results on internet use from an inequality perspective, taking into account the context of algorithmized digital societies: the first section focuses on a survey-based longitudinal investigation of access and usage divides for the internet in general (Articles I, II). The second section specifically addresses usage divides for selected algorithmic-selection applications drawing on a combination of survey and tracking data (Articles III, X).

4.1 Socially Stratified Internet Use: Longitudinal Perspective

Traditional societal fault lines continue being replicated for internet use vs. non-use

In Switzerland, there were significant increases in those who reported using the internet (2011: 77%, 2019: 92%) and mobile internet (2011: 20%, 2019: 80%) in the past decade. Self-reported overall time spent online doubled (2011: 12.6 hours per week, 2019: 24.9 hours per week) in the same time period. Despite these high diffusion and usage rates, we found that traditional inequalities in internet use and access were still relevant in Switzerland in 2019: higher age, lower educational attainment, unemployment, and lower income were still significant predictors of being an internet user (vs. non-user)[10]. While this is an important finding and underlines the relevance of continuing research on digital inequalities in digital societies, this thesis mainly contributes longitudinal results to digital-inequality research on internet use in general.

Increasing access divides: marginalization of those aged 70+

Focusing on first-level digital divides, Articles I and II revealed that while the negative effects of higher education and higher income on the likelihood of being an internet user remained relatively stable between 2011 and 2019, the negative effect of higher age on the likelihood of being an internet user drastically increased over the period of investigation. In 2019, those in the age groups 50–69 and 70+ were over 20 times and 125 times, respectively, less likely to be internet users compared to the youngest age group (14–29). Overall, the proportion of explained variance in internet use (vs. non-use) based on social background increased between 2011 and 2019, indicating that even this basic access divide is deepening. In terms of the devices used to access the internet, especially a tertiary education and younger age strongly increased the likelihood of using mobile internet. Higher-income internet users also persistently had higher odds of using the internet through mobile devices.

Proxy-use could help bridge access gaps

Given the persisting existence of internet non-users, Article II shed light on this minority. In terms of reasons for internet non-use, a lack of interest or feeling too old to use the internet were the most widespread. More straightforwardly

[10] In the most recent wave of the WIP-CH in 2021 (Latzer et al., 2021), these results were confirmed: for instance, while almost everyone in the general population (96%) reported using the internet, those aged 70+ and those with a low level of educational attainment were the groups with particularly low access rates (75% and 83%, respectively).

inequality-related reasons such as a lack of skills, cost, or lack of physical access decreased in importance between 2011 and 2019 according to the self-reported survey data. Social desirability effects can not completely be ruled out here because similar research in the field recently showed that for a representative sample of the Dutch population, first-level divides shifted from inequalities in physical access to inequalities in material access, indicating the persisting relevance of variables like cost of hardware and software for inequalities in access, skills, uses, and outcomes (van Deursen & van Dijk, 2019).

Results from Article II showed that from 2015 onward, being a proxy-user was significantly associated with an increased willingness to become an internet user in the future.

Persistent usage divides, widening age gaps for internet skills and differentiated use types

For second-level divides, the longitudinal results were similar as for first-level divides: especially higher age was strongly associated with lower internet skills, and this effect increased over time. Inequalities also remained present for more differentiated types of internet use. While there were weaker effects of different sociodemographic variables (e.g., lower income predicted less internet use for information purposes), the starkest differences were found between age groups. We found that especially those aged 50+ consistently used the internet less frequently for all purposes under investigation (information, entertainment, commercial transactions, and communication), and this gap is widening.

Internet experience, skills, and mobile internet use as important variables for bridging usage gaps

Empirical indications for the exacerbation of digital inequalities over time

Additionally to sociodemographic predictors, Article I also included internet experience (i.e., for how many years someone has been using the internet), mobile internet use, and internet skills as predictors of more differentiated types of use. We found significant effects of these variables, which indicates that an advantaged majority in a digital society is using the internet through different devices, adopting more differentiated types of internet usage, and rapidly developing their internet skills. Based on the assumption that the pace and scope of acquiring new knowledge is proportional to already acquired knowledge, this indicates that extant inequalities are being exacerbated.

4.2 Socially Stratified Use of Algorithmic-Selection Applications

Differences between social groups in usage shares and times for algorithmic-selection applications: higher for younger groups

To account for the increasingly algorithmic nature of widely used internet services and use a more updated sample of them, Article III specifically addressed usage divides for six algorithmic-selection applications (Google Search, YouTube, WhatsApp, Instagram, Facebook, 20 Minuten) in 2019. These widespread algorithmic-selection applications were generally more commonly used in younger age groups. We also found that younger age and lower levels of educational attainment predicted spending more time online every day. There were no significant differences between genders. The differences in daily use time between social groups were stark: based on the tracking data, young male internet users, for instance, spent 1 hour and 39 minutes more online on average compared to female internet users aged 70 and over.

Differences between social groups in devices used: lower share of mobile accesses among older internet users

For the entire sample, the results revealed that the majority of time spent on the internet was through mobile devices (*M* = 1.34 hours per day). This tendency was apparent for all age and education groups and for both genders. However, the share of internet use time that was spent on mobile devices was subject to social differences and decreased with higher age. Across all social groups, the proportion of mobile accesses varied across different algorithmic-selection applications: while WhatsApp, Instagram, and 20 Minuten were overwhelmingly used through mobile devices (92–99% mobile accesses), the mobile-desktop/laptop-ratio was relatively balanced for Facebook, Google Search, and YouTube. Results from the tracking data illustrated how these algorithmic-selection applications have become embedded in internet users' everyday lives: the number of tracked usage events showed a steady increase from early in the morning (6am), peaked in the early afternoon (between 4 and 5pm), and decreased to a lower level over the course of the night. This daily usage pattern was similar for all algorithmic-selection applications included in the study.

Algorithmic self-tracking applications for health and fitness gaining popularity in Switzerland, no differences between social groups

Article X addressed the use of algorithmic-selection applications for a specific life domain, namely self-tracking applications for health and fitness. In Switzerland, the proportion of internet users who engage in self-tracking for health has increased: 41% use them in 2021, while only 29% used them in 2017 (results based on WIP-CH; see Latzer et al., 2021). Swiss self-tracking users almost exclusively track their physical activity (steps, training) and related vital data (e.g., heart rate). Based on the tracking data (Article X), the results revealed no noteworthy differences in the frequency of use with regards to gender, age, or education. Accordingly, the very apparent usage divides that we found for the six algorithmic-selection applications included in the analysis of Article III were not found for self-tracking applications.

Referring back to section 4.1, it is important to note that general internet services and algorithmic-selection applications can and should no longer be distinguished when asking questions about internet use: when we ask internet users about their internet use without specifying the platforms that we are referring to, they choose their own reference points and answer based on the services they use in their everyday lives. These services are very likely to be algorithmic given the ongoing transformation processes (especially algorithmization). The tracking data further confirmed this strong weight on algorithmic-selection applications in terms of the high proportion of daily use time that is attributed to them.

Strong and increasing effect of higher age on first- and second-level digital divides

Synthesizing the results from the previous two subsections that addressed inequalities in internet use (4.1) and inequalities in algorithmized internet use (4.2), it becomes apparent that the group of older individuals warrants further attention. The results showed that older people are less likely to use the internet.

Among those who have bridged the access divide, older internet users use the internet less on mobile devices and for different purposes (i.e., information, entertainment, communication, and commerce). They also have lower internet skills, use widespread algorithmic-selection applications less frequently, and spend less time online. There is a general trend toward a widening of all these gaps, indicating an increasing marginalization of older individuals in algorithmized digital societies.

Persisting digital inequalities in terms of internet access, usage types and time, and skills in digitized algorithmized societies

Altogether, these results indicate that inequalities in internet access and use, otherwise described as first- and second-level digital divides, persist and widen over time. Arguably, such inequalities are particularly relevant when they manifest in specific implications for people's everyday lives. The next chapter empirically addresses a set of these implications, which helps paint a more nuanced picture of socially stratified internet use in algorithmized digital societies.

5 Empirical Results on Selected Implications

This chapter summarizes the empirical results on selected implications of socially stratified internet use in algorithmized digital societies. In particular, the first section addresses implications of internet use in general. The second section focuses on algorithmic-selection applications and provides empirical results on the implications of algorithmized internet use on everyday life, conceptualized as the significance of algorithmic governance.

5.1 Implications of Internet Use on Subjective Well-Being

In line with the generalized model presented in chapter 2.4, the first set of articles particularly addressed implications of internet use on subjective well-being. Article V empirically tested the associations of digital participation (operationalized as frequency of engaging in four common activities online), digital potential (operationalized as internet skills required to participate in the information society), and digital perception (operationalized as a feeling of belongingness to the information society) with social well-being as a specific dimension of subjective well-being.

Stronger sense of belonging among internet users, but no difference in social well-being compared to non-users

The results revealed that internet users and non-users did not differ in their social well-being, indicating that merely bridging the access divide does not translate into differences in social well-being. However, internet users did score significantly higher in their digital belongingness to the contemporary information society than non-users.

Perceptions about digital belongingness and potential much more important for social well-being than digital participation behavior

For the subset of internet users in the sample, structural equation modeling revealed the following results: digital participation did not have a direct significant association with social well-being. Digital potential did not have a direct association with social well-being either but was very strongly and positively related with digital participation and belongingness. Digital belongingness was substantively positively associated with social well-being. Digital potential was indirectly significantly positively associated with social well-being via an increase in digital belongingness. Sociodemographic variables did not affect the relationships between these variables of theoretical interest, though they may affect the levels of digital participation, potential, and belongingness. The results show that *perceptions*—how strongly people feel they belong to the contemporary information society and how good they assess their own digital skills to be—are associated with social well-being much more than *behavior* in the sense of manifest digital participation.

Internet use (vs. non-use) and internet skills are relevant inequality-related predictors of digital belongingness

Interpreting these results from an inequality perspective, we found that digital inequalities seem to translate to well-being outcomes indirectly: internet users (compared to non-users) as well as those who assess their digital potential in terms of internet skills as higher are more likely to feel a strong sense of belonging to the contemporary information society. This digital belongingness was strongly and positively associated with social well-being, which is a measure of quality of life in general and is conceptually unrelated to the information society or to effects of internet use.

The explanatory power of the included variables needs to be interpreted in this context. Overall, digital participation, potential, and belongingness accounted for 8% of the variance in social well-being. Rather than concluding that internet-use related variables do not contribute much to social well-being, there are three plausible explanations for this relatively low number:

Model explains little variance in social well-being: is internet use irrelevant for quality of life?

The first interpretation of the small effect size needs to be kept in mind for any theoretical or empirical research on internet use and well-being: naturally, there are many other predictors of well-being that are devoid of any online nature such as physical health (Helliwell & Putnam, 2004; Lissitsa & Chachashvili-Bolotin, 2016). It is straightforward that subjective well-being is correlated with other quality of life measures: there is, for instance, robust evidence that physical health status is associated with (subjective) well-being (for an overview see Ryan & Deci, 2001).

No, because variables not related to internet use naturally matter more for subjective well-being

Second, the model relied on a specific dimension of subjective well-being, namely social well-being. The results do not allow any conclusion of the association of internet use to broader conceptions of subjective well-being, such as expanding the outcome dimension by integrating hedonic and psychological well-being, thereby expanding the understanding to a model of “digital flourishing” (see Keyes, 2014).

…, only a specific dimension of subjective well-being was addressed

Third, the model relied on a narrow definition of internet use. It appears plausible that the close to zero net effect of internet use on well-being is the result of competing mechanisms. To better understand the effect of Internet use on the appraisal of one’s functioning in society, positive and negative effects should be studied in more detail. While the theoretical background for this study suggested that internet use connects individuals to information and communication relevant for their social lives with minimal transaction costs and thus impacts one’s social well-being positively, recent research has also described digital overuse (Gui, Fasoli, & Carradore, 2017) and perceptions of feeling overwhelmed (Stephens et al., 2017) as an emerging social phenomenon. Gui et al. (2017) argued that the overabundance of information and social relationships in everyday life, combined with the social pressure to function digitally, can impair well-being. Privacy concerns are another path through which internet use can negatively affect well-being. Both of these risks are addressed below.

…, and harms (e.g., overuse, privacy violations) and benefits of internet use likely cancel each other out

The second two reasons are directly addressed and partially resolved in Articles IV and VI as they address two specific risks that internet users can be exposed to, namely internet overuse (Article VI) and privacy violations (Article IV).

Article VI focused on perceived digital overuse as one harm associated with internet use. Almost half of Swiss internet users (46%) agreed with at least one of the three statements measuring perceived digital overuse. Accordingly, a substantial share of the online population reported experiencing this concrete harm induced by their everyday internet use.

Perceived digital overuse widespread among Swiss internet users

Results from a linear regression revealed that this perceived digital overuse was negatively associated with subjective well-being. Digital coping skills were positively associated with subjective well-being. Social digital pressure also had a positive, yet weak association with subjective well-being. Overall, the regression model explained 48% of the variance in subjective well-being. The sociodemographic variables as well as amount of internet use as a control variable were not significantly associated with subjective well-being. A subsequently calculated structural equation model confirmed these results: most importantly, perceived digital overuse was substantially negatively associated with subjective well-being. Digital coping skills were equally strongly, but positively associated with subjective well-being. The association of social digital pressure with subjective well-being was positive, but not significant. In contrast to the regression, the structural equation model allowed for path modeling: perceived digital overuse was conceptualized as a mediator. Social digital pressure was strongly and positively associated with perceived digital overuse, digital coping skills were weakly negatively associated with perceived digital overuse. In addition, the covariance between social digital pressure and digital coping skills was positive.

Strong negative association between perceived digital overuse and subjective well-being

Experiencing a harm in form of digital overuse is negatively associated with well-being. These results are in line with the findings from Article V presented above: the amount of internet use in general is not meaningfully related to perceptions about one's quality of life. Rather, personal reflections about this use are important for subjective well-being. Further, the results revealed that not only perceptions, but also skills matter: a techno-deterministic understanding in which the availability or abundance of a technology induces harms is not in line with these empirical results. Rather, the risk of overuse, which has amplified given the changed affordances of the internet, requires a new set of skills from internet users to maintain high subjective well-being despite these risks.

Personal reflections about internet use are more important for well-being than internet use itself

The positive association of social digital pressure and perceived digital overuse reveals that context matters and that those who are expected to use the internet in their daily lives are also more at risk to digital overuse. The positive association of social digital pressure and subjective well-being was not in line with the hypotheses. It is likely that this measure is confounded with a feeling of social belongingness, which was shown to be important for subjective well-being in Article V.

Article IV addressed another specific risk of internet use in everyday life, namely privacy violations. A path model confirmed all hypotheses and revealed the following results: privacy-breach experiences, online privacy attitudes, general internet skills, and amount of internet use were all significantly and positively associated with online privacy protection. Accordingly, having one's privacy violated in the past, feeling that it is more important that only they or those they have authorized know information about their location when they use the internet or the websites they visit, rating one's ability to perform internet-use-related tasks such as opening downloaded files as higher, and engaging in internet applications such as reading the news or messaging more frequently were all positively associated with engaging in online privacy protection such as changing privacy settings, managing cookies, or providing fake information about oneself online more frequently.

Inequalities in privacy protection: higher age has strong direct and indirect effects on less frequent online privacy protection

In terms of social differences, we found that older age had a strong negative effect on internet use and on levels of internet skills. Additionally, women had lower levels of internet use and skills, and those with higher levels of educational attainment also used the internet significantly more. Additionally to these indirect effects of the sociodemographic variables on the frequency of online privacy protection, there were also direct effects: higher age significantly negatively affected online privacy protection. Higher education (vs. lower education) also weakly predicted privacy protection. Gender was not directly associated with the frequency of engaging in privacy-protective behaviors. Altogether, these sociodemographic and internet-use-related variables predicted 40% of the variance in online privacy protection, which is a substantial number. We found that the internet-use related variables (amount of internet use and internet skills) strongly depended on sociodemographic variables. The explained variance in the privacy-related mediator variables was low in comparison.

This section established empirical evidence for the association of digital perceptions on belongingness and overuse with subjective well-being. While overall internet use did not meaningfully relate to well-being, we directly established a relationship between the harm of perceived digital overuse with subjective well-being and indirectly introduced online privacy concerns as a risk of internet use that is likely relevant for the complex relationship between internet use and subjective well-being. The section further revealed that traditional digital inequalities translate into differences in social well-being and online privacy protection, but perceived digital overuse was more common among traditionally advantaged social groups (younger, higher level of educational attainment). While all these results addressed implications of internet use in general, the following section specifically focuses on algorithmic-selection applications.

5.2 Implications of Algorithmized Internet Use on Everyday Life

This section summarizes the results on implications of internet use with a specific focus on algorithmic-selection applications along the five dimensions of the measurement model for algorithmic governance from Article VII, drawing on a method-mix consisting of qualitative interviews, an online survey, and tracking data.

Algorithmic-selection applications widely and frequently used

For **amount and frequency of use**, as was discussed in chapter 4.2, both the survey and tracking data confirmed the starting point of claims on the social power of algorithms: algorithmic-selection applications are used by the majority of the Swiss internet-user population on a daily basis. For instance, 96% of Swiss internet users reported using Google Search. Algorithmic-selection applications further accounted for most of the time spent online: of the 3.53 hours that internet users reported spending online every day on average, the majority (2.45 hours) was spent on only six common algorithmic-selection applications (WhatsApp, Google Search, YouTube, Facebook, Instagram, and 20 Minuten). While using widespread algorithmic-selection applications was more common among younger internet users and this group also spent more time using them, algorithmic-selection applications have become embedded in most internet users' everyday routines. This underlines the relevance of investigating potential implications.

Internet users rarely mention using online services that do not apply algorithmic selection for any life domain

Concerning the dimension of **subjective significance**, the sorting technique for studying cross-media practices applied in the interviews (Hasebrink & Hepp, 2017) resulted in a wide array of activities and online and offline alternatives for algorithmic-selection applications for all life domains (for an overview, see Festic, 2020, p. 8). In the qualitative interviews, we found that the interviewees mentioned a very limited number of online services that do not employ algorithmic selection across all life domains. This observation emphasizes the high importance of algorithmic selection for widely used internet services and corresponds with the finding that the majority of time spent online is spent using algorithmic-selection applications. The qualitative interviews revealed reasons why the subjective significance assigned to certain algorithmic-selection applications was low, e.g., because people perceived personalized recommendations as predatory. Another noteworthy result was that the relevance that the interviewees assigned to offline contacts or their own intuition was unmatched for all life domains.

Algorithmic-selection applications are assigned low significance for all life domains, especially compared with offline alternatives

The results from the quantitative survey confirmed these results on a population level: contrary to common speculations about the importance of algorithmic-selection applications, Swiss internet users assigned much higher significance to offline alternatives such as conversations with friends or family than to algorithmic-selection applications in all life domains. Overall, algorithmic-selection applications were assigned relatively low significance for all life domains, especially compared to offline alternatives, which consistently ranked the highest. It is noteworthy that especially social media—an example of an algorithmic-selection application for which the presumed effects are particularly high—was assigned low significance. Among different functional types of algorithmic-selection applications, Swiss internet users assigned the highest significance to search engines across all life domains.

Differences in subjective significance of algorithmic-selection applications between social groups

Over all five life domains, younger internet users generally assigned higher significance to algorithmic-selection applications (and social media in particular), while higher age was associated with a higher relevance assigned to print media. With a few exceptions, female internet users tended to assign greater relevance to offline activities and lower relevance to algorithmic-selection applications. Those with higher levels of educational attainment generally assigned lower relevance to some algorithmic-selection applications such as social media or YouTube for political and social orientation, entertainment, commercial transactions, and health. Generally, those who used the internet for more hours every day tended to ascribe higher relevance to algorithmic-selection applications and social media in particular.

The qualitative interviews revealed that while the interviewees reported using algorithmic-selection applications in all life domains, the amount and frequency of use did not necessarily correspond with the subjective significance assigned to them. This was confirmed in the survey data: we found that use times of applications do not necessarily correspond with the subjective significance assigned to them for different life domains. This was especially true for social media like Facebook, which was used extensively, but was assigned very low significance for all life domains, including for political and social orientation.

An important finding from the qualitative interviews was that experiences with algorithmic moods, in particular with personalized advertisements across different platforms, appeared to be the main drivers of **awareness of algorithmic selection** and rendered this otherwise opaque process intelligible to users. The in-depth conversations with internet users further provided a few clear indications for low awareness of specific algorithmic modes of operation: it was very apparent that the interviewees lacked knowledge of the appropriate terminology to describe their everyday experiences with algorithmic selection. For instance, although the automated nature is a crucial element of algorithmic selection, an anthropomorphizing of algorithmic selection was widespread; the interviewees tended to discuss these processes as if they talked about humans. The very vague knowledge about how algorithmic selection works was accompanied by substantial unease toward these processes. Further, the interviewees tended to express high levels of awareness about their unawareness of algorithmic selection. The awareness of algorithmic selection was higher for life domains in which there is a lot of media coverage on algorithms (e.g., news) than for entertainment, health, socializing, or commercial applications. The knowledge of specific modes of operation was very vague and went hand in hand with feelings of resignation.

The survey data confirmed that the Swiss internet-user population generally has little awareness of how the algorithmic-selection applications that are deeply embedded in their everyday routines function. Ignorance and a high degree of uncertainty characterized the public's knowledge about algorithmic processes such as the curation of news feeds or the personalization of search results. To illustrate this, the survey revealed that only 19% of Swiss internet users knew for certain that it is not individual Facebook employees who curate news feeds. A third (33%) of Swiss internet users believed that Google searches for the same search terms always lead to the same results for everyone (14%) or were uncertain about the accuracy of this statement (19%). In particular, the survey results revealed that a noteworthy share of Swiss internet users reported a high degree of uncertainty about how algorithmic-selection applications function, which is arguable a necessary prerequisite for a skillful and autonomous use of these applications.

Swiss internet users know little about how algorithmic-selection applications work

For **risk awareness**, the qualitative interviews revealed that the interviewees were most aware and concerned about potential threats to their privacy online. The diminishing variety of content – a risk that has been theoretically derived and regarded as important – was perceived as not important by users – partly due to their diverse media repertoires and comparatively low subjective significance they assigned to algorithmic-selection applications compared to online and offline alternatives in all life domains. We further found that, in line with the finding on low awareness of algorithmic selection, the interviewees were not able to distinguish between risks from internet use in general and risks that are specifically induced by algorithmic selection. The interviews also provided indications for internet overuse and related sentiments of an overabundance of online content to algorithmic selection: the interviewees blamed the personalization of online content as well as autoplay settings for their digital overuse. The interviews revealed that when discussing the sharing of self-tracking data for health, the interviewees were particularly concerned about concrete risks like rising healthcare costs.

Uncertainty and unease dominant among interviewees when asked about implications of algorithmic selection

On a population level, a diffuse awareness of potential risks (e.g., privacy breaches, overuse) was common among the survey respondents and many were left with a feeling of resignation. For instance, a third (33%) of Swiss internet users reported often thinking about spending to much time online and another 61% think about this risk at least rarely. The violation of individual privacy through the collection of large amounts of data by online services is a risk that 95% of internet users think about at least rarely. While there was no clear trend between age groups for the risk of danger of one-sided or distorted information, overuse was a risk that younger internet users thought about significantly more often. For all other risks (e.g., misinformation, privacy violations, deception through bots), risk awareness was higher for older groups of the Swiss internet-user population.

The interviewees mentioned an array of **coping practices** (for an overview, see Festic, 2020, p. 12) to deal with these risks. They reported applying most practices when it comes to information consumption and did so most frequently in this life domain. They were inclined to apply practices where they felt that a lot was at stake, especially in light of diffuse fears of privacy violations. The results from the qualitative interviews were used as input for the development of questions and answer scales for the representative online survey. For coping practices, we categorized the practices mentioned in the interviews into three groups: physical or cognitive (e.g., conscious use, using offline information to verify online information), general digital (e.g., deleting cookies, using ad-blockers) or platform-specific digital (e.g., adjusting privacy settings on YouTube, consciously using hashtags on Instagram).

Coping practices rarely applied by Swiss internet users

In terms of coping practices, we found in the survey that despite a widespread sense of helplessness and loss of control, only small shares of Swiss internet users actively engaged in practices to cope with risks. For cognitive coping practices we found that while seven out of ten (70%) Swiss internet users ignore automated personalized recommendations on the internet at least frequently, only 13% frequently try to use the internet less. This is although awareness about this risk is very widespread. Applying cognitive coping practices was more common for older internet users and those with higher educational attainment. For digital coping practices, we found that half of internet users (50%) at least frequently deny certain rights to apps on their mobile devices and a third (32%) report changing their privacy settings at least frequently. These digital coping practices were applied more often by younger and higher-educated internet users.

Self-trackers: low risk awareness and rare application of coping practices

For health and fitness self-tracking, a specific type of algorithmic-selection application, the results from Article X revealed that Swiss self-trackers' awareness of the four surveyed risks was low. Self-trackers were only partially familiar with facets of algorithmic functioning and with a narrow range of associated risks. Merely 8% of Swiss self-trackers agreed or completely agreed that they used their tracking device too much and 21% were concerned that they do not know how their application calculates health results. About a quarter to a third (27% and 30%, respectively) agreed or completely agreed that they were uncertain about the accuracy of their device's measurements and that they were concerned about what happens with their data. Coping practices were also used only rarely. About a quarter (24%) check the measurements of their devices at least sometimes and 34% consciously refraining from using their devices at least sometimes. The most common practice was reflecting on the results which 71% of self-trackers reported engaging in at least sometimes.

The application of coping practices was only weakly related with the awareness of associated risks among self-trackers. The model was not influenced by gender and education, and age only weakly negatively affected the awareness of one risk (measurement inaccuracy). For the entire list of risks, we found that a higher awareness of algorithmic selection significantly corelated with risk awareness (Latzer et al., 2020, p. 11).

Self-trackers with higher risk awareness are not those who apply coping practices more often

Article X also shed light on the underlying incentive systems of sharing self-tracked data; against an unspecified financial benefit, a substantial share of Swiss self-trackers (43%) reported to be willing to share their potentially sensitive health and fitness data with their insurance company for an unspecified financial benefit despite having been made aware of potential risks that this could entail. Older people and females were slightly less willing to share this but other than that the willingness was relatively uniformly distributed in the self-tracking population

Both of these results—the weak relationship between risk awareness and coping practices as well as the high willingness to share personal self-tracking data for a financial benefit—point to a "calculus" logic present among self-trackers: although they are moderately aware of risks that can be associated with their practice, they still engage in the automatic collection and analysis of their health or fitness data and do not engage in coping practices frequently.

Self-trackers likely apply a calculus logic when deciding how to respond to perceived risks of their practice

Comprehensive descriptive results on internet use in general[11] and with a specific focus on algorithmic selection[12] as well as on a wide variety of implications are available in multiple thematic project reports that the author of this thesis contributed to.

This concludes the presentation of selected empirical results from the articles included in this cumulative thesis. The discussion section below will synthesize these results, situate them in a broader context, discuss the limitations of this thesis, and provide directions for further research on internet use and implications in the context of algorithmized digital societies.

[11] https://mediachange.ch/research/wip-ch-2021/
[12] https://mediachange.ch/research/algosig/

6 Discussion

This discussion will proceed by summarizing and synthesizing the empirical results on internet use and implications in algorithmized digital societies, deriving methodological conclusions, presenting limitations, and providing a brief outlook for future research in the field.

6.1 Synthesizing the Results

To begin with, this thesis empirically confirmed that internet use in a myriad of its facets is highly unequally distributed in digital societies. All articles in this thesis addressed the ongoing digitization from a digital-inequality perspective. This thesis contributed hitherto lacking representative empirical results on the evolution of digital inequalities, taking into account the context of an algorithmized digital society, and used a combination of survey and tracking data to establish these results. First and foremost, the results from Article I and Article II provided robust empirical evidence for persistent digital divides for internet access, different use types, and internet skills. Article III confirmed the presence of these divides for user shares of and time spent on algorithmic-selection applications.

Digital inequalities in access and use widen and deepen

Adding a hitherto largely neglected longitudinal perspective, Article I and Article II further showed that these gaps are not resolving themselves, but rather widening. These results support theoretical assumptions on the stratification of internet use and the deepening of digital divides (van Dijk, 2020), and reject the normalization hypothesis, which indicates a resolution of divides over time. The ITU (2018, p. 3) agrees that "digital inequalities are not a generational thing and will persist into the future". The results emphasize that these inequalities remain relevant in digital societies. In terms of bridging these gaps, Article II revealed that being a proxy-user is positively associated with likelihood of wanting to become internet user in the future.

Digital inequalities translate to well-being outcomes

Additionally to these first- and second-level divides, this thesis also addressed implications of internet use from an inequality perspective (third-level divides). Combining digital-inequality literature with well-being theory, subjective well-being was established as a relevant outcome measure and empirical assessments of the relationship between internet-use related variables with different subjective well-being dimensions as outcomes were provided. Article V and Article VI showed that differences in internet usage and especially one's perceptions thereof can have implications for subjective well-being. A stronger feeling of belongingness to the information society was associated with higher levels of social well-being, indicating real-life benefits for those who have bridged basic access or use gaps. Relying on an integrated framework of co-occurring harms and benefits of internet use that can ultimately affect well-being, this thesis also provided results on harms of internet use: Article VI provided a more differentiated view on well-being outcomes of a specific type of internet use—perceived digital overuse—for which it is no longer necessarily the traditionally disadvantaged groups, but rather younger and more highly educated members of a society, who feel most pressured and suffer most from negative effects on their subjective well-being by perceived digital overuse. In terms of inequalities in the exposure to certain risks and in how people deal with them, Article IV further showed that especially those who use the internet rarely, have poor internet skills, and are of older age engaged less in online privacy protection and may therefore be especially vulnerable to experiencing harmful outcomes to their privacy online. The significance of algorithmic governance was also investigated through the lens of digital inequalities. The results revealed that there are multiple variables related to internet use in algorithmized digital societies (e.g., awareness of algorithmic selection, awareness of risks, application of coping practices) that are subject to digital inequalities and that warrant further attention in terms of ensuring equal opportunities and access for all social groups.

Situating results on implications of internet use on well-being in current literature

Another prominently debated discussion that this thesis contributes to revolves around implications of internet use on well-being. Overall, based on the results of this thesis, it can be constated that "the internet" certainly does not *increase* or *decrease* personal well-being across the board, in a meaningful and measurable way, and long-term. However, this thesis does—in line with extant research in the field—provide empirical indications that certain types of internet use or particularly internet users' perceptions thereof can be strongly associated with different levels of subjective well-being. Since the publication of the articles included in this cumulative thesis that address well-being outcomes of internet use (Articles V and VI), more research has emerged that investigates internet use and well-being in a nuanced way. For instance, Schemer and colleagues (2021) assessed the effect of the frequency of internet and social media use on depression and life satisfaction. They found that neither the frequency of internet use in general nor the frequency of using social media were meaningfully associated with subjective well-being based on panel data collected in five waves over nine years. This was true both for between-person as well as within-person variance. To date, this is one of the most recent studies that takes into account the theoretical and methodological advances in the field, and it confirms the results of Article V for a similar definition of internet use, but a different operationalization of subjective well-being. In their "umbrella review" of 25 reviews (composed of meta-analyses, systematic reviews, and narrative reviews to equal parts), Valkenburg et al. (2021) confirmed that the associations of social media use and mental health among adolescents were mostly interpreted as "weak" or "inconsistent", but they emphasize that very similar effect sizes—sometimes even for the same data set worked on by different authors—were interpreted as "substantial". While some of these inconsistencies—as they argue—could be explained by varying definitions and operationalizations of social-media use and mental health, the authors see the main reason for this in differential susceptibilities to media effects between people (Valkenburg & Peter, 2013) and propose person-specific approaches to measuring effects of internet use on well-being: drawing on a person-specific approach, a recent study (Valkenburg et al., 2022) revealed that social media browsing led to negative well-being outcomes for some adolescents (because they felt envy), to positive well-being outcomes for another group (because they enjoyed their browsing activity), and had no significant effect on well-being for the rest (Valkenburg et al., 2022). This finding provides indications for an additional explanation of diverging empirical results for the relationship between internet use and well-being that goes beyond co-occurring harms and benefits: the effect likely differs between individuals and effects with different directions cancel each other out in population-wide empirical studies (e.g., Articles V and VI).

Altogether, digital well-being provides a helpful framework for studying internet use and implications. The results from both the qualitative interviews (Article VIII) and the online survey (Article IX) revealed that personal well-being was most indicative of personal health compared with any other online or offline alternative. Given the difficulties in measurement and that effect sizes on well-being are likely small, especially when considering broader conceptions of internet use, this does not mean that well-being should be included as a dependent variable in all models measuring implications of internet use. This thesis rather suggests that including well-being outcomes implicitly when researching internet use and interpreting results is helpful. Understanding digital well-being as a dynamic construct (Vanden Abeele, 2021) and acknowledging that "people [can] live a good life both thanks to and despite the constant use of digital media" (Büchi, 2021, p. 1) provides a fruitful conceptualization for further studies on diverse implications of internet use on well-being.

Significance of algorithmic governance is context-dependent (e.g., in terms of applications, life domains)

This thesis presented a myriad of facets through which algorithmic governance is constituted in everyday life. It provides a nuanced view situated between initially fatalistic risk assessments that were purely derived from theoretical considerations on the one hand and trivializing judgements of the power that algorithms can exert over everyday life on the other hand. This was possible by placing everyday internet users as responsible actors who can exert agency and their perceptions at the center.

Internet users' role in coping with risks of internet use

Given the strong debate on risks of (algorithmized) internet use, questions about appropriate measures to mitigate these risks arise. While deriving evidence-based input for policy decisions was not the main motivation for the articles included in this dissertation, this thesis offers a couple of specific contributions to this topic. The governance of everyday life *by* the co-evolving processes of datafication, algorithmization, and platformization is in a constant interplay with the governance *of* this trifold digitization process, entailing questions on the need, options, and actual policy reactions to shape and control algorithms and their uses (Latzer, 2021). Since the focus of this thesis is on individual internet users, one pressing question in terms of the governance of online services is the role of individuals and their self-help behavior as a governance mode. Article IV revealed that internet users engage in privacy protective behaviors to some extent—though this self-help is subject to inequalities: younger internet users engage in privacy protective behaviors significantly more frequently. Similarly, Article VI illustrated that individuals have coping skills and can take an active role in dealing with the risk of digital overuse they are exposed to. The role of internet skills in dealing with internet-use related risks is well-established (see e.g., Büchi et al., 2017): to use the internet in a meaningful way that is also beneficial for or at least not harmful to one's well-being, a basic understanding of the services we use is required. This has become more difficult—and probably subject to more severe inequalities—since the emergence of opaque algorithmic-selection applications. The coping practices against algorithmic risks revealed in Article VIII and specifically for self-tracking applications in Article X can be understood as self-help behavior. While privacy protective behavior (Article IV) appeared to be highly stratified across traditional societal fault lines, this was not as pronounced for coping practices against general algorithmic risks (see Latzer et al., 2020). For self-tracking, there were no such differences between social groups and we also found that the application of these coping practices did not appear to be meaningfully explained by the awareness of risks that these practices would be directed against.

What role self-help behavior can play in a broader governance mix consisting of state, corporate, self-regulatory, and self-help measures is a question this thesis cannot answer—this would require an in-depth analysis of all governance modes that are in place and entails questions of responsibilities and accountability. One important qualifying factor to consider when assessing the relevance of self-help governance measures—be it targeted against risks to online privacy, algorithmic risks in general, or risks that can be associated with self-tracking applications for health—is how effective they can be, even if applied regularly and in a skillful way. Especially owing to the opacity of algorithmic-selection applications, the efficacy of these coping practices remains unclear and it is likely that they are relatively toothless. It remains an open research question how well individual internet users can realistically exert agency against the data-grabbing infrastructures (Fraser & Kitchin, 2017) and all implications of being exposed to these strategies by powerful companies and nation states.

Unless they gather significant momentum across society, individual actions will likely not change the wide application of data-grabbing practices by platforms much like placing the weekly shop in reusable bags or taking the train instead of the plane will probably not reverse climate change (Wagner, 2021). This argument is amplified by the mere observation that not participating—not using the internet—is not an option: merely "living" in a algorithmized digital society means that the arguably most effective form of protection from risks of internet use—not using the internet altogether or not using certain services[13]—is not viable because the digitization of everyday life is too profound: the benefits tied to online participation are necessary to participate in everyday life.

Who are the "disadvantaged" in algorithmized digital societies?

Altogether, this cumulative thesis provides indications that it is necessary to readdress whom we consider to be the disadvantaged social groups in algorithmized digital societies. Traditional research on digital inequalities departed from the initially relatively uncontested assumption that internet use (compared to internet non-use), more internet use (compared to less internet use), and skilled internet use (compared to less skilled internet use) is generally preferable. Accordingly, traditionally disadvantaged members of social groups (i.e., female, older, lower-income individuals with lower levels of educational attainment) were found to engage less in the digital society and were therefore outlined as the disadvantaged groups. The fast diffusion of the internet, its algorithmization, and changed affordances of the services used, paired with advancements in the field of digital-inequality research, has resulted in a more nuanced theoretical understanding of digital inequalities that accounts for co-occurring and inseparable harms and benefits of internet use (see e.g., Blank & Lutz, 2018). Higher social status was initially believed to be a solely positive predictor of digital engagement on all levels (access, use, skills, benefits, etc.). The results of this thesis confirmed that higher social status remains a predictor of internet use in terms of access, frequency, amount, different types of use, and skills (Articles I, II, III). This results in increased exposure to digital content and a stronger dependence on internet services that likely employ algorithmic selection; this is, for instance, reflected in the finding from Article VIII that younger internet users and those who spend more time online assign a higher relevance to algorithmic-selection applications. In line with extant research (Abril, 2016; Gottfried et al., 2016; Shearer, 2018; Shearer & Matsa, 2018; Smith, 2016), they appear to be integrating algorithmic-selection applications more profoundly into their everyday lives. Accordingly, while this may lead to advantages, it also means that they are more likely to be exposed to risks that can be associated with using algorithmic-selection applications and experience harms in terms of overuse (Article VI) or privacy violations (Article IV). In algorithmized digital societies, the narrative of digital inequalities appears to be shifting from scarcity as a threat to overabundance. It is important to note that traditionally advantaged people have higher internet skills and therefore are also more likely to be able to cope with these risks and engage in coping practices. However, it is unclear whether this is enough: Article VI provides indications that the effect of perceived digital

[13] It must be noted that even strict internet non-use can not protect internet users from potential harms to, for instance, their online privacy in a networked world (see e.g., boyd & Crawford, 2012; Xu & Jia, 2015).

overuse on well-being is still negative even when controlled for skills. This raises questions about whether the term “inequalities” still applies to these social differences: risks like digital overuse seem to be specific to groups who are traditionally understood as advantaged in societies and who use the internet more heavily.

Inseparability of the internet and algorithms

It is important to note that while some articles in this thesis explicitly studied algorithmic-selection applications, algorithmic selection is equally relevant for all other articles included in this dissertation: the algorithmization (Latzer, 2013) of the internet was rapid and has gone so far that most of the internet services that everyday internet users engage with rely on algorithmic selection to some capacity. Merely embedding a search function or placing personalized ads transforms a website into an algorithmic-selection application. A key takeaway, therefore, is that “the internet” nowadays essentially equates “algorithmic-selection applications”. Accordingly, internet studies and critical algorithm studies can no longer be claimed to be separate fields for they are inevitably intertwined: critical algorithm studies can be viewed as a natural development of internet studies, which takes into account ongoing transformation process in the object of study. Similarly to how the line between online and offline behaviors has become blurry because so many everyday activities are digitally mediated, the “internet” and algorithmic-selection applications should no longer be conceptually separated. This observation leads to the finding that the concept of algorithmic governance is well-suited to address implications of internet use in general from an institutional governance perspective. Referring back to the integrated model for co-occurring risks and opportunities of internet use that this thesis proposed (see Figure 4), it becomes apparent that while the highlighting of the dimensions of algorithmic governance in the grey rectangle was helpful for systematizing the contributions of this thesis, this separation is conceptually not required. Measures on using widespread internet services, internet skills, or risks related to internet use are fundamentally shaped by algorithmic selection, indicating that the five variables measuring the significance of algorithmic governance in everyday life can be extended to understanding internet use and its implications from a governance perspective.

From a methodological standpoint, this thesis presented and executed an innovative mixed-methods approach. The methodological conclusions that can be derived from this cumulative thesis are presented in the following section.

6.2 Methodological Conclusions

As part of this thesis, a few methodological conclusions resulted from the empirical, mixed-methods engagement with socially stratified internet use and selected implications

From a methodological perspective, this thesis engages with a relatively novel method of data collection and analysis for the field of internet studies. The first set of conclusions particularly concerns this tracking data.

Costly method of data collection

Compared to qualitative-interview or survey data, the tracking data that a set of articles included in this thesis relied on was costly to collect. This is especially the case when the tracking data is collected over a long timespan, for a representative sample, and for multiple devices, yet these are necessary prerequisites for a valid measurement of internet use in algorithmized digital societies. The predominance of mobile over desktop internet use in Switzerland provides indications for the relevance of gathering behavioral data on internet use through mobile devices including apps. The main drivers of these costs are recruiting participants and building the necessary infrastructure for collecting and storing the data.

High-volume tracking data: implications for handling and interpretation of results

To illustrate this last point, it can be noted that the tracking data that was accumulated within the project "The significance of algorithmic selection for everyday life: the case of Switzerland" and enriched through a web-crawling resulted in roughly 120 terabytes of data. In contrast, a data set from a representative survey only has a negligible size and can easily be stored locally and for a long period of time as well as shared widely. Additionally to these straightforward implications, the volume of the collected data also affects the soundness of the theoretical hypotheses that are required to empirically test social phenomena: tracking data can typically be categorized as big data, which has the property that "effects" are much more likely to be significant and correlations and patterns emerge that were not ex ante expected. While this can sometimes be due to spurious correlations where a third variable explains an otherwise nonsensical correlation between two variables such as between iPhone sales and deaths caused by falls down stairs (see e.g., Vigen, 2015), this is not always the reason for such effects (Latzer, 2021; Wiegerling, 2020). While it can easily happen that in big data, significant correlations are found that are not meaningful, interpreting them as causal effects is even worse. Especially when dealing with implications of internet use on well-being, this can lead to dangerous claims about how internet use "affects" mental health of children, for instance. Such risk assessments could be widely shared without control and context. This emphasizes the need for sound theoretical hypotheses that can lead to the causal interpretation of effects (Baecker, 2013). One way to ensure theoretical foundations for studies relying on large data sets is to preregister them, especially when they aim at confirmatory testing of hypotheses (see e.g., Center for Open Science, 2021).

Even answering basic questions requires substantial preprocessing of the data

Not only the data collection, but also the data analysis process tends to be more complex for tracking data compared to survey data consisting of questions with closed answer categories. A large amount of tracking data has to be analyzed using syntax-based analysis methods. This requires sufficient programming skills and potentially interdisciplinary collaborations with data or computer scientists. The tracking data that this thesis draws on was significantly more messy than the survey data and required more cleaning and preprocessing. Article X provided an example for how approaching a straightforward, empirical question such as “what are the most-used self-tracking applications in Switzerland?” from a computational perspective can be helpful, but requires effort: since the tracking data was initially raw in the sense that any uses of self-tracking applications were monitored and stored in the dataset, but they were not categorized. To detect all usage events that referred to self-tracking applications, we first compiled a comprehensive list of almost 700 self-tracking applications for health and fitness relying on a systematic search in the Apple App Store, the Google Playstore, and the Microsoft Store. In a next step, we automatically searched the entire tracking dataset for all occurrences of these application names. These cases were then extracted from the dataset since they represented uses of self-tracking applications. We used this to get descriptive results on the self-tracking applications used. This is an example for preprocessing that is not necessary when trying to get descriptive results on the use of self-tracking applications with survey data. It also has to be noted that this analysis process is difficult to standardize because it depends heavily on the raw data as well as the research question. For instance, the list of self-tracking applications that we included in our search naturally had to take into account the devices on which the participants were tracked. If the tracking only included desktop devices or mobile devices using other operating systems, the list would have to be adapted accordingly. Investigating internet use in this phase of digitization (Latzer, 2021) requires an investigation of mobile internet use. Not taking it into account is likely to provide highly skewed results because the bulk of internet use is neglected.

However, this openness in the tracking data also has advantages: when trying to acquire an encompassing understanding of what self-tracking applications are used in Switzerland drawing on survey data, the list of possible answer categories (i.e., self-tracking applications) to include is constrained (e.g., due to the survey duration). This could lead to important applications being falsely disregarded. This could also, for instance, lead to the problem that specific applications that are heavily used from a population minority are not included. This advantage is similar in qualitative data, but tracking data allows to expand it to representative, population-level data.

The error-proneness in the stage of analyzing tracking is further amplified by the fact that certain applications or websites can have very different names in the dataset, for instance due to differences in the devices used as well as in language or privacy settings. While the field of computational social science is growing, standards for the collection and analysis of data such as tracking data are only just emerging (see e.g., Engel et al., 2021) and it will presumably take some time for methods that can be described as computational to be established so that tests of validity and reliability, for instance, are available.

Method of data collection impacts results: basic questions on internet use need to be readdressed

While the results in Article III confirm extant differences in the extent of internet use between social groups, the article also indicates meaningful differences in results on use time depending on the data collection method (survey vs. internet use tracking). The answer to the seemingly simple question of how much time is spent online every day varied greatly depending on the mode of data collection: the self-reports were consistently higher in all age and educational groups and across both genders. The mean time that internet users spent online was 1.70 hours based on the tracking data and 3.45 hours based on the survey data, and these measures were only weakly correlated. This emphasizes the need for future research on these methodological implications for the extant body of research on media use, media change, and internet studies.

In addition to these conclusions concerning behavioral internet-use tracking data, this thesis also illustrated the value of drawing on a mixed-methods approach.

Answering the same question with different methods leads to different answers

While Article III revealed bold indications for how method matters, Articles VIII, IX and X allow more subtle indications for the relevance of the chosen methods. The articles share the same basic research interest; empirically assessing the significance of algorithmic selection for everyday life. However, the contributions that the different methods of data collection and analysis can provide differ profoundly (see Table 3).

The value of mixed-methods approaches for internet and critical-algorithm studies

When we recognize the importance of users' perceptions (which this thesis has provided indications for), this means that periodical qualitative interview are necessary for the evolution of any subfield of internet studies. This is necessary because the subject of research (i.e., the internet) evolves so fast and any validated survey instrument (e.g., for internet skills) requires a constant update and reassessment whether this is still relevant because the services people use, their affordances, the devices, etc. are subject to constant and profound transformation processes. Further, it can not be stressed enough that additionally to choosing a suitable methodological design in light of a research question, it is highly relevant to take into account the applied methodology when discussing the scope of potential results as well as the actual results. For a valid empirical measurement of internet use, it is important to combine methods because such a combination allows certain methods to cancel the limitations of others out. When deciding on a methodological design and empirically investigating social phenomena, research always has to rely on an imperfect representation of reality. This dissertation offers indications for what tradeoffs are better than others.

As has been stated and can be seen in Table 3, some empirical articles included in this thesis rely on internet-use tracking data. This can be viewed as a computational method, which is in line with a larger trend toward such approaches in empirical communication-science research. In communication science and many related fields, there is a trend toward answering old and new research questions applying so-called "computational" methods. While the definition is unclear and a matter of on-going debates, automated content analyses, tracking data, or simulations are often subsumed under this category. Although "computational communication science is embraced by many as a fruitful methodological approach to studying communication in the digital era", there is a lack of theoretical advances that provide the necessary background for these new methods of data collection and analysis (Waldherr et al., 2021).

Computational methods (e.g., tracking) should complement, not substitute more traditional approaches

According to Waldherr et al. (2021), complexity theories are especially helpful for addressing topics that are popularly investigated through computational methods because these topics have the characteristics that complex systems have: multi-level dynamics and interdependencies. These considerations provide sound reasoning for the fact that contrary to current debates in the field, computational methods are not always the superior choice when studying internet use and implications. Rather, a careful consideration of different methodological approaches is required. Computational methods are a helpful addition to the extant repertoire of methodological approaches in internet studies. Implementing them well means being clear about their definition, understanding and addressing limitations, and placing an emphasis on the required theoretical basis.

In addition to pursuing mixed-methods approaches, openly sharing empirical data and/or the analysis process (both for qualitative and quantitative data) is a crucial way to mitigate some of the issues mentioned above. While privacy and ethical reasons can provide plausible reasoning for not sharing original data, there is no valid reason to the best of the author's knowledge for not making the code used for both preprocessing as well as analyzing the data openly available. This should be required to demonstrate and maintain credibility.

Privacy and ethical considerations important when handling personal data

Since every method of data collection applied in this cumulative thesis relies on personal data, a discussion of an ethical and lawful handling of the data that respects and protects the respondents' or participants' privacy is paramount. During the duration of the internet-use tracking, essentially all internet activities of the participants were monitored. This presents a stark difference to survey or interview data where the scope of the answers that the respondents share is constrained by the questionnaire or the respondents' willingness to share. When participating in a tracking study, the individuals do not have the same agency over their data during the collection process. Accordingly, it is important to address before the study begins what potentially undesirable contents (illegal, disturbing content) could be found and how this will be dealt with.

People can provide self-reported data about concepts they are unaware of

This thesis empirically deals with different concepts and mechanisms that people are not necessarily aware of. This may be true to some extent for most research relying on self-reports; for latent constructs, it is common for respondents to be unaware of the construct that different items that they are responding to are jointly measuring. This unawareness applies to the concept of algorithmic selection as the core functionality of widespread internet services. Empirically investigating the use of algorithmic-selection applications and implications entails the specific challenge of having to talk to respondents about a concept they may not understand or even know of. In the qualitative interviews as well as in the online survey, a solution to this problem was talking to the respondents about specific services they use. Further, specific functions of algorithmic-selection applications (e.g., recommendation, search; see Latzer et al., 2016) were much more accessible and comprehensible for the interviewees since they encounter these manifestations of algorithmic selection in their everyday internet use and accordingly feel capable of voicing opinions about them. Achieving this level of detail in the conversations with internet users allowed us to gather results that the perceptions of very similar types of algorithmic-selection applications differed between life domains (e.g., recommendations were perceived as helpful for entertainment, but as annoying for commercial transactions). Choosing a practice-related approach to everyday life further allowed us to gather information about the use of algorithmic-selection applications embedded in very mundane activities. Further, situating the use of algorithmic-selection applications within the space and time of everyday life proved very fruitful for an assessment of different types of uses and their context-dependent implications. A similar rationale was applied when gathering self-reports about risk awareness: while people may not be aware of certain risks, it is the task of researchers to theoretically derive a list of risks, make them salient to the respondents, and ask about them.

6.3 Limitations

For the interpretation of the overarching results of this cumulative thesis, there are a couple of limitations to consider.

User perspective on implications of internet use is important, but only part of the puzzle

In terms of the goal of a realistic assessment of the risks associated with using the internet in an algorithmized digital society, this thesis provides empirical insights from a user perspective, which are to be understood as complementary to results that apply other approaches. Certain developments can be seen as risky from a societal perspective without individuals realizing it. Also, certain risks can be a problem on an aggregate level, but are not as problematic for individuals. In this context, the list of risks that can be associated with using the internet and algorithmic-selection applications in particular is certainly not exhaustive. Depending on different use-contexts, future research should take others into consideration, too.

Correlation vs. causality

The models that establish a relationship between different variables, e.g., between internet use and well-being (Article V, Article VI) or between risk awareness and coping strategies (Article X) all rely on cross-sectional data. While this data provides a solid empirical basis for establishing correlations and we can derive indications for effect directions based on sound theoretical hypotheses, omitted-variable bias or reverse causality cannot be ruled out. The latter is particularly relevant for the articles concerned with the relationship between internet use and well-being: while the articles included in this thesis considered differences in internet use to be predictive of well-being outcomes, the reverse relationship has also been addressed in extant research (Kim et al., 2009). Given the complex dynamic between internet use and well-being, a mutual shaping of both concepts is most likely. The reliance on cross-sectional data is less of an issue for the inequality-related articles investigating effects of sociodemographic variables on internet use and implications because the sociodemographic variables can be viewed as exogenous. However, even for such studies, panel data would be helpful to investigate feedback effects such as potential dynamics of social upward mobility over time prompted by internet use (see Eynon et al., 2018 for an example). To take this into account, a conscious effort was made in this thesis to reflect this general limitation in the language used to describe the empirical results.

Limitations of the specific methods

Additionally, the different methodological approaches that jointly constitute the empirical part of this cumulative thesis have specific limitations. For instance, the tracking software allowed the participants of the tracking study to temporarily disable the tracking at any time, which is important for research ethical reasons. While there were indications for that happening rarely (e.g., widespread pornographic video consumption which is arguably a type of internet use that people would be more likely to disable the tracking for due to social desirability effects), it can not be ruled out that this possibility affected the results. Further, the tracking data was collected on the participants' private devices, but it is likely that some of them also used their devices for work and that this section of their internet use is also included in the tracking data. Internet use for work was, however, explicitly included for the measures on overall internet use time in the survey. In order to gather an accurate approximation of internet use, a constant observational tracking in natural internet usage situations embedded in the participants' everyday life is required. Effects on the participants' behavior from the participation in this study are likely negligible because once the software is installed, it does not interfere with the participants' online engagement anymore. A comprehensive discussion of other limitations that are specific to certain approaches can be found in the respective articles.

This cumulative thesis illustrated implications of personalized algorithmic selection and the importance of investigating this topic from a social-sciences perspective. These approaches have in common that the actual extent to which content that people consume in their everyday lives is personalized remains unknown or hypothesized. However, the degree of personalization across different kinds of algorithmic-selection applications likely varies greatly. While this cumulative thesis offered a nuanced understanding of algorithmic-selection applications in terms of different functional types, different life domains, and a platform-centered approach, it can not account for the likely variance regarding the actual extent to which online content is subject to algorithmic selection. A project that draws on the same data set as this thesis, but is still work in progress at the time of publication, attempts to contribute to filling this gap (Festic et al., 2020) by crawling the websites that the internet users accessed in four user configurations (with/without ad-blockers, with/without private browsing mode) and comparing the output in order to quantify the extent of personalized content—one key example for algorithmically selected output— that Swiss internet users are exposed to.

6.4 Directions for Further Research

The previous sections in this discussion chapter already included various suggestions for future research on internet use and its implications in the context of algorithmized digital societies. This section explicitly highlights those that appear particularly relevant to the author of this thesis.

First, one of the main takeaways of this thesis is that individual associations with personal well-being are highly varied and depend, among other things, on the definition of two key concepts, namely internet use and well-being. Emerging empirical approaches in the field are trying to account for the strong context-dependence of well-being outcomes, for instance by relying on mobile experience sampling (Beyens et al., 2020). Commonly used cross-sectional designs can not sufficiently account for the complexity of the relationship between internet use and well-being. To understand the heterogeneity of internet-use effects on well-being, future research should focuses on specific use contexts and move toward qualitative research to unveil hitherto unknown mechanisms or particularly vulnerable groups, experimental or longitudinal designs to uncover causal effects, and a combination of internet-use tracking and experience sampling methods (Myin-Germeys et al., 2021) to gather in-situ data on digital well-being. This thesis discussed the advantages of tracking data in the context of internet use on mobile or desktop devices. However, given the convergence of the communications sector, this method of data collection will increasingly also be relevant for other, traditionally offline media (TV, radio) that are digitally mediated. Further, current data analysis strategies should be complemented by computer modeling (e.g., agent-based models or simulations) that enable researchers to take into account emergent processes on the individual and societal level when studying facets of internet use and implications.

Second, this thesis provided indications for the need of updated conceptualizations on digital inequalities in highly connected societies. How can we ensure that currently excluded groups, be it in terms of actual non-use or in terms of limited use or skills, adopt the internet in a way that is helpful for their lives without the potential pitfalls (e.g., overuse, harms from algorithmic risks) outweighing the benefits from being connected? Not least due to the unprecedented dependence on the internet during the COVID-19 pandemic for anything from family gatherings to vaccine certificates, there is an urgent need for more research on how internet non-users navigate their everyday lives, not least because evidence-based input is required for suitable digitization policies that should aim to enable members of marginalized groups to participate in digital societies at least at a minimum level.

7 Conclusion

This cumulative thesis addressed socially stratified internet use and implications in the context of algorithmized digital societies from an empirical communication-science perspective. It emphasizes the relevance of including the distinct properties of algorithmic-selection applications in this assessment. The increasing and often unquestioned dependence on algorithmic-selection applications in all life domains is uncontested. This leads to an increased scope for opportunities as well as risks. The dominance of algorithmic-selection applications is accompanied by an increasing opacity of internet services that are used for a wide range of mundane activities.

This thesis provides empirical answers to a selected set of pressing questions concerning the ongoing transformation process of digitization. Specifically, it provides necessary representative and long-term data that can provide indications for governance decisions and confirm that internet use and implications are fundamentally affected by social predispositions.

The empirical and conceptual contributions of this thesis also contribute to the broader question of the role of the internet in society. Public policies tend to be geared toward promoting the adoption of new technologies such as the internet or, more specifically, algorithmic-selection applications without thoroughly investigating longer-term implications. This thesis presented an integrated framework of co-occurring risks and opportunities that can affect well-being drawing on scholarship from the digital-inequality framework, subjective well-being theory, and literature on algorithmic governance. While acknowledging benefits of the internet, this thesis questions the assumption that more internet use is generally favorable and should be encouraged in all population groups by providing conceptual and empirical indications for how internet use can have adverse effects on quality of life. Perceived digital overuse or a general unease when dealing with opaque algorithmic-selection applications are two exemplary drivers of such effects. While internet users can engage in coping practices to deal with risks, the scope of their action is limited.

The empirical engagement with this topic provides indications for a realistic risk assessment of the increasing use of algorithmic-selection applications. The results show that these risks should not be overestimated because algorithmic-selection applications are only one component of people's diverse media repertoires. Referring back to the co-evolutionary approach followed in this thesis, it becomes apparent, for instance, that algorithms can not be made responsible for the spread of misinformation online, which has been a widely acknowledged problem during the COVID-19 pandemic. However, if such a technology is used in a society that provides an ideal breeding ground for polarization, algorithms are likely playing their role: it is plausible that misinformation is spreading faster and more easily through personalized news feeds or recommendations, but there are other societal circumstances factoring into this development. In that vein, it must be noted that risks that may appear relatively harmless on an individual level can likely be amplified when conceptualizing them as societal problems.

An evidence-based assessment of the significance of algorithmic governance requires nuance in handling the term “algorithm”: instead of throwing around this buzzword, we have to be precise about what constitutes algorithmic procedures, what the actual affordances of the services we study are, and how profound the role of these services is compared to online and offline alternatives. Further, we need to be careful when designing empirical studies to address these issues and derive theoretically-founded conclusions, especially when dealing with large data sets.

Virtually all online services that are deeply embedded in people’s everyday lives are algorithmic-selection applications that rely on datafied representations of the world and act as platforms. How internet users with different social predispositions can benefit from these technologies while limiting their exposure to potential harms to maintain high personal well-being and what effects this trifold digitization has for societies is a question that warrants continued attention from research in various disciplines.

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APPENDIX

A1: List of Articles

Article I Festic, N., Büchi, M., & Latzer, M. (2021). **It's still a thing: Digital inequalities and their evolution in the information society**. *Studies in Communication and Media, 10*(3), 326–361. https://doi.org/10.5771/2192-4007-2021-3-326

Article II Kappeler, K., Festic, N., & Latzer, M. (2021). **Left behind in the digital society – Growing social stratification of internet non-use in Switzerland**. In G. Keel & W. Weber (Eds.), *Media literacy* (pp. 207–224). Nomos.

Article III Festic, N., Büchi, M., & Latzer, M. (2021). **How long and what for? Tracking a nationally representative sample to quantify internet use**. *Journal of Quantitative Description: Digital Media, 1*(2021), 1–23. https://doi.org/10.51685/jqd.2021.018

Article IV Büchi, M., Festic, N., Just, N., & Latzer, M. (2021). **Digital inequalities in online privacy protection: Effects of age, education, and gender**. In E. Hargittai (Ed.), *Handbook of digital inequality* (pp. 293–307). Edward Elgar Publishing.

Article V Büchi, M., Festic, N., & Latzer, M. (2018). **How social well-being is affected by digital inequalities**. *International Journal of Communication, 12*(2018), 3686–3706.

Article VI Büchi, M., Festic, N., & Latzer, M. (2019). **Digital overuse and subjective well-being in a digitized society**. *Social Media + Society, 5*(4), 1–12. https://doi.org/10.1177/2056305119886031

Article VII Latzer, M., & Festic, N. (2019). **A guideline for understanding and measuring algorithmic governance in everyday life**. *Internet Policy Review, 8*(2), 1–19. https://doi.org/10.14763/2019.2.1415

Article VIII Festic, N. (2020). **Same, same, but different! Qualitative evidence on how algorithmic selection applications govern different life domains**. *Regulation & Governance.* Advance online publication. https://doi.org/10.1111/rego.12333

Article IX Reiss, M., Festic, N., Latzer, M., & Rüedy, T. (2021). **The relevance internet users assign to algorithmic-selection applications in everyday life**. Studies in *Communication Sciences, 21*(1), 71–90. https://doi.org/10.24434/j.scoms.2021.01.005

Article X Festic, N., Latzer, M., & Smirnova, S. (2021). **Algorithmic self-tracking for health: User perspectives on risk awareness and coping strategies**. *Media and Communication, 9*(4), 145–157. https://doi.org/10.17645/mac.v9i4.4162

A2: Disclosure of Author's Contributions to Co-Authored Publications

This is a disclosure of the author's own contributions for all joint publications in accordance with §7(3) of the "Regulations for Obtaining the Doctoral Degree at the Faculty of Arts and Social Sciences, University of Zurich, July 8, 2009 (PVO 2009)". The tables below detail the author's contributions to all co-authored publications included in this cumulative thesis. Article VIII is a solo-authored publication and therefore not listed.

The main supervisor of this thesis, Prof. Dr. Michael Latzer, hereby confirms the accuracy of the author's contributions to all publications included in this cumulative thesis as declared below and in agreement with all involved co-authors.

Zurich, December 2021

Article I

Title: It's Still a Thing: Digital Inequalities and their Evolution in the Information Society

Authors: Noemi Festic, Moritz Büchi & Michael Latzer

	Minor contribution	**Major / main contribution**
Conceptualization		x
Methodological design		x
Data collection		x
Data analysis		x
Original draft preparation		x
Review and editing		x
Conference contributions		x

Article II

Title: Left Behind in the Digital Society – Growing Social Stratification of Internet Non-Use in Switzerland

Authors: Kiran Kappeler, Noemi Festic & Michael Latzer

	Minor contribution	**Major / main contribution**
Conceptualization	x	
Methodological design		x
Data collection		x
Data analysis	x	
Original draft preparation	x	
Review and editing		x
Conference contributions	x	

Article III

Title: How Long and What For? Tracking a Nationally Representative Sample to Quantify Internet Use

Authors: Noemi Festic, Moritz Büchi & Michael Latzer

	Minor contribution	Major / main contribution
Conceptualization		x
Methodological design		x
Data collection		x
Data analysis		x
Original draft preparation		x
Review and editing		x

Article IV

Title: Digital Inequalities in Online Privacy Protection: Effects of Age, Education, and Gender

Authors: Moritz Büchi, Noemi Festic, Natascha Just & Michael Latzer

	Minor contribution	Major / main contribution
Conceptualization	x	
Methodological design		x
Data collection		x
Data analysis	x	
Original draft preparation	x	
Review and editing		x
Conference contributions	x	

Article V

Title: How Social Well-Being Is Affected by Digital Inequalities

Authors: Moritz Büchi, Noemi Festic & Michael Latzer

	Minor contribution	Major / main contribution
Conceptualization		x
Methodological design		x
Data collection		x
Data analysis		x
Original draft preparation		x
Review and editing		x
Conference contributions		x

Article VI

Title: Digital Overuse and Subjective Well-Being in a Digitized Society

Authors: Moritz Büchi, Noemi Festic & Michael Latzer

	Minor contribution	Major / main contribution
Conceptualization	x	
Methodological design	x	
Data collection		x
Data analysis	x	
Original draft preparation		x
Review and editing		x
Conference contributions		x

Article VII

Title: A Guideline for Understanding and Measuring Algorithmic Governance in Everyday Life

Authors: Michael Latzer & Noemi Festic

	Minor contribution	Major / main contribution
Conceptualization	x	
Original draft preparation	x	
Review and editing		x
Conference contributions		x

Article IX

Title: The Relevance Internet Users Assign to Algorithmic-Selection Applications in Everyday Life

Authors: Michael Reiss, Noemi Festic, Michael Latzer & Tanja Rüedy

	Minor contribution	Major / main contribution
Conceptualization		x
Methodological design		x
Data collection		x
Data analysis	x	
Original draft preparation		x
Review and editing		x
Conference contributions	x	

Article X

Title: Algorithmic Self-Tracking for Health: User Perspectives on Risk Awareness and Coping Strategies

Authors: Noemi Festic, Michael Latzer & Svetlana Smirnova

	Minor contribution	**Major / main contribution**
Conceptualization		x
Methodological design		x
Data collection		x
Data analysis		x
Original draft preparation		x
Review and editing		x

A3: Curriculum Vitae

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Education

2017 MA in Media and Communication Science (Major), Management & Economics (Minor), University of Zurich

2015 BA in Media and Communication Science (Major), Management & Economics (Minor), University of Zurich

Academic Appointments

since 2017	Research and Teaching Associate, Department of Communication and Media Research, University of Zurich
2014–2017	Student Research and Teaching Assistant, Department of Communication and Media Research, University of Zurich

Publications

Journal articles (peer-reviewed)

Büchi M, Festic N, Latzer M (in press): The chilling effects of digital dataveillance: a theoretical model and an empirical research agenda. *Big Data & Society.*

Festic N, Latzer M, Smirnova S (2021): Algorithmic self-tracking for health: user perspectives on risk awareness and coping strategies. *Media and Communication, 9*(4), 145–157. https://doi.org/10.17645/mac.v9i4.4162

Festic N, Büchi M, Latzer M (2021): It's still a thing: digital inequalities and their evolution in the information society. *Studies in Communication and Media, 10*(3), 326–361. https://doi.org/10.5771/2192-4007-2021-3-326

Festic N, Büchi M, Latzer M (2021): How long and what for? Tracking a nationally representative sample to quantify internet use. *Journal of Quantitative Description: Digital Media, 1*(2021)*,* 1–23. https://doi.org/10.51685/jqd.2021.018

Reiss M, Festic N, Latzer M, Rüedy T (2021): The relevance internet users assign to algorithmic-selection applications in everyday life. *Studies in Communication Sciences, 21*(1), 71–90. https://doi.org/10.24434/j.scoms.2021.01.005

Festic N (2020): Same, same, but different! Qualitative evidence on how algorithmic selection applications govern different life domains. *Regulation & Governance*. Advance online publication. https://doi.org/10.1111/rego.12333

Büchi M, Festic N, Latzer M (2019): Digital overuse and subjective well-being in a digitized society. *Social Media + Society, 5*(4), 1–12. https://doi.org/10.1177%2F2056305119886031

Latzer M, Festic N (2019): A guideline for understanding and measuring algorithmic governance in everyday life. *Internet Policy Review, 8*(2), 1–19. https://doi.org/10.14763/2019.2.1415

Büchi M, Festic N, Latzer M (2018): How social well-being is affected by digital inequalities. *International Journal of Communication, 12*, 3686–3706. https://ijoc.org/index.php/ijoc/article/view/8780

Chapters in edited volumes

Kappeler K, Festic N, Latzer M (2021). Left behind in the digital society – Growing social stratification of internet non-use in Switzerland. In G Keel, W Weber (Eds.) *Media literacy* (pp. 207–224). Nomos.

Büchi M, Festic N, Just N, Latzer M (2021): Digital inequalities in online privacy protection: effects of age, education, and gender. In E Hargittai (Ed.) *Handbook of digital inequality* (pp. 293–307). Edward Elgar Publishing.

Research reports

Latzer M, Büchi M, Kappeler K, Festic N (2021): Digitalisierungsschub durch die Covid-19-Pandemie in der Schweiz [Digitization push through the Covid-19 pandemic in Switzerland]. Spezialbericht aus dem World Internet Project – Switzerland 2021. University of Zurich. https://mediachange.ch/research/wip-ch-2021/

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Latzer M, Büchi M, Kappeler K, <u>Festic N</u> (2021): Vertrauen und Sorgen bei der Internetnutzung in der Schweiz 2021 [Trust and concerns of internet users in Switzerland 2021]. Themenbericht aus dem World Internet Project – Switzerland 2021. University of Zurich. https://mediachange.ch/research/wip-ch-2021/

Latzer M, <u>Festic N</u>, Kappeler K (2020): Coping practices related to algorithmic selection in Switzerland. Report 4 from the project: The significance of algorithmic selection for everyday life: the case of Switzerland. University of Zurich. http://mediachange.ch/research/algosig

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Latzer M, Büchi M, <u>Festic N</u> (2020): Internet use in Switzerland 2011–2019: trends, attitudes and effects. Summary report from the World Internet Project – Switzerland. University of Zurich. https://mediachange.ch/research/wip-ch-2019/

Latzer M, Büchi M, <u>Festic N</u> (2020): Nutzung audiovisueller Onlineinhalte und Informationsquellen von Offlinern in der Schweiz 2019 [Use of audio-visual online content and information sources of offliners in Switzerland 2019]. Spezialbericht aus dem World Internet Project – Switzerland 2019 für das Bundesamt für Kommunikation BAKOM. University of Zurich. https://mediachange.ch/research/wip-ch-2019/

Latzer M, Büchi M, <u>Festic N</u> (2019): Internetverbreitung und digitale Bruchlinien in der Schweiz 2019 [Internet diffusion and digital divides in Switzerland 2019]. Themenbericht aus dem World Internet Project – Switzerland 2019. University of Zurich. https://mediachange.ch/research/wip-ch-2019/

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Latzer M, Büchi M, Festic N (2019): Vertrauen und Sorgen bei der Internetnutzung in der Schweiz 2019 [Trust and concerns of internet users in Switzerland 2019]. Themenbericht aus dem World Internet Project – Switzerland 2019. University of Zurich. https://mediachange.ch/research/wip-ch-2019/

Latzer M, Büchi M, Festic N, Just N (2017): Internetverbreitung und digitale Bruchlinien in der Schweiz 2017 [Internet diffusion and digital divides in Switzerland 2017]. Themenbericht aus dem World Internet Project – Switzerland 2017. University of Zurich. https://mediachange.ch/research/wip-ch-2017/

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Other publication

Latzer M, Festic N, Büchi M (2018): Informationsgesellschaft Schweiz: Internetnutzung und digitales Wohlbefinden [Information society Switzerland: internet use and digital well-being]. *DemoSCOPE News*, April 2018, 6–7. https://mediachange.ch/media//pdf/publications/2018_01_demoscope_news_03.pdf

Media coverage

Pilatus Today (2021, March): Warum Google bei dir andere Resultate anzeigt als bei mir [Why Google shows different results for you than for me]. https://www.pilatustoday.ch/schweiz/warum-google-bei-dir-andere-resultate-anzeigt-als-bei-mir-141118119

Pilatus Today (2021, March): Nidwaldnerin weiss, wie das Internet unseren Alltag steuert [«Nidwaldnerin» knows how the internet governs our everyday lives]. https://www.pilatustoday.ch/schweiz/nidwaldnerin-weiss-wie-das-internet-unseren-alltag-steuert-141117421

Miss Moneypenny (2020): Was ist überhaupt … ein Algorithmus [What is … an algorithm, anyway]? https://www.missmoneypenny.ch/article/was-ist-ueberhaupt%E2%80%89-ein-algorithmus

PRESENTATIONS

Conference presentations (peer-reviewed)

Büchi M, Festic N, Latzer M (2021, September): Theorizing chilling effects of dataveillance. *European Communication Conference of the European Communication Research and Education Association*. Braga, Portugal (virtual event).

Festic N, Pfreundtner F, Latzer M (2021, September): Quantifying the opaque – a method to measure personalized algorithmic selection with tracking data. *European Communication Conference of the European Communication Research and Education Association.* Braga, Portugal (virtual event).

Kappeler K, Festic N, Latzer M (2021, September): Who remains offline in a highly digitized society and why? The evolution of individual factors influencing internet non-use from 2011 to 2019. *European Communication Conference of the European Communication Research and Education Association.* Braga, Portugal (virtual event).

Kappeler K, Festic N, Latzer M (2021, July): «I'm missing out" – How perceived disadvantages from non-use influence the intention to use the internet. *International Association for Media and Communication Research Annual Conference.* Nairobi, Kenia (virtual event).

Festic N, Pedrazzi S, Fehlmann F, Dogruel L, Studer S, Saurwein F, Steinmaurer K (2021, April): Governance von Online-Plattformen: Ansätze und Perspektiven aus der DACH-Region [Governance of online platforms: approaches and perspectives from the DACH region]. *Dreiländertagung für Kommunikationswissenschaft: DGPuK, ÖGK und SGKM.* Zurich, Switzerland (virtual event).

Büchi M, Festic N, Latzer M (2020, November): The chilling effects of dataveillance: analyzing internet users' behavioral modifications and counter-practices. *Swiss Association of Communication and Media Research Annual Conference.* Winterthur, Switzerland (virtual event).

Büchi M, Festic N, Latzer M (2019, May): Widespread digital overuse impairs subjective well-being. *International Communication Association Annual Conference.* Washington, DC.

Latzer M, Festic N (2019, May): Understanding and measuring algorithmic governance in everyday life. *International Communication Association Annual Conference.* Washington, DC.

Büchi M, Festic N, Latzer M (2019): Too much tech? Conceptualizing and measuring digital overuse in Switzerland. Comparative evidence of users' perceived relevance for five life domains. *Swiss Association of Communication and Media Research Annual Conference.* St. Gallen, Switzerland.

Festic N, Latzer M, Reiss M, Rüedy T (2019): How important are algorithmic selection applications for Swiss internet users? Comparative evidence of users' perceived relevance for five life domains. *Swiss Association of Communication and Media Research Annual Conference.* St. Gallen, Switzerland.

Büchi M, Festic N, Latzer M (2018, November): Functioning digitally: How digital overuse and coping skills affect subjective well-being. *European Communication Conference of the European Communication Research and Education Association.* Lugano, Switzerland.

Festic N, Büchi M, Latzer M (2018, November): The evolution of digital inequalities: a longitudinal analysis of internet use and attitudes. *European Communication Conference of the European Communication Research and Education Association.* Lugano, Switzerland.

Latzer M, Festic N (2018, November): The role of algorithmic selection for everyday life: a user-centered approach. *European Communication Conference of the European Communication Research and Education Association.* Lugano, Switzerland.

Büchi M, Festic N, Just N, Latzer M (2018, October): Inequality in online privacy: direct and indirect sociodemographic effects on self-protection. *Amsterdam Privacy Conference*. Amsterdam, Netherlands.

Büchi M, Festic N, Latzer M (2018, October): Functioning digitally: How digital overuse and coping skills affect subjective well-being. *Association of Internet Researchers Annual Conference.* Montreal, Canada.

Latzer M, Festic N, Gerwoll-Ronca B, Witzenberger K (2018, October): The importance of algorithmic selection for everyday life: results from a qualitative, user-centered approach. *Association of Internet Researchers Annual Conference.* Montreal, Canada.

Büchi M, Festic N, Latzer M (2018, July): Internet use and well-being: insights from the World Internet Project Switzerland. *World Internet Project Annual Conference.* Brest, France.

Büchi M, Festic N, Latzer M (2018, May): How digital inequalities affect social well-being. *International Communication Association Annual Conference.* Prague, Czech Republic.

Festic N, Büchi M, Latzer M (2018, April): Evolution of and divides in the Swiss information society 2011–2017. *Swiss Association of Communication and Media Research Annual Conference.* Lugano, Switzerland.

Büchi M, Festic N, Latzer M (2017, October): Consequences of digital divides: how internet use affects social well-being. *Association of Internet Researchers Annual Conference.* Tartu, Estonia.

Büchi M, Festic N, Latzer M (2017, July): Digital well-being: theoretical model and empirical results from the World Internet Project Switzerland. *World Internet Project Annual Conference.* Moscow, Russia.

Invited talks

Latzer M, Büchi M, Festic N (2021, January): Internetnutzung in der Schweiz: Daten aus dem World Internet Project Switzerland und dem SNF-Projekt «Die Bedeutung algorithmischer Selektion für den Alltag in der Schweiz» [Internet use in Switzerland: data from the World Internet Project Switzerland and the SNF project: The significance of algorithmic selection for everyday life: the case of Switzerland]. *Bundesamt für Kommunikation* (virtual event).

Latzer M, Büchi M, Festic N (2020, November): Drei Dimensionen der digitalen Ungleichheit in der Schweiz: Zentrale Befunde aus dem World Internet Project Switzerland 2011–2019 [Three dimensions of digital inequality in Switzerland: Key findings from the World Internet Project Switzerland 2011–2019]. *Bundesamt für Kommunikation* (virtual event).

Festic N (2019, October): Datenkommunikation im Media Change [Data communication in times of media change]. *Netzwerkanlass und Fachveranstaltung zum Thema «Datenkommunikation im Wandel», Eidgenössisches Departement für Wirtschaft, Bildung und Forschung WBF, Bundesamt für Landwirtschaft BLW, Fachbereich Marktanalysen*. Muttenz, Switzerland.

Other talks and workshops

2021	Participant in the roundtable discussion “Me, myself and AI” at the *BSI Customer Summit* (2021, November). Rüschlikon, Switzerland. https://www.youtube.com/watch?v=9aBZ4a-CeYw.
2017–2019	Research presentations at the Department of Communication and Media Research, University of Zurich: Digital well-being, the role of algorithmic selection for everyday life. Zurich, Switzerland.
2018	Selected participant at the Doctoral Colloquium of the Association of Internet Researchers 2018 conference. Montreal, Canada.

TEACHING

Lectures and seminars

since 2017	*Introduction to academic work,* BA lecture and tutorials, University of Zurich, main instructor and supervision of student teaching assistants
2022	*Privacy, dataveillance, and algorithms on the internet*, BA seminar, University of Zurich, sole instructor
2021	*Governing risks of algorithms in everyday life*, MA research seminar, University of Zurich, co-instructor
2021	*Facets of media change*, BA lecture, University of Zurich, co-instructor
2018, 2020	*Media change: social, economic, and political aspects*, BA seminar, University of Zurich, sole instructor
2017	*Facets of media change*, BA lecture, University of Zurich, co-instructor
2016	*Social impacts of internet diffusion and use*, MA research seminar, University of Zurich, student teaching assistant
2014–2016	*Introduction to academic work*, BA lecture and tutorials, University of Zurich, student teaching assistant
2014–2016	*Empirical methods*, BA lecture and tutorials, University of Zurich, student teaching assistant

Student thesis supervision

Master's theses at the University of Zurich: Access routes to online news (Feltscher I, 2022), mhealth tracking among people with diabetes (Odermatt C, 2022), algorithmic systems in the insurance industry (Palanchova B, 2020), reputation systems in e-commerce (Wick C, 2019), internet non-use (Kappeler K, 2019)

SERVICE

Activities

since 2020	Member of the "Exchange" taskforce at IKMZ, University of Zurich
since 2019	Spokesperson of the Media Politics, Media Structures Section of the Swiss Association of Communication and Media Research (SACM)
2020	Member of the working group developing an action paper on organizational development at IKMZ, University of Zurich

Reviewing

Journal manuscript reviews for Information, Communication & Society; International Journal of Communication; Internet Policy Review; Journal of Communication; New Media & Society; Regulation & Governance; Social Media & Society

Conference submission reviews for Association of Internet Researchers; German Communication Association; International Communication Association; Swiss Association of Communication and Media Research

Session chair for Association of Internet Researchers

MEMBERSHIPS

International Communication Association; Association of Internet Researchers; European Communication Research and Education Association; Swiss Association of Communication and Media Research

A4: Plagiarism Statement

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Erklärung

Hiermit erkläre ich, dass die Dissertation von mir selbst ohne unerlaubte Beihilfe verfasst worden ist und diese Dissertation noch an keiner anderen Fakultät eingereicht wurde.

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University of Zurich[UZH]

Internet Use in Algorithmized Digital Societies:

Selected Implications of a Socially Stratified Practice

Thesis (cumulative thesis): List of articles

by Noemi Festic

This is a compilation of the ten articles included in the cumulative thesis. Depending on the copyright situation, publisher versions or accepted preprints are presented here.

Articles

Article I	Festic, N., Büchi, M., & Latzer, M. (2021). **It's still a thing: Digital inequalities and their evolution in the information society**. *Studies in Communication and Media, 10*(3), 326–361. https://doi.org/10.5771/2192-4007-2021-3-326
Article II	Kappeler, K., Festic, N., & Latzer, M. (2021). **Left behind in the digital society – Growing social stratification of internet non-use in Switzerland**. In G. Keel & W. Weber (Eds.), *Media literacy* (pp. 207–224). Nomos.
Article III	Festic, N., Büchi, M., & Latzer, M. (2021). **How long and what for? Tracking a nationally representative sample to quantify internet use**. *Journal of Quantitative Description: Digital Media, 1*(2021), 1–23. https://doi.org/10.51685/jqd.2021.018
Article IV	Büchi, M., Festic, N., Just, N., & Latzer, M. (2021). **Digital inequalities in online privacy protection: Effects of age, education, and gender**. In E. Hargittai (Ed.), *Handbook of digital inequality* (pp. 293–307). Edward Elgar Publishing.
Article V	Büchi, M., Festic, N., & Latzer, M. (2018). **How social well-being is affected by digital inequalities**. *International Journal of Communication, 12*(2018), 3686–3706.
Article VI	Büchi, M., Festic, N., & Latzer, M. (2019). **Digital overuse and subjective well-being in a digitized society**. *Social Media + Society, 5*(4), 1–12. https://doi.org/10.1177/2056305119886031
Article VII	Latzer, M., & Festic, N. (2019). **A guideline for understanding and measuring algorithmic governance in everyday life**. *Internet Policy Review, 8*(2), 1–19. https://doi.org/10.14763/2019.2.1415
Article VIII	Festic, N. (2020). **Same, same, but different! Qualitative evidence on how algorithmic selection applications govern different life domains**. *Regulation & Governance.* Advance online publication. https://doi.org/10.1111/rego.12333
Article IX	Reiss, M., Festic, N., Latzer, M., & Rüedy, T. (2021). **The relevance internet users assign to algorithmic-selection applications in everyday life**. *Studies in Communication Sciences, 21*(1), 71–90. https://doi.org/10.24434/j.scoms.2021.01.005
Article X	Festic, N., Latzer, M., & Smirnova, S. (2021). **Algorithmic self-tracking for health: User perspectives on risk awareness and coping strategies**. *Media and Communication, 9*(4), 145–157. https://doi.org/10.17645/mac.v9i4.4162

Article I

It’s Still a Thing: Digital Inequalities and their Evolution in the Information Society

Noemi Festic, Moritz Büchi & Michael Latzer

Abstract
Internet diffusion has prompted research into differences in internet access, use and consequences. Exploiting the full potential of the ongoing digital transformation in all spheres of life—a proclaimed goal of governments and international organizations—requires ensuring equal opportunities and supporting disadvantaged individuals in their internet use. Using representative, population-level survey data from Switzerland spanning nearly a decade (2011–2019; N_{total} = 5,581), multiple multivariate regression analyses tested the effects of demographic and internet-use related variables on access (general and mobile), on internet skills and on different types of use (information, entertainment, commercial transactions and communication). Results indicated that despite high access rates (92% in 2019), considerable usage inequalities persist in the Swiss information society: in particular, we found an increasing marginalization of older individuals regarding the adoption of the internet and revealed the importance of internet skills, experience and mobile internet use for adopting differentiated types of use. The extreme differences between the highly connected majority and an increasingly marginalized minority raise concerns about the latter group’s opportunities for personal, social and economic benefits in an information society. This study provides unique results on current digital inequalities and their evolution which are crucial for assessing the success, suitability and legitimacy of digitization policies.

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SC|M
Studies in Communication and Media

FULL PAPER

It's still a thing: digital inequalities and their evolution in the information society

Es gibt sie noch: Digitale Ungleichheiten und ihre Entwicklung in der Informationsgesellschaft

Noemi Festic, Moritz Büchi & Michael Latzer

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FULL PAPER

It’s still a thing: digital inequalities and their evolution in the information society

Es gibt sie noch: Digitale Ungleichheiten und ihre Entwicklung in der Informationsgesellschaft

Noemi Festic, Moritz Büchi & Michael Latzer

Abstract: Internet diffusion has prompted research into differences in internet access, use and consequences. Exploiting the full potential of the ongoing digital transformation in all spheres of life—a proclaimed goal of governments and international organizations—requires ensuring equal opportunities and supporting disadvantaged individuals in their internet use. Using representative, population-level survey data from Switzerland spanning nearly a decade (2011–2019; N_{total} = 5,581), multiple multivariate regression analyses tested the effects of demographic and internet-use related variables on access (general and mobile), on internet skills and on different types of use (information, entertainment, commercial transactions and communication). Results indicated that despite high access rates (92% in 2019), considerable usage inequalities persist in the Swiss information society: in particular, we found an increasing marginalization of older individuals regarding the adoption of the internet and revealed the importance of internet skills, experience and mobile internet use for adopting differentiated types of use. The extreme differences between the highly connected majority and an increasingly marginalized minority raise concerns about the latter group’s opportunities for personal, social and economic benefits in an information society. This study provides unique results on current digital inequalities and their evolution which are crucial for assessing the success, suitability and legitimacy of digitization policies.

Keywords: Digital inequality, digital divide, information society, internet use, digital skills, social inequality, survey.

Zusammenfassung: Die Verbreitung des Internets hat Forschung zu Unterschieden im Internetzugang, in der Internetnutzung und in Folgen davon angeregt. Die Ausschöpfung des vollen Potenzials der fortschreitenden digitalen Transformation in allen Lebensbereichen—ein erklärtes Ziel von Regierungen und internationalen Organisationen—erfordert die Gewährleistung von Chancengleichheit und die Unterstützung benachteiligter Personen bei ihrer Internetnutzung. Anhand repräsentativer, bevölkerungsweiter Befragungsdaten aus der Schweiz, die beinahe ein Jahrzehnt umspannen (2011–2019; N_{total} = 5’581), werden in mehreren multivariaten Regressionsanalysen die Effekte von demografischen und Internetnutzungs-Variablen auf den Internetzugang (allgemein und mobil), auf Internetfähigkeiten und auf verschiedene Nutzungsarten (Information, Unterhaltung, kommerzielle Transaktionen und Kommunikation) getestet. Die Ergebnisse deuten darauf hin, dass trotz hoher Zugangsraten (2019: 92%) erhebliche Nutzungsungleichheiten in der Schweizer Informationsgesellschaft fortbestehen: insbesondere zeigt sich eine zunehmende Marginalisierung älterer Personen bei der Internetnutzung und die grosse Bedeutung von Internetfähigkeiten, Erfahrung mit dem Internet und mobiler Nutzung für die Internetnutzung zu verschiedenen Zwecken. Die extremen Unterschiede zwischen der hochvernetzten Mehrheit und einer zunehmend marginalisierten Minderheit geben Anlass zur Sorge über deren Chancen auf persönlichen, sozialen und wirtschaftlichen Nutzen in einer Informationsgesellschaft. Die vorliegende Studie liefert bislang fehlende Ergebnisse zu aktuellen digitalen Ungleichheiten und deren Entwicklung, die für die Beurteilung des Erfolgs, der Eignung und der Legitimität von Policy-Massnahmen im Bereich der Digitalisierung entscheidend sind.

Schlagwörter: Digitale Ungleichheiten, Digital Divide, Informationsgesellschaft, Internetnutzung, Soziale Ungleichheiten, Befragung.

1. Introduction

Digitization and its implications for everyday life have been a matter of lively public debate. During the past decade, the importance of digital information and communication technologies (ICTs) has been used as an indicator of a nation's development status across the globe. In this context, many countries are proclaimed as and aspire to be *information societies*, characterized by the ubiquity of the internet in everyday life, increasing use time (ITU, 2018, pp. 3–5) as well as anytime/anywhere access as a societal standard (Büchi et al., 2019, p. 2).

With the goal of exploiting the full potential of the digital transformation, the Swiss government stated that one of their main goals was for the population to profit from advancing digitization in all spheres of life (Bundesamt für Kommunikation, 2018). A prerequisite to achieve this is ensuring equal access and opportunities to ICTs and supporting potentially disadvantaged citizens in their ICT use. Research in the broader field of internet studies has addressed various negative effects of internet use on everyday life (e.g., privacy violations or displacement of offline social interaction, see Liu et al., 2019; Waldman, 2013). Still, the notion of an information society as a normative target, which is supported by the OECD for instance, is very much in line with the basic assumption of the digital divide framework: skilled internet use is understood to be advantageous in one way or another (DiMaggio et al., 2004, p. 355; Robinson et al., 2015, p. 570) and is believed to facilitate political opinion formation and informed participation in a democratic society (Bundesamt für Kommunikation, 2018).

In such information societies, near-universal access to ICTs is often regarded as a given. However, even very high internet diffusion does not automatically resolve digital inequalities. Rather, there may be a shift in inequalities from access to usage (Büchi et al., 2016, p. 2713), entailing questions of how differential internet use leads to inequalities and disadvantages in the information society (van Deursen & van Dijk, 2014, p. 508). Not having access to the internet or the capacity to use it is particularly detrimental for people who are already part of disadvantaged groups in information societies. For example, the Swiss railway operator offers discounted tickets for underutilized connections. These tickets are exclusively available through a smartphone app. The company justified this decision as follows: "The supply and prices for discounted tickets change constantly. Online is the easiest and quickest way to find the most suitable option for you" (SBB, 2020). This offer systematically excludes individuals who do not or cannot use the internet, in this case incurring a direct financial cost. This mundane example reflects a broader underlying mechanism in the mutual shaping of technological and societal developments (see Schroeder & Ling, 2014, p. 790; Witte & Mannon, 2010, p. 2): ICTs structured to provide benefits to already advantaged groups incentivize intense use and the requisite skills development for this population, leading to continuous technological restructuring to more fully cater to their preferences, thereby exacerbating the relative disadvantages of the excluded.

The goal of this study is to reveal persisting digital inequalities in a highly connected information society at various levels and investigate whether and how they have changed. The strong and widespread pursuit of prompting the formation of information societies by governmental and non-governmental organizations lies at the core of this approach: we are investigating digital inequalities *within* a social context in which there is a strong push for increasing and manifesting the importance of ICT use in all life domains, which brings about certain disadvantages for those who are not (as) highly connected. This article thus addresses the following research questions: *What are the usage patterns of the (mobile) internet and specific uses over time? Which digital inequalities regarding use and skills persist in an information society and how have they changed?*

In spite of the ongoing and broad public debate on issues related to the information society in many countries with high internet diffusion, clear empirical grounds for evidence-based policy-making are lacking, especially regarding representative and long-term data on internet use that go beyond purely access-related variables. This article answers the call for more representative and long-term data on digital inequalities (e.g., White & Selwyn, 2013, p. 4). Such data provides reliable results on current digital inequalities and insights into their evolution. A broad view on internet use and related perceptions is needed to complement existing, more specific analyses (e.g., use of voting applications or health information seeking) to locate digital inequalities in the information society. The case of Switzerland as a European country with very high internet penetration offers indications for other social democracies where the internet is essential in everyday life. This article's main contributions consist of a comprehensive review of the extant theoretical and empirical literature on the evolution of digital inequalities and representative empirical results to illustrate these mechanisms.

2. Theoretical perspectives

2.1 Information society and digital inequality

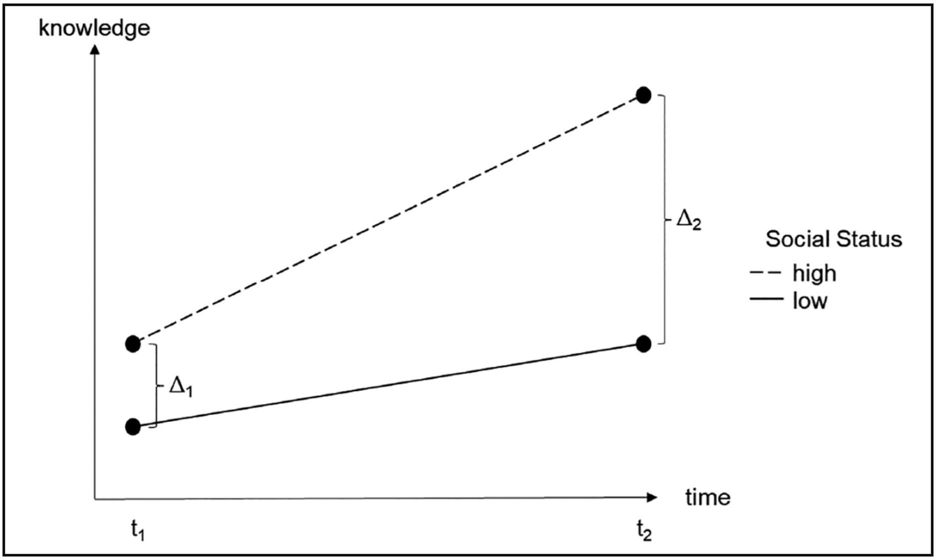
Before investigating how innovations diffuse in different social groups and what empirical results are available for the diffusion of the internet, we first establish a better understanding of the concept of an information society. Information societies are generally characterized by a key role of information in all aspects of society and the proliferation of ICTs (Feenberg, 2019, p. 240; Floridi, 2009, p. 153; Webster, 2014, p. 3). The International Telecommunication Union (ITU) measures its ICT Development Index (IDI) through three different types of indicators: ICT infrastructure and access, ICT usage, and ICT skills. The development towards an information society is assessed based on mean scores or population shares for each country (ITU, 2020b). While these indicators are tied to specific countries in this case, societal structures that transcend nation borders are another relevant layer. Overall, there is an emphasis in the literature on the importance of ICTs for the development of societies, for instance with Castells (2002, p. 12) arguing that the diffusion of ICTs in a society greatly affects its prosperity and growth.

In global comparison, internet adoption in Switzerland is very high: 92% of the population used the internet in 2019 (Latzer et al., 2020). In comparison, 54% of the world population were internet users according to the ITU's (2020a) most recent data. In its ongoing global assessment of information societies, the ITU (2017) classifies Switzerland as "one of the leading countries in ICT development" (p. 182) in an internationally comparative perspective. Reliable broadband internet access is considered a universal service in Switzerland and has to be granted to every citizen (ComCom, 2019). However, even in a country like Switzerland where internet use is so widespread, whether different dimensions of digital inequalities remain significant must be addressed empirically: functioning in an information society not only requires access to information but also the knowledge and skills to acquire, process and classify information. According to van Dijk and Hacker (2003, p. 324), information can also be understood as a positional good, since early access can lead to different kinds of advantages. Shedding light on those who potentially are left behind is vital, even in countries where population-wide averages paint a promising picture: especially when a nation fulfills the criteria of a highly connected information society, not being included in the use of new technologies becomes a more extreme personal disadvantage. As soon as internet use for different purposes is a societal standard, non-use becomes a clear disadvantage, reflecting the *relative* nature of digital inequalities. This problem has been amplified by constant availability and connectivity becoming societal norms (Büchi et al., 2019, p. 2; Ling, 2016, p. 130). It has recently also been shown that dealing with innovations like the Internet-of-Things requires a new set of skills, which are likely to be subject to digital inequalities and reinforce them (van Deursen & Mossberger, 2018, p. 130).

Before we continue to elaborate on the need for research on social differences within information societies, it is important to note that the concept of an information society as a normative goal for nation states has also received criticism from the outset (see e.g., Garnham, 2000; Mansell, 2010) and its suitability as an ideal has been questioned, especially against the backdrop of digital inequalities. Nevertheless, the characteristics that determine a nation's stage of development towards an information society are factors that not only nation states (e.g., see Bundesamt für Kommunikation, 2018 for Switzerland) but also international organizations measure and actively promote. So long as there is this push for countries to become information societies, we need to assess the evolution of internet use against this conceptual background.

Such national-level assessments do not sufficiently account for social differences within a population: The state of an entire nation with regard to the diffusion of ICTs says little about the adoption of innovations by specific societal groups. In addition to international comparisons and research on country-level predictors of digital inequalities, it is therefore highly relevant to also consider potentially prevalent divides *within* proclaimed information societies. Considerations on individual factors influencing internet usage variables have given rise to an extensive body of research on *digital divides* in the last two decades (Robinson et al., 2015, p. 570): Not long after significant shares of the population began using the internet, social science research recognized the connections between social and digital inequalities (see e.g., Bonfadelli, 2002; DiMaggio et al., 2001; Nie & Erbring, 2002; Norris, 2001; van Dijk, 2005; Warschauer, 2004; Witte & Mannon, 2010). The knowledge gap hypothesis (Tichenor et al., 1970, p. 160) is foundational for research on digital inequalities: when the flow of information into a social system increases, there are differences in acquiring new knowledge between individuals of different social status. Those population segments with higher social status acquire information faster, resulting in an increasing knowledge gap over time (see Figure 1).

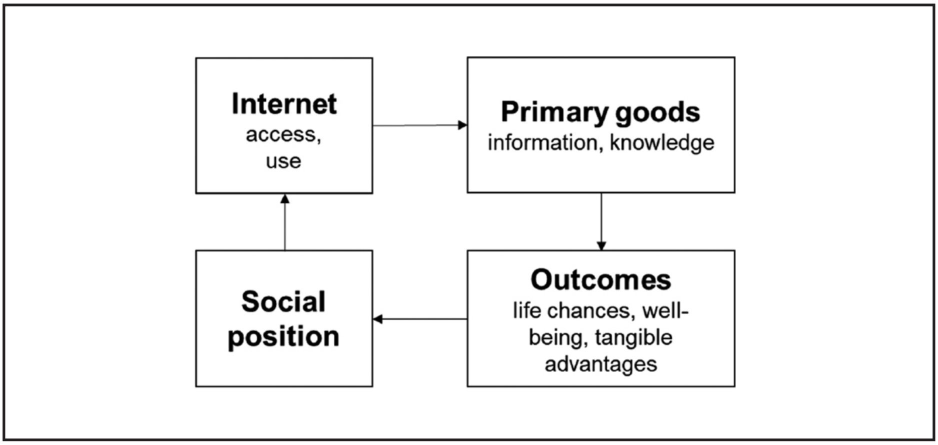
Figure 1. Relative inequality: Evolution of knowledge differences over time



The digital divide research tradition has primarily been concerned with how demographic and socioeconomic factors like sex, age, educational attainment, employment and income relate to internet access (first-level digital divides), internet use (second-level digital divides) and outcomes (third-level digital divides) (see e.g., Büchi et al., 2016; DiMaggio et al., 2004; Hargittai, 2001; Reisdorf & Groselj, 2017; van Deursen & Helsper, 2015; Zillien & Hargittai, 2009). The basic assumption is that social inequalities cause differences in skills and usage, while using the internet prompts the acquisition of different primary goods that determine an individual's social position in a society (Duff, 2011; Ragnedda & Muschert, 2015; Stern, 2010) (see Figure 2).

While these various outcomes of internet use have been theoretically derived and empirically confirmed, a technology-deterministic view should be avoided. Rather, social and technological change are co-evolutionary processes that depend on and shape each other. This is partly reflected by the arrow depicting how an individual's social position feeds back into their internet access and use in Figure 2.

Figure 2. Basic digital inequality assumptions

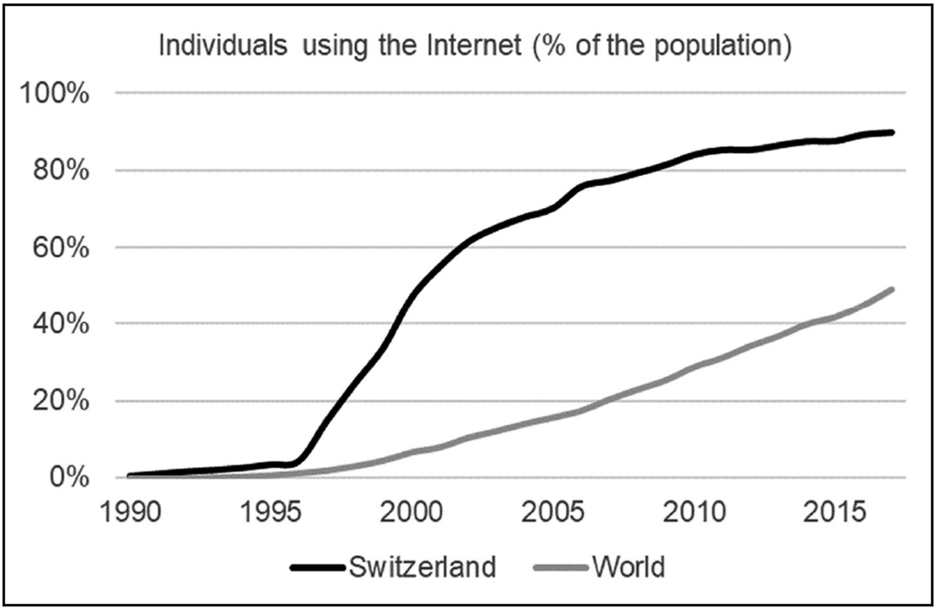


This section has established why studying digital divides remains relevant even—or especially—in so-called information societies. In the next section, we continue by explaining why adding a longitudinal perspective to this general research goal is vital.

2.2 Diffusion of innovations over time

At its core, this study deals with the diffusion of an innovation (the internet) over time and in different societal groups. Following the tenets of Rogers' (1962, 2003) innovation diffusion theory, innovations tend to diffuse in a social system following an S-shaped curve. Figure 3 shows that the empirical diffusion of the internet closely matches the theoretical prediction, both for the world (high growth phase) and Switzerland (saturation phase).

Figure 3. Individuals using the internet in Switzerland and the world



Data Source. World Bank (2018).

This adoption process differs between societal groups; people with higher social status generally adopt innovations earlier. The "innovativeness-needs paradox" (Rogers, 2003, p. 263) is relevant in this context: The members of a social system who could arguably benefit most from adopting an innovation tend to do so later than more advantaged groups. One reason for this gap is that new products are generally costly to adopt. Applied to internet adoption, for example, older people or socially marginalized groups could particularly benefit from online communication and commercial transactions given their potentially limited mobility and distance to social support systems (Hofer et al., 2019, p. 4427). In contrast, groups who traditionally adopt innovations earlier (male, young, educated members of a social system) are less dependent on the affordances of online engagement.

Existing literature on the adoption of innovations in various social groups over time permits two plausible predictions for the evolution of digital inequalities: they can either resolve themselves over time—this is generally captured by the term *normalization*—or they can persist or even increase, indicating a process of *stratification*. As a technology becomes more easily available, its diffusion is generally expected to reach a point of saturation and eventually reach all parts of society, with socioeconomic status no longer a predictor of adoption. Following this normalization argument, the digital divide can be understood as a digital delay, which will resolve itself over time (Nguyen, 2012, p. 252). In contrast, among the approaches that predict stratification, the question is where differences in internet use are rooted. Arguably, if it were simply the case that certain societal groups make an informed and autonomous choice to not use the internet, there would be no need for policy intervention. However, the current literature points more towards the notion that these digital inequalities reflect structural social inequalities rather than deliberate non-use (van Dijk, 2020).

According to Rogers (2003), the "paradoxical relationship between innovativeness and the need for benefits of an innovation tends to result in a wider socioeconomic gap between the higher and lower socioeconomic individuals in a social system" (pp. 263–264). These theoretical considerations suggest that the diffusion of the internet reinforces existing social inequalities instead of resolving them. Further, it is likely that the differences in internet usage and outcomes (van Deursen & Helsper, 2015) feed back into an individual's social status, further exacerbating existing social inequalities. This logic predicts stratification, i.e., the persistence or even an increase of existing digital inequalities over time. Accordingly, internet diffusion could only decrease social inequalities over time if socially disadvantaged members of a population used the internet more in beneficial ways than those with a higher socioeconomic status (Hargittai & Hsieh, 2013, p. 15), for which there are currently no indications in the literature.

Following the dynamics of online news adoption and use, Lister (2009, p. 231) and Nguyen (2012, p. 261) have also argued that—partly due to the internet's "logic of upgrade culture"—digital inequalities are here to stay: Since the internet constantly evolves and keeping up with this change demands ever-new skills and resources, there will always be societal groups who are far in advance compared to other groups regarding their internet usage. As the internet evolves, the affordances of new technologies change; and using them to their full potential and incorporating them into everyday life requires additional skills (Eynon et al., 2018, p. 318). Accordingly, it is likely that groups who have an advantage over others also reap more benefits from their skilled internet use, such as tangible outcomes or an increase in their overall well-being. This scenario predicts that digital inequalities remain prevalent, but constantly shift from basic ways of internet usage to more elaborate and up-to-date types of use (van Dijk, 2020).

The evolution of digital inequalities is both a theoretical and empirical question. The next section summarizes existing empirical findings on the evolution of these inequalities regarding internet access and use.

3. Existing empirical results on the evolution of digital inequalities

The main theoretical hypothesis of the digital divide research tradition—i.e., social and digital inequalities are related (see Figure 2)—is empirically well supported: a rich body of literature has repeatedly shown for different contexts that traditionally advantaged societal groups (especially male, younger, higher-educated, higher-income individuals) are more likely to have access to the internet, use it for different purposes and in a skillful way, and reap more benefits from their internet use (see e.g., Billon et al., 2020; Büchi et al., 2016; DiMaggio et al., 2004; Hargittai, 2001; Reisdorf & Groselj, 2017; Robinson et al., 2015; van Deursen & Helsper, 2015; Zillien & Hargittai, 2009).

While there are these extensive cross-sectional studies on digital inequalities for various countries and also a number of qualitative studies (e.g., Eynon & Geniets, 2012; Reisdorf et al., 2012) that mainly focus on internet nonusers, the long-term *evolution* of these inequalities remains empirically largely unobserved. Research on the evolution of digital inequalities was more prevalent in the early days of the development of the internet (e.g., Hoffman et al., 2000), but subsided later—presumably entailing the assumption that the internet had or would eventually ubiquitously spread.

Table 1 presents a systematic collection of existing studies that investigate the evolution of digital inequalities for individual (or a few) countries with longitudinal or multiple cross-sectional samples. It includes studies that investigate individual differences affecting internet use rather than macro or national-level effects, because this analysis focuses on individually varying factors that affect different variables related to internet use. However, it is important to keep in mind that internet adoption depends on an interplay between such individual factors like socioeconomic status and macro factors (e.g., infrastructure, urbanization) at different levels (nation, region, community, etc.) (e.g., Feng, 2015).

These existing empirical results do not offer a conclusive picture concerning the evolution of digital inequalities and do not permit an answer to the question of whether these gaps have been closing over time. However, most point in the direction that despite the progressing diffusion of the internet and various policy initiatives, digital divides remain prevalent since "it is impossible to close the digital divide without reducing other social inequalities" (van Dijk, 2020, p. 131).

This review of existing empirical research reveals several research gaps. Very few studies use recent empirical data for countries where having access to and using the internet for many different purposes is the norm and the non-users accordingly represent a small minority. Additionally, there has been a focus on developing countries in research on the evolution of digital divides (Bornman, 2016). While these are clearly valuable, empirical analyses in saturation-phase information societies additionally point to new disadvantages—which many countries currently in the growth phase will soon face as well—and subsequently devise governance options.

Regarding the operationalization of internet use, there is a focus on first-level digital divide indicators, while differentiated types of internet usage and skills are under-researched and newer types like social media use are even scarcer. As Table 1 reveals, digital divide research has also been characterized by a lack of consistent terminology. Reisdorf et al. (2017, p. 115) pointed at how results on internet diffusion in different temporal and geographical contexts are significantly affected by the operationalizations of digital divides. They consequently argue for the inclusion of broader definitions of internet use to study the evolution of inequalities. When it comes to the predictors of digital divides, most studies rely on socioeconomic background and do not take account of variables like internet skills or experience, which are especially relevant when investigating usage and outcome divides and account for the notion that differences in internet use can feed back into the social position of individuals in a society (see Figure 2).

Table 1. Literature overview of empirical studies on the evolution of individual factors influencing internet use

Study	Data	Operationalization of Internet Use (Dependent Variables)	Inequality-Related Predictors of Internet Use (Independent Variables)	Method of Data Analysis	Main Results
White & Selwyn, 2013	Nationally representative, UK, repeated cross-sectional data with sample drawn each year, 2002–2010	Access to internet, use of internet for accessing government services, personal banking, purchasing goods and services, looking for jobs	Sex, age, ethnicity, occupational class, economic activity, age of leaving full-time education, presence of children in household, participation in current or recent learning	Set of logistic regression analyses for each dependent variable and survey period	Steady increase in internet access and use; divides based on social, occupational and educational backgrounds remain; age, education & occupational class strongly associated with internet access for whole period, economic activity only becomes relevant in later years; slightly different trends for each use variable; participants with higher social status use internet more for purchasing, banking or accessing government services; educational participation consistently associated with purchasing goods and accessing government services online; sex had no consistent relationship with any dependent variable
Van Deursen & van Dijk, 2014	Annual, representative online surveys in the Netherlands 2010–2013	Internet skills (operational, formal, information, strategic), internet use (frequency of performing a range of online activities)	Sex, age, education	Multiple linear regression analyses with interaction terms for examining changes over time	Overall increase in skill levels; being male, younger and more educated positively associated with skill levels; sex gap remains consistent; no clear results on the development of the age gap; increase in gap between higher and lower/middle educated
Bornman, 2016	Afrobarometer surveys 2008 and 2011, countrywide probability samples of South African population 18+, total of 2,400 respondents, personal interviews	Frequency of computer and internet usage, mobile phone use (to access the internet), use of internet to access news	Sex, population group, level of education	Descriptive comparisons of distribution figures	Increase in daily and non-computer users; similar but less profound tendency for internet usage; digital divides prevalent for computer and internet usage regarding sex, population group belongingness (race) and education; divides for mobile phones & their use for internet regarding population group and education (lower differences than for internet / computer usage); considerable sex gaps, noteworthy gaps regarding education, deep division between population groups

Study	Data	Operationalization of Internet Use (Dependent Variables)	Inequality-Related Predictors of Internet Use (Independent Variables)	Method of Data Analysis	Main Results
Bergström, 2017	Longitudinal surveys, representative of Swedish population, 1998–2015, 3,000–17,000 people per year, for this analysis they used age group 60–85	Frequency of internet use (binary and for different purposes) in last year	Sociodemographic variables (sex, age), socioeconomic status (educational level), social capital (variables of household composition & frequency of socialising with friends)	Bivariate analyses, multivariate regressions	Uptake of internet slow among older part of population compared to population average, but large differences between different groups of elderly: uptake among people aged 80+ only recently started, effect of age remains similar, impact of sex decreased, older seniors persistently use different types of digital activities (email, news services, information search, online banking and social networking) less, also when controlled for other variables; digital gap due to age closing, but very slowly
Helsper & Reisdorf, 2017	GB: OxIS, nationally representative, 14+, face-to-face interviews SWE: WIP, representative sample 16+, panel data Bi-annual waves 2005–2013	Likelihood of being an internet non- or ex-user vs. being an internet user	Socioeconomic background, self-reported reasons	Logistic regressions	Belonging to a vulnerable group (older, less educated, more likely to be unemployed, disabled, socially isolated) became stronger predictor of being offline in Britain and Sweden; increases in lack of interest in internet as reason for non-use; results partly contradict other research indicating replacement of primary digital divides (cost and access) by second-level digital divides (interest and skills) access and costs become less important over time as reasons for non-use in comparison with lack of skills

Study	Data	Operationalization of Internet Use (Dependent Variables)	Inequality-Related Predictors of Internet Use (Independent Variables)	Method of Data Analysis	Main Results
Nishijima et al., 2017	Representative data of Brazilian population, 2005, 2008, 2011 and 2013	Access to internet in last 3 months and mobile phone ownership for individual use	Individual characteristics and external factors related to ICT access: socioeconomic, demographic & geographical variables	Concentration index, logistic regressions	Younger, white, educated individuals with higher income more likely to have internet access; (negative) effect of being elderly on internet access was reduced due to improvements in educational attainment levels; while impact of external barriers to ICT access declined, education remains main barrier for personal capacity of ICT goods utilization over time (connected to digital illiteracy) Being male, white, employed, student, higher income and higher education positively influence probability of mobile phone ownership; inequalities in mobile phone ownership decrease greatly over time compared to inequalities in internet access; decrease in negative effect of being elderly & increase in positive effect of education indicates that mobile utilization may involve higher complexity in comparison to internet access
Eynon et al., 2018	British Household Panel survey (and successing survey), four waves 1997–2013, *N* = 2,155	Internet use (binary)	Social class (based on employment status and relationships with employers); controls: age, sex, health, education	Reciprocal effect model (estimation of autoregressive and cross-lagged paths)	Social class and internet use are positively associated; internet use predicted social class in the two latter panel waves (controlled for previous social class, age, sex, health, and education)
Koiranen et al., 2020	Representative biannual cross-sectional surveys of Finnish population 2008–2016, phone & web	Social media use (having a registered profile), purpose of social media use (e.g., social, work-related, political)	Sex, age, education, residential area	Proportion comparisons across different populations, tests of temporal variance with logit models	Increase in social media use in all population groups, increasing age gap, age had the strongest effect; effect of sex, education and region remain stable over time; divides between population groups remain present; diversification of use purposes and persisting sociodemographic differences; partial shift in digital divides from mere use to use purposes

This article seeks to contribute to filling these research gaps with representative, long-term, population-level data from a highly connected information society where internet use is socially expected. Analyses rely on a broader and more up-to-date operationalization of internet use, predicted by demographic and socioeconomic variables as well as by internet skills, experience and mobile internet use for differentiated uses.

4. Method

4.1 Data collection and participants

This study uses nationally representative, repeated cross-sectional survey data (N_{total} = 5,581) collected in Switzerland in 2011, 2013, 2015, 2017 and 2019 (see Table 2 for a detailed overview of the sample). Computer-assisted telephone interviews were conducted in order to reach a representative sample that included both internet users and non-users. The interviews were conducted exclusively by landline in 2011 and 2013. Thereafter, a fifth to a quarter of the participants were reached by mobile phone (2015: 21%, 2017: 21%, 2019: 25%).

Table 2. Repeated cross-sectional survey overview

Year	*N* total	Max. margin of error	Internet users	Mobile internet users
2011	1,104	±2.95%	77%	20%
2013	1,114	±2.94%	85%	39%
2015	1,121	±2.93%	88%	63%
2017	1,120	±2.93%	90%	72%
2019	1,122	±2.93%	92%	80%

The bi-annually conducted survey includes varying questions on attitudes towards the internet, online privacy, and digital well-being. One important asset of this data set is that the core variables of the questions on internet use, skills and personal background including their exact wordings have remained the same over the entire period of investigation. Asking the same, detailed questions on various aspects of life in an information society allows us to trace its evolution. In repeated, cross-sectional surveys, this is often not the case (see Table 1), which is a source of bias and can lead to error-prone interpretations due to the uncertainty about whether effects can be attributed to actual change or reflect methodological modifications.

4.2 Data analysis

In addition to descriptive comparisons over time, a series of multivariate regression analyses were conducted in order to test the association of demographic and socioeconomic variables, internet skills and experience and mobile internet use with different use variables (see Table 3 for the detailed analytical strategy). We estimated models with the *glm* function in R (Rdocumentation.org, 2020) using binomial logit regressions for binary dependent variables (internet use, mobile internet use, internet skills) and gaussian identity regressions for the ordinal dependent variables (internet skills mean score, internet use types). We performed multiple imputation of missing values using predictive mean matching with the *mice* package in R (all variables had less than 3.5% missing values at the start).[1]

Table 3. Analytical strategy for the multiple regression models

		Dependent variables			
		Internet use	Mobile internet use	Internet skills	Types of internet use
Independent variables	Demographic & social background	●	●	●	●
	Internet experience		●	●	●
	Mobile internet use			●	●
	Internet skills				●

4.3 Measures

Internet use. Internet use was a binary variable: respondents reported whether they were currently using the internet or had done so at least once in the last three months. The question specified that this did not mean internet use in the actual moment but referred to their life in general. Using the internet is a first, basic measure of participating in the information society. As such, it corresponds to van Dijk's (2017, p. 2) concept of access in the broader sense and acknowledges that digital divide research needs to take "the whole process of appropriation of a particular technology" into account. This is why we avoid mere "physical access" as a first variable here and measure internet use instead.

Mobile internet use. The internet users in the sample further reported whether they used the internet on the go via portable devices such as mobile phones. This was a binary variable.

Internet skills. The measurement of general internet skills relied on a single-item question. Respondents assessed their ability to use the internet on an ordinal scale with the following response options: 1 = *bad*, 2 = *sufficient*, 3 = *good*, 4 = *very good*, 5 = *excellent*. For the regression, we assigned all users who perceived their own skills as at least good value 1 and all others served as the reference group (0), relying on the idea that purposeful internet use in an information society requires being able to use online services well.

Since the measurement of internet skills through a one-item question relying on self-reports has potential biases, the measurement was extended to a validated survey instrument for general populations (van Deursen et al., 2016, p. 816) for the survey periods 2015, 2017 and 2019. Respondents rated their ability to perform internet-use-related tasks on a five-point Likert agreement scale. The five

1 All syntax files and results are available at: https://osf.io/pesuh/?view_only=144329ea72c5482ea03bcd24874ee967

tasks in question were: opening downloaded files, finding suitable search terms, changing sharing settings, creating and uploading content, and installing mobile applications. For 2015, 2017 and 2019, where these measures were available, a mean score index was created for these five items. These results can be used to underline the plausibility of the results obtained with the one-item question available for the entire period of investigation.

Types of internet use. The survey included a broad number of online activities that comprehensively reflect individuals' day to day internet use in an information society (Latzer et al., 2020). We distinguish between four different *usage types*: information, entertainment, commercial transactions, and communication. In the context of studying the information society, internet activities that are most widespread and part of everyday life for the vast majority of the population represent meaningful usage types. For each of these four types of internet use, the four commonest activities among the Swiss population that were part of all survey periods were therefore selected. For each activity, the internet users in the sample reported their frequency of use on a six-point scale ranging from 1 = *never* to 6 = *multiple times a day*. Sum indices were calculated with these frequencies for each type of use. *Informational* use measured the use of search engines, searching for health information online, looking for news online, and checking the meaning of a word on the internet. For *entertainment* use, respondents answered how frequently they used the internet for listening to or downloading music, for watching or downloading videos, and for watching TV online live or time-delayed. Using the internet for *commercial transactions* was measured through the following activities: looking up product information online, purchasing goods on the internet, comparing prices of goods or services, and making travel bookings or reservations. Internet use for *communication* purposes entailed using email, online messaging, making phone calls over the internet, and the use of social networking sites.

Demographic and socioeconomic variables. The dichotomous variable female was assigned the value 1 for women and 0 for men. Respondents were asked to report their age, which was recoded into four groups. For measuring income, respondents stated their household income on a six-category scale. The lowest (below CHF 4,500) and highest (over CHF 9,000 for 2011 and 2013 and over CHF 10,000 for 2015–2019) income categories were included as dummies and people with an income in between served as the reference group. High education took the value 1 for individuals with tertiary qualifications (university degree or similar). Low education took the value 1 for respondents whose highest completed education level was primary school. Employment status was categorized as part-time or full-time, with unemployed respondents serving as the reference group.

Internet experience. Further, internet experience measured how many years respondents reported having used the internet.

5. Results

Results are presented separately for each dependent variable. The data fit the models well consistently: the variance inflation factor (VIF) was lower than 2.5

for all independent variables in all models, indicating low levels of multicollinearity. For all binomial regressions, the Hosmer-Lemeshow test was not significant ($p < .05$), meaning that the expected and observed values for the dependent variables did not differ in subgroups, further indicating good model fit.[2]

5.1 Internet use

Internet diffusion in the Swiss population continuously increased between 2011 and 2019. While 77% of the Swiss reported using the internet in 2011, the number rose to 85% in 2013. The growth rate subsequently slowed with diffusion at 88% in 2015, 90% in 2017 and 92% in 2019.

The figures below show odds ratios with confidence intervals for all independent variables and each year. When the confidence interval of an odds ratio includes 1—i.e., the error bars intersect the dashed line at $OR = 1$—this corresponds to a non-significant effect.

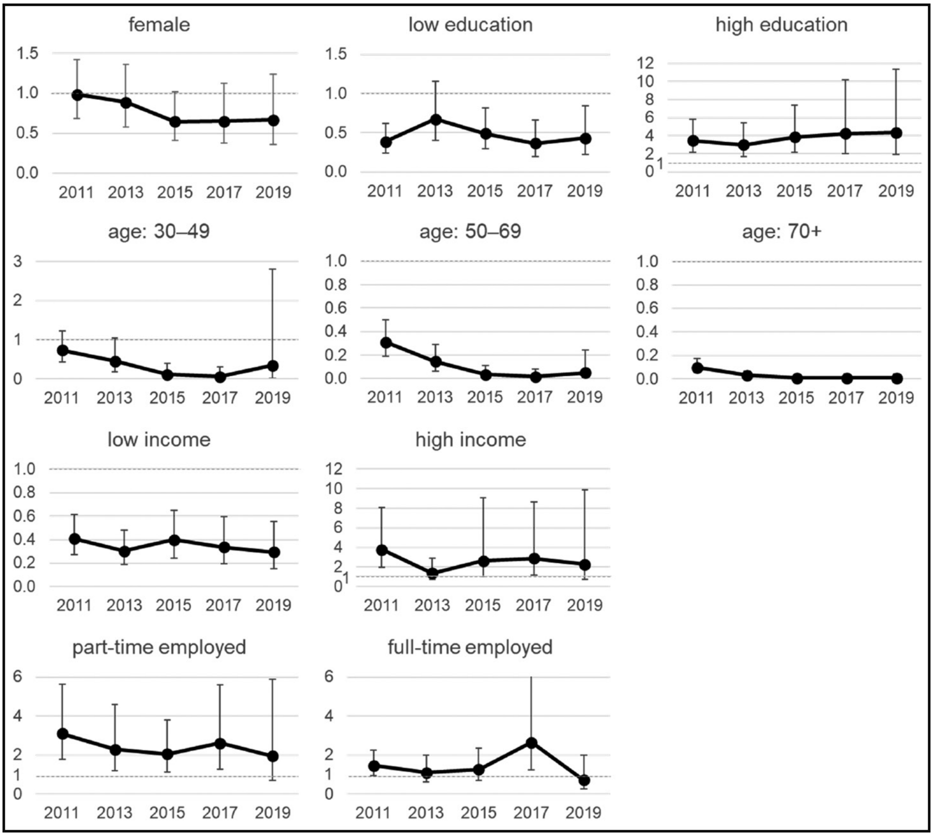
Figure 4 reveals that education, age and income were strongly and persistently related to internet adoption across all years. Sex was unrelated to the adoption of the internet: the odds of being an internet user did not significantly differ between males and females between 2011 and 2019. Educational attainment remained a persistent predictor of internet use throughout the period of investigation: while individuals with low educational attainment were significantly less likely to be internet users, high educational attainment was significantly and positively associated with internet usage. In 2019, individuals with high educational attainment were four times more likely ($OR = 4.37$) to be internet users than those with medium educational attainment. At the same time, individuals with low educational attainment were more than twice as likely to *not* use the internet ($OR = 0.43$).

Age was the variable most strongly related to the likelihood of being an internet user. It is particularly apparent that while those aged between 30 and 49 no longer significantly differ from the reference group (individuals aged 14 to 29) in their internet adoption rates in 2019, it is especially older individuals who are increasingly less likely to be internet users. The negative effect of higher age on internet use generally increased over time, indicating its growing importance as a predictor. Swiss people aged 50–69 or 70+ were more than 20 times ($OR = 0.05$) and 125 times ($OR = 0.008$) less likely, respectively, to be online in 2019 than those aged between 14 and 29, revealing a persistent and increasing marginalization of older individuals when it comes to the adoption of the internet. While there were already differences in internet adoption between age groups in 2011, they were far less pronounced, with those aged 70+ being only ten times ($OR = 0.1$) less likely to be online compared to the youngest group (14–29). Another group that is becoming increasingly marginalized are those with low income: they were 2.4 ($OR = 0.41$) and 3.4 ($OR = 0.29$) times less likely to be online compared to the group with a medium level of income in 2011 and 2019, respectively. The significant advantage of individuals on higher incomes compared to those

2 The separate fit statistics for all models are available at: https://osf.io/pesuh/?view_only=144329ea72c5482ea03bcd24874ee967

with a medium level of income diminished and disappeared over time. Similarly, the small but initially significant positive effect of being employed is no longer apparent.

Figure 4. Odds ratios with confidence intervals for predictors of being an internet user 2011–2019



Note. Omitted categories: male, medium education, age 14–29, medium income, unemployed. Significant (i.e., CI does not intersect dashed line at *OR* = 1) odds ratios above (below) 1 indicate a higher (lower) likelihood of using the internet compared to the omitted category.

In order to make more nuanced statements about the predictors of different types of internet usage, we continue by investigating differences in specific types of online engagement among Swiss internet users. The subset of those who did use the internet was therefore used for all subsequent analyses.

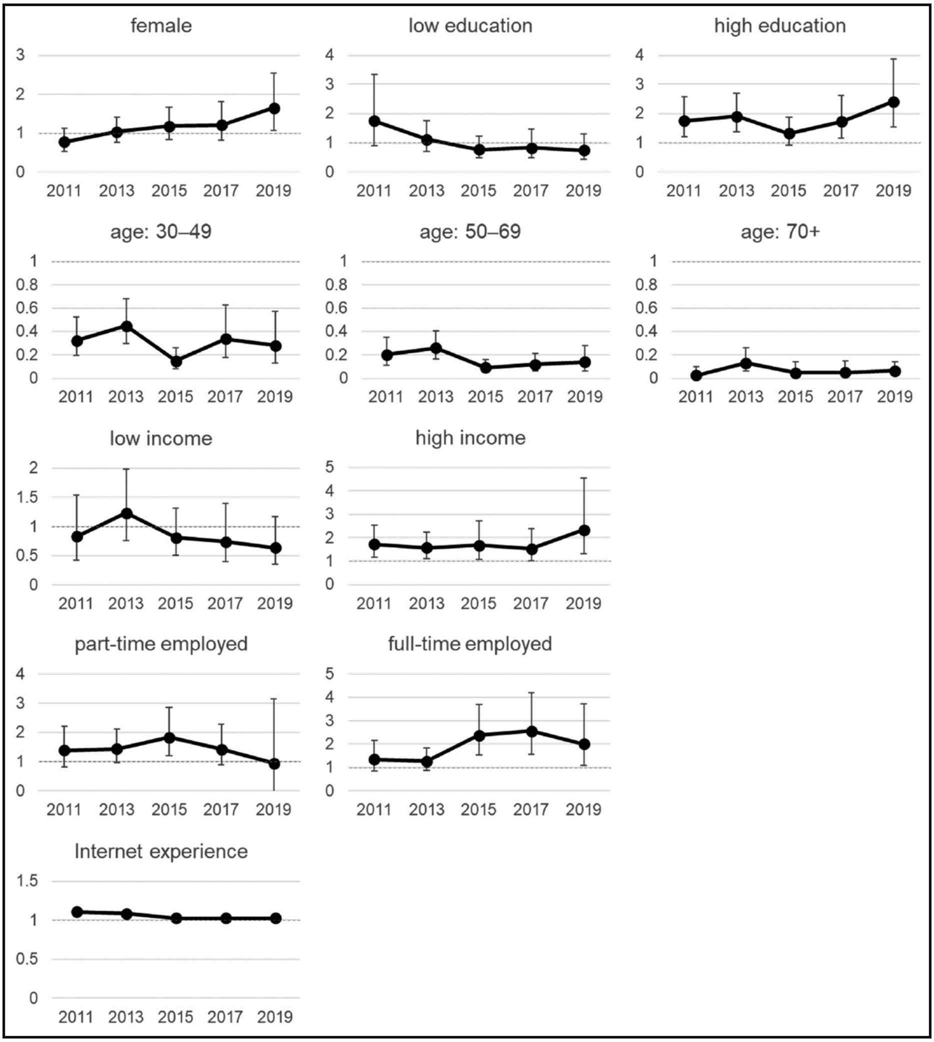
5.2 Mobile internet use

Analogous to the diffusion of the internet, the proportion of the Swiss population that report using mobile internet via portable devices has strongly increased between 2011 and 2019. While the diffusion of the mobile internet doubled in the first two years of investigation (20% in 2011 and 39% in 2013), the diffusion rate of the mobile internet in the Swiss population subsequently decelerated. Mobile internet diffusion reached 63% in 2015, 72% in 2017 and 80% in 2019.

Sex was not significantly related to mobile internet use until 2019 when the odds of mobile internet use were 1.65 times higher among female internet users. While internet users with low and medium levels of educational attainment did not significantly differ in mobile internet use, with the exception of 2015, a tertiary qualification consistently increased the likelihood of accessing the internet via mobile devices. The effect appears to be increasing slightly, with highly-educated internet users being 2.4 times more likely to be mobile internet users compared to those with medium levels of educational attainment in 2019. Age had a strong and persistent negative effect on mobile internet use between 2011 and 2019 with no clear trend regarding effect size—older internet users are in general much less likely to use the internet on the go.

While internet users with low- and medium-income levels did not significantly differ with regard to mobile Internet use, high-income internet users had higher odds of using mobile internet throughout the period of investigation, and the effect is increasing.

Figure 5. Odds ratios with confidence intervals for predictors of mobile internet use 2011–2019.



Note. Omitted categories: male, medium education, age 14–29, medium income, unemployed. Significant (i.e., CI does not intersect dashed line at *OR* = 1) odds ratios above (below) 1 indicate a higher (lower) likelihood of using mobile internet compared to the omitted category.

In 2019, higher income increased the likelihood of mobile internet use among Swiss internet users by 2.34 as compared to those with medium income levels. While employment status was not significantly associated with mobile internet use in 2011 and 2013, since 2015 full-time employees in particular have become significantly more likely to use mobile internet. Internet experience was a predictor of mobile internet use throughout all survey waves. A marginal increase in internet experience of one year increased the likelihood of mobile internet use by a factor of 1.03. To illustrate this effect: an individual with 10 years in internet experience is 1.34 times more likely to be a mobile user than someone with no internet experience (see Figure 5).

5.3 Internet skills

For the one-item skills measure, the results reveal a slightly increasing sex gap, with female respondents reporting lower perceived levels of internet skills. While internet users with higher educational attainment were more likely to have good internet skills in 2011 and 2013, there have since been no skills differences between educational groups. Age had an increasingly negative effect on the ability to deal with the internet well. A positive effect of internet experience and mobile internet use on internet skills prevailed in 2011–2019. Income and employment status were not related to the respondents' perceived level of internet skills (see Figure 6).

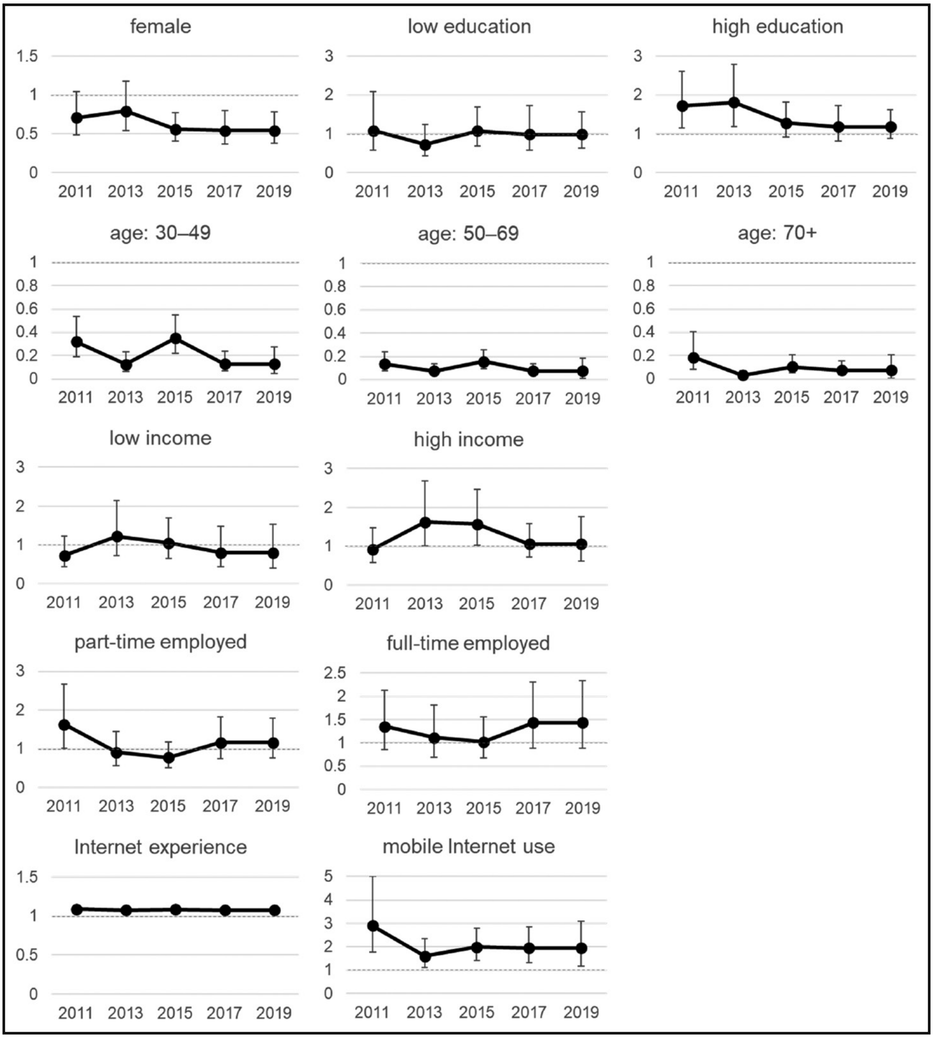
The five-item skill-question was only part of the survey in 2015, 2017 and 2019. The results confirm the conclusions from the one-item measure above. This more elaborate skills measure was also most heavily (and negatively) impacted by the internet users' age, indicating an even larger age gap than for the one-item question. Higher education and respondents' internet experience had the opposite effect, significantly increasing the perceived level of internet skills. The only noteworthy difference between the two skills measures was that there was no significant sex gap for the five-item measure.

5.4 Types of internet use

The mere use of the internet as opposed to non-use is not automatically advantageous for individuals. Rather, skillful and informed use of the internet for different purposes and in different life domains is likely more consequential. Digital inequalities with regard to specific types of internet use therefore matter (see Tables 4–7).

Over the period of investigation, a small but significant difference regarding sex emerged where females used the internet less for information purposes. Higher age has also become increasingly associated with less use of the internet for information purposes. Internet users with high educational qualifications tended to use the internet more for information purposes until 2013, but this difference between educational groups has since disappeared. At the same time, low-income individuals have been obtaining information online significantly less frequently since 2017, indicating a widening income gap regarding this type of internet use. Using mobile internet, good internet skills as well as more internet experience had the opposite effect and persistently contributed to the frequency of using the internet for information purposes.

Figure 6. Odds ratios with confidence intervals for predictors of having good internet skills 2011–2019



Note. Omitted categories: male, medium education, age 14–29, medium income, unemployed, mobile internet non-use. Significant (i.e., CI does not intersect the dashed line at *OR* = 1) odds ratios above (below) 1 indicate a higher (lower) likelihood of having good internet skills compared to the omitted category.

Table 4. Predictors of internet use for information 2011–2019

	2011			2013			2015			2017			2019		
	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*
Intercept	10.51	0.49	< .001	9.02	0.47	< .001	12.69	0.48	< .001	12.63	0.49	< .001	11.89	0.51	< .001
Female	-0.08	0.27	.765	-0.86	0.26	.001	-0.18	0.23	.425	-0.14	0.24	.551	-0.46	0.23	.045
Age 30–49	0.07	0.35	.834	0.97	0.35	.006	-1.04	0.30	.001	-1.58	0.32	< .001	-0.70	0.31	.024
Age 50–69	-0.47	0.39	.224	0.62	0.38	.099	-1.26	0.34	< .001	-1.81	0.33	< .001	-1.64	0.32	< .001
Age 70+	-0.20	0.58	.726	-0.96	0.54	.075	-1.26	0.51	.014	-2.99	0.46	< .001	-1.54	0.45	.001
Low education	0.05	0.45	.912	0.35	0.37	.342	-0.50	0.31	.114	-0.67	0.33	.042	0.58	0.33	.075
High education	1.35	0.27	< .001	1.18	0.28	< .001	0.12	0.24	.611	0.26	0.24	.286	0.29	0.23	.206
Low income	-0.31	0.39	.426	0.54	0.39	.169	-0.05	0.35	.895	-1.25	0.43	.003	-1.16	0.39	.003
High income	0.54	0.30	.074	1.23	0.30	< .001	0.14	0.28	.614	0.41	0.24	.083	0.23	0.24	.352
Part-time employed	0.47	0.35	.185	0.27	0.33	.418	0.49	0.31	.110	-0.02	0.29	.952	0.07	0.29	.801
Full-time employed	0.05	0.32	.866	-1.13	0.31	< .001	0.34	0.30	.257	0.02	0.29	.951	-0.06	0.30	.855
Internet experience	0.02	0.02	.296	0.07	0.02	< .001	0.05	0.02	.001	0.07	0.01	< .001	0.06	0.01	< .001
Mobile internet use	1.68	0.29	< .001	2.67	0.25	< .001	1.14	0.26	< .001	1.49	0.28	< .001	1.79	0.31	< .001
Good internet skills	1.59	0.29	< .001	0.51	0.30	.092	1.52	0.24	< .001	0.95	0.26	< .001	1.02	0.25	< .001

Note. N_{2011} = 1,104, N_{2013} = 1,114, N_{2015} = 1,121, N_{2017} = 1,120, N_{2019} = 1,122. Omitted categories: male, age 14–29, medium education, medium income, unemployed, mobile internet non-use, bad internet skills.

Table 5. Predictors of internet use for entertainment 2011–2019

	2011			2013			2015			2017			2019		
	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*	Estimate	*SE*	*p*
Intercept	9.79	0.45	< .001	7.88	0.46	< .001	11.15	0.52	< .001	11.29	0.53	< .001	10.76	0.60	< .001
Female	-0.97	0.25	< .001	-0.82	0.25	.001	-1.16	0.25	< .001	-0.85	0.26	.001	-1.08	0.27	< .001
Age 30–49	-2.61	0.32	< .001	-1.40	0.34	< .001	-3.23	0.33	< .001	-4.12	0.34	< .001	-2.76	0.37	< .001
Age 50–69	-3.87	0.36	< .001	-2.25	0.36	< .001	-4.35	0.37	< .001	-4.98	0.36	< .001	-4.90	0.38	< .001
Age 70+	-4.29	0.54	< .001	-3.12	0.52	< .001	-5.38	0.56	< .001	-5.84	0.50	< .001	-5.62	0.53	< .001
Low education	1.70	0.42	< .001	0.43	0.36	.227	0.32	0.34	.351	0.95	0.36	.007	1.63	0.38	< .001
High education	0.48	0.25	.062	0.48	0.27	.083	0.43	0.26	.099	0.79	0.26	.002	0.45	0.27	.090
Low income	-0.68	0.36	.063	0.58	0.38	.128	-0.41	0.38	.282	-1.02	0.46	.027	-0.50	0.46	.274
High income	0.38	0.28	.180	0.35	0.29	.225	-0.05	0.30	.858	0.21	0.26	.411	0.93	0.29	.001
Part-time employed	0.40	0.33	.218	0.26	0.32	.413	-0.57	0.33	.085	0.32	0.31	.307	0.08	0.34	.810
Full-time employed	0.16	0.30	.600	-0.35	0.30	.239	-0.63	0.32	.051	0.73	0.32	.021	-0.55	0.36	.124
Internet experience	0.00	0.02	.975	0.03	0.02	.074	0.02	0.02	.298	0.02	0.02	.302	0.04	0.02	.021
Mobile internet use	1.61	0.27	< .001	2.44	0.24	< .001	1.47	0.28	< .001	1.31	0.31	< .001	1.57	0.36	< .001
Good internet skills	1.02	0.27	< .001	0.64	0.29	.028	1.63	0.27	< .001	0.92	0.29	.001	0.91	0.29	.002

Note. N_{2011} = 1,104, N_{2013} = 1,114, N_{2015} = 1,121, N_{2017} = 1,120, N_{2019} = 1,122. Omitted categories: male, age 14–29, medium education, medium income, unemployed, mobile internet non-use, bad internet skills.

While older people have reported less internet use for entertainment purposes since the first survey period, the age gap has widened over the years. Further, we found a persistent sex gap, with female respondents reporting less use of online entertainment. Contrary to using it for information purposes, individuals with lower levels of educational attainment used the internet slightly more frequently for entertainment between 2011 and 2019. In 2019, high-income individuals used online entertainment services slightly more often. Mobile internet use and good internet skills were also positively related to using the internet for various entertainment activities. While more experience with the internet had the same association with internet use for entertainment, this effect was weak.

For using the internet for commercial transaction purposes, we found a significant and constantly widening sex gap: females have been using the internet for this purpose less frequently since 2011. Similar to the results for information and entertainment, higher age was strongly and negatively associated with using the internet for commercial purposes. However, the results reveal that the gap between the two youngest age groups has been closing, while individuals aged 50 and over remain significantly less frequent users of such services. Except for 2013, there was no association between educational attainment and internet use for commerce. On the contrary, the results revealed a widening income gap. Individuals with lower levels of income in particular have become increasingly less frequent users of online services for commercial transactions. Again, mobile internet use, good internet skills and more internet experience had a stable positive association with using commerce services.

While females used the internet significantly less often for communication in 2011, this association has changed direction: female internet users have used online communication services more frequently since 2017. Higher age was consistently and strongly associated with less internet use for communication. This negative effect increased over the period of investigation. Individuals with lower levels of educational attainment used the internet (increasingly) more frequently for communication. At the same time, there was a widening income gap, indicating that individuals with higher income used communication services more often in 2019. As for all other types of internet use, mobile internet use and good internet skills were persistently positively related to using the internet for communication.

Another way to assess the importance of various factors for the dependent variables is an investigation of the explained variance in the dependent variables (see Figure 7).

Table 6. Predictors of internet use for commerce 2011–2019

	2011			2013			2015			2017			2019		
	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*
Intercept	7.63	0.43	< .001	6.29	0.38	< .001	7.52	0.42	< .001	7.96	0.42	< .001	8.27	0.47	< .001
Female	-0.69	0.23	.003	-0.71	0.21	0.001	-0.74	0.20	< .001	-0.85	0.20	< .001	-0.95	0.21	< .001
Age 30–49	0.03	0.30	.915	0.47	0.29	0.103	-0.21	0.26	.434	-0.80	0.27	.003	0.01	0.28	.968
Age 50–69	-1.06	0.34	.002	-0.24	0.30	0.438	-0.60	0.29	.040	-1.23	0.28	< .001	-0.94	0.29	.002
Age 70+	-1.56	0.51	.002	-1.09	0.44	0.013	-1.20	0.44	.007	-2.10	0.40	< .001	-1.38	0.41	.001
Low education	-0.61	0.40	.126	-0.56	0.30	0.065	-0.29	0.27	.290	-0.22	0.28	.440	0.20	0.30	.501
High education	0.36	0.24	.135	0.62	0.23	0.007	0.27	0.21	.202	0.01	0.21	.968	0.35	0.21	.094
Low income	-0.44	0.34	.204	0.17	0.32	0.584	-0.47	0.30	.118	-0.92	0.36	.012	-1.04	0.36	.004
High income	0.84	0.26	.001	1.30	0.24	0.000	0.60	0.24	.014	0.31	0.20	.129	0.53	0.22	.017
Part-time employed	0.78	0.31	.012	0.29	0.27	0.273	0.55	0.27	.038	0.40	0.25	.107	-0.01	0.27	.963
Full-time mployed	0.64	0.28	.022	-0.32	0.25	0.203	0.39	0.26	.133	0.69	0.25	.006	0.38	0.28	.169
Internet experience	0.05	0.02	.001	0.08	0.01	< .001	0.07	0.01	< .001	0.07	0.01	< .001	0.04	0.01	.001
Mobile internet use	0.85	0.25	.001	1.85	0.20	< .001	1.20	0.22	< .001	0.94	0.24	< .001	1.13	0.28	< .001
Good internet skills	1.06	0.25	< .001	0.67	0.25	0.006	1.19	0.21	< .001	1.05	0.23	< .001	1.19	0.23	< .001

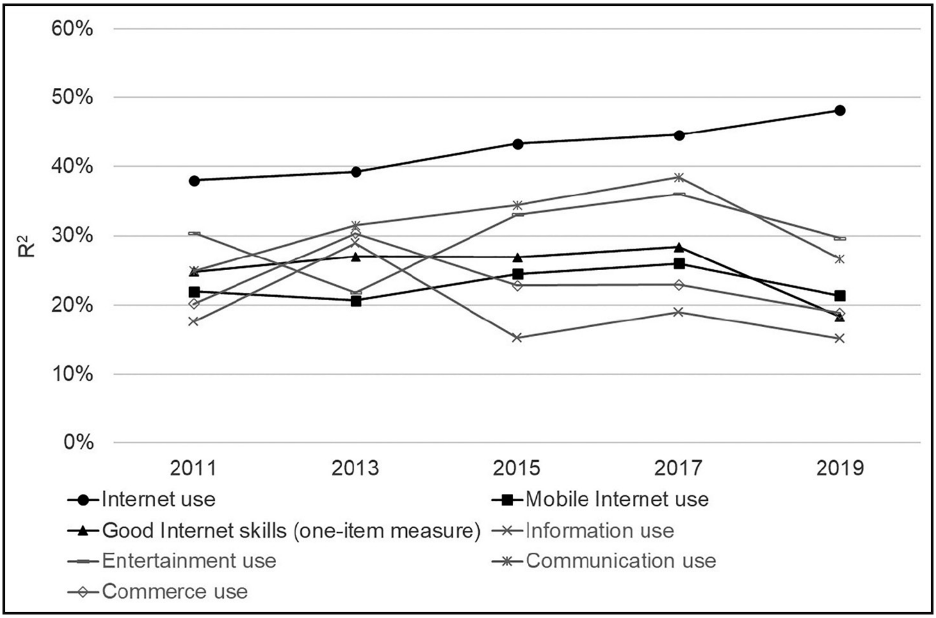
Note. N_{2011} = 1,104, N_{2013} = 1,114, N_{2015} = 1,121, N_{2017} = 1,120, N_{2019} = 1,122. Omitted categories: male, age 14–29, medium education, medium income, unemployed, mobile internet non-use, bad internet skills.

Table 7. Predictors of internet use for communication 2011–2019

	2011			2013			2015			2017			2019		
	Esti-mate	*SE*	p	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*	Esti-mate	*SE*	*p*
Intercept	12.89	0.50	< .001	12.37	0.43	< .001	12.79	0.55	< .001	12.39	0.53	< .001	13.86	0.57	< .001
Female	-0.61	0.27	.026	-0.36	0.24	.128	0.29	0.26	.254	0.92	0.26	< .001	0.66	0.26	.010
Age 30–49	-2.47	0.36	< .001	-2.22	0.32	< .001	-1.98	0.34	< .001	-2.60	0.34	< .001	-1.48	0.34	< .001
Age 50–69	-3.77	0.39	< .001	-3.67	0.34	< .001	-3.87	0.38	< .001	-3.14	0.35	< .001	-2.53	0.36	< .001
Age 70+	-3.87	0.59	< .001	-4.95	0.49	< .001	-4.67	0.58	< .001	-5.04	0.49	< .001	-5.04	0.50	< .001
Low education	-0.04	0.46	.930	0.18	0.34	.588	-0.09	0.36	.797	0.23	0.35	.515	0.94	0.36	.009
High education	0.03	0.28	.913	0.10	0.26	.711	0.10	0.27	.713	-0.04	0.26	.888	-0.17	0.25	.508
Low income	0.11	0.40	.784	-0.35	0.36	.332	-0.19	0.40	.630	-1.26	0.46	.006	-0.10	0.43	.810
High income	0.51	0.31	.096	0.26	0.27	.333	-0.19	0.31	.555	0.02	0.25	.924	0.97	0.27	< .001
Part-time employed	-0.08	0.36	.814	-0.95	0.30	.002	0.01	0.35	.968	0.07	0.31	.832	-0.24	0.32	.461
Full-time employed	0.23	0.33	.485	-0.24	0.28	.393	0.08	0.34	.808	0.36	0.31	.253	-0.35	0.34	.293
Internet experience	-0.02	0.02	.295	0.02	0.02	.256	0.01	0.02	.420	0.05	0.02	.001	0.03	0.01	.063
Mobile internet use	1.45	0.30	< .001	1.99	0.23	< .001	2.98	0.29	< .001	4.07	0.30	< .001	3.05	0.34	< .001
Good internet skills	1.53	0.29	< .001	1.23	0.28	< .001	1.53	0.28	< .001	0.83	0.28	.004	0.85	0.27	.002

Note. N_{2011} = 1,104, N_{2013} = 1,114, N_{2015} = 1,121, N_{2017} = 1,120, N_{2019} = 1,122. Omitted categories: male, age 14–29, medium education, medium income, unemployed, mobile internet non-use, bad internet skills.

Figure 7. ***R²*** **of dependent variables over time**



Note. Nagelkerke's R^2 is reported for internet use, mobile internet use and good internet skills and adjusted R^2 for information, entertainment, commerce and communication internet use.

The results revealed that the proportion of variance explained by the set of socio-economic variables on internet use increased between 2011 and 2019, which means that the inequality-related predictors have become more important in explaining the likelihood of using the internet in Switzerland. Inequalities in mobile internet use and internet skills appear to have remained relatively stable. Using the internet for information or commerce was most unequally distributed among internet users in 2013. Inequalities for more leisurely types of internet use (communication, entertainment) peaked in 2017 and have declined since. The proportion of explained variance in the models is comparable to similar studies (e.g., Bergström, 2017), indicating that variance in internet-related variables is predicted by social exclusion-related variables at about a quarter to a third.

6. Discussion

With internet access and usage becoming a global imperative, investigating inequalities in the adoption of ICTs remains relevant. As initially addressed, at 92%, internet penetration in Switzerland is very high. Using the internet for various purposes has, therefore, become a societal standard. Assuming that internet use can be beneficial for individuals in their everyday lives, the diffusion of the internet is often understood as a socially desirable development. However, being part of a disadvantaged group is likely to have broader negative implications when this group is smaller and divides deepen.

Internet diffusion, mobile internet usage, internet skills and different types of internet use steadily increased in Switzerland between 2011 and 2019. However, even for very basic internet access variables, digital inequalities persist along traditional societal fault lines (e.g., age, sex, education). These findings are in line with the basic hypothesis of the digital divide framework (see p. 13) and the same was, for instance, found for Britain and Sweden, where access divides remain relevant (Helsper & Reisdorf, 2017). This empirical finding partially contradicts or at least qualifies van Deursen and van Dijk's (2014, p. 521) prediction that access divides regarding sex and age will disappear as the internet spreads across societies and is more in line with their more recent results that highlight the importance of material access to the internet (van Deursen & van Dijk, 2019).

These inequalities also remain relevant for more differentiated types of internet usage. This finding is in line with the constant upgrade culture of the internet (Lister, 2009; Nguyen, 2012): Although traditionally disadvantaged societal groups are increasingly moving online, the advantaged majority of an information society is adopting more differentiated types of internet usage and rapidly developing their internet skills: a basic mechanism is that acquiring new knowledge is proportional to already acquired knowledge. Disadvantaged groups therefore keep falling behind and being asked to play catch-up. In the same vein, structural differences in internet skills are relevant because—as van Dijk (2017, p. 2) puts it—"obtaining physical access makes no sense when people are not able to use the technology".

As for predictions for the future evolution of digital inequalities in Switzerland, our results do not allow a definite answer. The fact that basic access divides are not shrinking, but rather widening, suggests that it is likely that these inequalities will not resolve themselves. As the technology evolves, not using it to its full potential involves many disadvantages for everyday life. Our results suggest that the internet and the expected scope of online engagement are evolving faster than inequalities are resolving themselves. One argument that allows more optimistic predictions for the future is that initial internet adoption is a much higher hurdle than experimenting with more complex types of use when one is already online.

There are limitations to acknowledge when considering the implications and results of this study. Long-term cross-sectional surveys, i.e., repeatedly drawing new representative samples from the Swiss population, is necessary to make statements about the evolution of digital inequalities. However, panel data might complement this analysis by allowing a more detailed understanding of individuals' decision processes when moving online. Since this article's aim was to trace the evolution of indicators of digital inequalities, it relied on a set of unmodified variables. While this was necessary to enable comparisons over time, it simultaneously meant that on-going research in the past decade, which has advanced our understanding of how to best measure certain concepts, could not be considered for the empirical part of this article. Future research should use these updated measurements and scales, while also including a broader set of sociodemographic predictor variables in order to account for emergent intersectional understandings of inequality. Further, the assumption that more internet use is generally preferable has been at the core of digital divide research. It remains plausible that using the internet for information seeking or commercial transactions is generally desirable from both an individual and a societal perspective. However, other dimensions of using the internet with potentially more negative outcomes have also been identified. As we have initially mentioned, there is a growing public and academic interest in internet overuse or even addiction, although the latter is highly contested. While conceptual and empirical studies on this phenomenon are emerging (see e.g., Aagaard, 2020; Büchi et al., 2019; Helsper & Smahel, 2020; Kardefelt-Winther, 2014; Sutton, 2020), an encompassing picture of how digital inequalities relate to overuse and its implications is hitherto lacking. However, recent results have shown that sections of the population deal with the abundance of ICTs in their everyday lives differently and experience digital overuse at different rates (Gui & Büchi, 2021). Considering digital overuse in the realm of digital inequality research could mean to understand it as a form of a digital divide outcome (see van Deursen & Helsper, 2015) and stresses the importance of including individual reflections of everyday internet use into these kinds of studies. Reconciling these emerging, potentially harmful forms of internet use with the general pursuit of information societies, which has hitherto mainly relied on the assumption that internet use is solely beneficial from both an individual and a societal perspective, remains a challenging task.

The results of our analyses have shown that Switzerland has a shrinking group of internet non-users, yet access is not universal. Attempts to bring these people online have to specifically focus on these excluded groups and their various reasons for not engaging online. The variance in circumstances, internet skills, online experience and reasons for non-use must be accounted for when developing tailored (policy) interventions that promote internet use. As White and Selwyn (2013) have noted, digital inequalities and online disengagement have to be understood as both technological and social issues.

Waiting for ageing to resolve inequalities is an unviable option for two reasons: first, since societies are ageing, existing digital inequalities are likely to remain a problem for longer and affect ever larger proportions of societies. Second, the results of this study show that inequalities are likely to remain, merely partially shifting to other forms of internet usage. Consequentially, it is necessary to take measures to uphold the quality of life and provide means for functioning in society, also for older societal groups (Bergström, 2017; Hofer et al., 2019). It is likely that a good solution would be to specifically target these disadvantaged groups (e.g., the elderly).

Future research should also include cross-country comparisons of inequality-related predictors of different types of internet usage that investigate the effects of political, economic, and cultural factors. It is likely that variables at the country level affect the evolution of digital inequalities (Helsper & Reisdorf, 2017). Research on the evolution of inequalities also lacks in-depth analyses of individual (sociodemographic) predictors of digital inequalities. For instance, Helsper (2010) calls for “an explicit comparison of sex differences within different generational, occupational, and other groups” (p. 353). Related to our understanding of (inequality-related) differences in internet usage as continua rather than binary distinctions, future research should also focus on more nuanced dependent variables that take into account the various possible modes of internet usage. Above all, it is important to stress that everyday internet use is a highly personal and context-dependent behavior, embedded into varying individual and societal contexts. Reasons for engaging in or refraining from certain activities are likely very diverse and more qualitative research is needed to understand these intricacies.

The results of this article emphasize that inferring the specific situations of various segments of society from the fact that a country as a whole, in this case Switzerland, is labeled an *information society* is problematic: the way some people actually live within an information society is likely to be very different from population averages. Even in highly connected information societies, great digital inequalities remain. Our results revealed that older individuals especially tend to be excluded from several facets of digitization. It has become especially apparent that those who do not engage in various types of internet use are at a higher risk of becoming part of a marginalized and shrinking group. It is vital to tackle this threat of digital exclusion and prevent specific parts of the population from suffering compound disadvantages in various spheres of life, especially considering the speed of digital transformation.

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Article II

Left Behind in the Digital Society – Growing Social Stratification of Internet Non-Use in Switzerland

Kiran Kappeler, Noemi Festic & Michael Latzer

Abstract

In a highly digitized society, internet use yields many advantages in everyday life. In Switzerland, today the share of non-users is dwindling. At the same time, disadvantages of internet non-use become increasingly severe. For more evidence-based public policies to mitigate the risks of digital and social exclusion, long-term results from representative surveys are needed. This chapter investigates how the digital divide – social differences in internet adoption – evolved in Switzerland from 2011 to 2019. The results of multiple binary logistic regressions reveal that internet use remains stratified along existing social differences. Non-use has become increasingly concentrated in traditionally disadvantaged societal groups: people with lower education and income and higher age are more likely to be non-users. Lack of interest and lack of skills are among the main reported reasons for non-use. This underlines that a basic level of media literacy is needed for internet adoption. Non-users feel less integrated into today's society, which highlights the relevance of promoting internet use among them, for instance by having them benefit from the internet indirectly through proxy-use.

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Abstract

In a highly digitized society, internet use yields many advantages in everyday life. In Switzerland, today the share of non-users is dwindling. At the same time, disadvantages of internet non-use become increasingly severe. For more evidence-based public policies to mitigate the risks of digital and social exclusion, long-term results from representative surveys are needed. This chapter investigates how the digital divide – social differences in internet adoption – evolved in Switzerland from 2011 to 2019. The results of multiple binary logistic regressions reveal that internet use remains stratified along existing social differences. Non-use has become increasingly concentrated in traditionally disadvantaged societal groups: people with lower education and income and higher age are more likely to be non-users. Lack of interest and lack of skills are among the main reported reasons for non-use. This underlines that a basic level of media literacy is needed for internet adoption. Non-users feel less integrated into today's society, which highlights the relevance of promoting internet use among them, for instance by having them benefit from the internet indirectly through proxy-use.

1. *Introduction*

In highly digitized societies such as Switzerland, skilled internet use is required or at least expected for a wide variety of everyday activities. Offline alternatives tend to be inferior or altogether non-existent. In the lockdown months during the covid-19 pandemic, using the internet has become even more critical. Very mundane activities like staying in touch with people, purchasing goods or getting work done suddenly required using the internet. This extraordinary situation has highlighted the present relevance of internet use on an unprecedented scale.

In today's digitized society, not being able to use the internet in a skilled way is thus highly problematic. Indeed, digital and social inclusion are closely intertwined (Helsper & Reisdorf, 2017; Witte & Mannon, 2010). Therefore, all members of a society should be enabled to use the internet in a skilled way to achieve social inclusion. To be able to develop increased internet skills, using the internet is a prerequisite (van Dijk, 2020). However, there is still a part of the Swiss population that does not use the internet at all.

Today, the digital divide – i.e., structural social differences between users and non-users of the internet – becomes increasingly severe. With a growing proportion of the population using the internet, those who cannot or do not profit from it are likely to become an increasingly disadvantaged minority. Promoting internet use – especially in traditionally disadvantaged groups with lower adoption rates – has therefore been a goal of public policies in many societies, including Switzerland (BAKOM, 2018). Not using the internet can either be a deliberate choice (Syvertsen, 2017) or reside in structural inequalities. Factors that predict internet non-use and the development of their influence are thus worth examining.

This chapter addresses the question of who the internet non-users in the highly digitized Swiss society are and how the digital divide has evolved, i.e., whether internet adoption has become normalized or remains stratified across societal groups. We also identify non-users' self-reported reasons for internet non-use and analyze how benefitting indirectly from the internet through proxy-use – i.e., by asking someone to do something online – relates to the intention to use the internet in the future.

We start by giving an overview over the theoretical concept of the digital divide as well as existing empirical research in this area. After having described the methodological approach of this study, the empirical results are presented and discussed. The chapter concludes with policy implications derived from the findings.

2. Theoretical considerations

2.1 Disadvantages due to internet non-use in a highly digitized society

Due to the omnipresence of the internet in today's information society, not using the internet in a skilled way leads to missing out on advantages that internet use offers (e.g., van Deursen & Helsper, 2015 a). This danger is even more severe for those who do not or cannot use the internet at all: drawbacks in various life domains such as work, education, socializing, culture, health, and institutional and political participation are possible (DiMaggio et al., 2004; van Dijk, 2005). Not using the internet can affect upward socioeconomic mobility negatively, even when age, gender and health are controlled for (Eynon et al., 2018). Meanwhile, internet users believe they have profited from a variety of advantages through internet use, such as receiving a discount on a product or booking a more affordable trip (van Dijk, 2013). Obtaining a job, discovering a matching political party, finding appropriate social associations, discovering facts about illnesses or finding potential partners are further advantages that internet users have experienced due to their internet use. Among older adults, a relationship between personal well-being and using the internet has been found, suggesting that digital and social exclusion can be linked (Seifert et al., 2018). Those who do not use the internet are excluded from these potential advantages (van Dijk, 2013).

All these disadvantages from not using the internet are likely to become even more severe in societies where using the internet is normal and expected (Groselj et al., 2019). For instance, the internet has become the primary mode of filling out one's tax returns in Switzerland. Those who cannot or do not want to do this online have to request a paper version to be sent to them via mail, which can be an additional burden for already disadvantaged groups (Kanton Zürich, 2020). Similarly, many companies have switched to sending invoices via e-mail. Paper invoices can usually be requested, but entail additional costs for customers, thus constituting an economic disadvantage. The covid-19 pandemic has demonstrated that in times of crises, the societal reliance on the internet appears to increase even further.

2.2 Social inequalities in internet non-use

Researchers have argued that technology use reflects the unequal power relations that are found in societies (Warschauer, 2004). Thus, digital and social exclusion are understood to be closely related (Witte & Mannon, 2010). From a normative perspective, under the assumption that internet use is predominantly beneficial, for instance in furthering social inclusion, promoting internet use is a social and political goal (van Dijk, 2020). Identifying the cause of internet non-use is essential to tackle digital exclusion (Eynon & Helsper, 2010). Digital-divide research has addressed differences in internet access and use that reside in existing social inequalities (Selwyn, 2006). Research in this tradition is based on the knowledge gap hypothesis, which stipulates that groups with lower socioeconomic background have worse access to media and profit less from using them. This results in a gap between societal groups and knowledge – or the lack thereof – is its cause (Tichenor et al., 1970).

This chapter focuses on the first-level digital divide, which is understood as the distinction between those who do and those who do not use the internet (Ragnedda, 2017). In van Dijk's (2005, 2020) terminology, this chapter thus concentrates on motivation and access divides, which are the most fundamental divides in internet use. These form the basis for further inequalities in usage and skills (second-level digital divide) and consequences of internet use (third-level digital divide).

2.3 Scenarios for the evolution of digital divides

With the increasing spread of the internet, two scenarios for the evolution of digital divides seem particularly plausible (Norris, 2001; van Dijk, 2013): (1) the normalization of existing differences in internet access and use across societal groups, and (2) stratification, where differences persist or increase.

According to the normalization thesis, the number of adopters of an innovation in a society follows an S-shaped curve with two tipping points. As it spreads, an innovation is understood to trickle down from the privileged groups who mostly constitute the innovators towards all population levels. Hence, the theory predicts early differences in internet access and use will fade and normalization will set in (Norris, 2001; Rogers, 2003).

In contrast, the stratification thesis argues that differences in internet use are not merely temporal. Rather, the positions of individuals in society and the relations between them are central to explaining these differences. During the internet appropriation process social inequalities can be reproduced and reinforced (Norris, 2001; van Dijk, 2005, 2013; Wessels, 2013). Groups with lower socioeconomic status can suffer from worse internet access. Consequentially, they are not able to profit from advantages of internet use to the same extent as people who have good access. As a result, differences between social groups are reinforced.

2.4 Policy measures to advance social and digital inclusion

The advantages of using and disadvantages of not using the internet have led to discussions on the need for policy measures to enable everyone to use the internet skillfully. This is especially the case in highly digitized societies, where using the internet is the norm and not being able use the internet in a skillful way is therefore highly problematic. Generally, the public and the private sector are engaged in trying to bridge the digital divide albeit with different motives (Rosston & Wallsten, 2020; van Dijk, 2005). Affordable and reliable broadband internet access of a certain quality is considered a universal service in Switzerland (ComCom, 2019). The Swiss federal office for communication is committed to grant every citizen the same basic infrastructure for digital communication purposes. This also entails promoting basic competences for internet use (BAKOM, 2018). From a normative perspective, the right to life-long learning highlights the importance of providing internet access and the opportunity to use it – especially for the elderly (Doh et al., 2015). The resources needed for participation should thus be granted to everyone (Wessels, 2013). In Switzerland, such initiatives are for instance provided through programs by a non-governmental organization for the elderly (Pro Senectute, 2020) and by the leading telecommunication provider, a private company of which the Swiss state holds the majority stake (Swisscom, 2020). In order to assess the legitimacy and success of existing policies aimed at bringing people online (e.g., Rosston & Wallsten, 2020 for the U.S.), long-term empirical research on the evolution of digital divides are required.

3. Existing empirical research and research gaps

Research on the (first-level) digital divide is concerned with factors that influence why certain people do not use the internet while others do. So far, it has been shown that sociodemographic and socioeconomic background predict internet non-use. Generally, individuals from socioeconomically disadvantaged backgrounds are consistently more likely to be non-users (e.g., Blank et al., 2019; Bonfadelli, 2002; Chia et al., 2006; DiMaggio et al., 2004; Dutton & Blank, 2013; Dutton & Reisdorf, 2019; Grishchenko, 2020; Scheerder et al., 2017; van Dijk, 2013; Zickuhr, 2013). Higher income and education level as well as lower age and positive attitudes towards the internet also appear to be stable predictors of internet use (Reisdorf & Groselj, 2017). In fact, social inequalities in internet use have even been shown to grow worse and the emergence of a digital underclass has been reported (Helsper & Reisdorf, 2017).

When non-users are asked why they do not use the internet, they mostly provide one of the following reasons: lack of (affordable) access, skills, time, or interest (Chia et al., 2006; Dutton & Blank, 2013; Helsper &

Reisdorf, 2017; Lenhart et al., 2003; Morris et al., 2007; Reisdorf et al., 2012; Seifert & Schelling, 2015; Selwyn, 2006; van Dijk, 2005; Zickuhr, 2013; Zillien, 2008). Lack of interest has become more important over recent years (Helsper & Reisdorf, 2017).

Several research gaps can be identified in the existing literature. So far, the effects of different sociodemographic variables on internet (non-)use have not been disentangled and effect sizes of predictor variables have not explicitly been compared (Helsper & Reisdorf, 2017). Also, it is not clear which societal groups have negative attitudes towards the internet. Moreover, the influence of non-users' social surroundings and the relation between proxy-use (Groselj et al., 2019) and the intention to use the internet has not been addressed in detail (van Deursen & Helsper, 2015 b). Finally, the evolution of digital divides has only rarely been studied, and analyses of longitudinal representative data at the population-level in a highly digitized country have so far been scarce (e.g., Helsper & Reisdorf, 2017). This chapter contributes to filling these research gaps using the methodological design described in the subsequent section.

4. Method

4.1 Nationally representative survey data

Data was collected from 2011 to 2019 through biannual cross-sectional representative surveys of the Swiss population aged 14 years and over (N_{2011}=1,104; N_{2013}=1,114; N_{2015}=1,121; N_{2017}=1,120; N_{2019}=1,120). Each sample is representative by gender, age, employment status and the three biggest Swiss language regions. Computer-assisted telephone interviews (CATI) were conducted using a dual-frame sampling framework to contact landline and mobile phone numbers. The repeated cross-sectional research design with representative samples for each period allows findings about structural societal changes in factors influencing internet non-use. The data was collected as part of the World Internet Project, an internationally comparative and long-term project on internet use.

4.2 Measures

Non-use. Respondents were asked whether they are currently using or have been using the internet in the past three months. We identified those who answered the question negatively as non-users of the internet.

Proxy-use. Non-users were questioned as to whether they have asked someone to do something for them online in the past year. A positive answer led to classification as a proxy-user. Proxy-users were subsequently questioned as to whom they had asked to do something for them online and what they had asked them to do (e.g., searching for information or buying something online).

Main reason for non-use. Non-users were asked to indicate their main reason for not using the internet from a list of reasons including financial, material, and skills-related reasons as well as reason related to negative experiences (Cole et al., 2019). Respondents also had the option to specify other reasons.

Intended future use. Non-users were also asked about their agreement with the statement that they would like to use the internet in the future on a scale from 1 = *do not agree at all* to 5 = *strongly agree*.

Feeling of inclusion in today's information society. At the end of the survey, after having answered several questions about the media, the internet and various communication technologies, respondents had learned what today's new information society entails. Hence, all respondents were asked about their agreement with the statement that they feel integrated in this new information society (1 = *do not agree at all*, 5 = *strongly agree*). This question was asked to find out about the presence of a perceived digital divide.

Sociodemographic and socioeconomic variables. Several sociodemographic variables such as gender (1 = *male*, 2 = *female*) and age were recorded. Age was recoded into the following categories: 1 = 14–19 years, 2 = 20–29 years, 3 = 30–49 years, 4 = 50–69 years, 5 = 70+ years. Education was measured by the highest level of educational attainment and recoded as follows: primary education, i.e., completion of compulsory school into 1 = *lower*, education on secondary level such as vocational school or higher school certificate into 2 = *intermediate* and tertiary education, i.e., university degree or higher into 3 = *higher*. Household income was measured in different categories in the years 2011 to 2013 and 2015 to 2019 and thus had to be recoded for approximate comparison (2011 and 2013: up to 7,000 Swiss francs = *low*, 7,001–12,000 Swiss francs = *medium*, more than 12,000 Swiss francs = *high*; 2015, 2017 and 2019: up to 6,000 Swiss francs =

low, 6,001–15,000 Swiss francs = *medium*, more than 15,000 Swiss francs = *high*).

4.3 Data Analysis

This study applies multiple binary logistic regression analyses to determine and compare the influence of sociodemographic and socioeconomic characteristics on the probability of being an internet non-user between 2011 and 2019 in Switzerland. In addition, we computed descriptive statistics to complement the findings with self-reported reasons for non-use and intention to use the internet as well as inclusion in the information society.

5. Results

In order to find out who the internet non-users in the highly digitized Swiss society are and how the digital divide has evolved in recent years, we will first provide some descriptive statistics on internet non-use and then present the results of the binary logistic regressions[1].

5.1 Influencing factors on internet non-use

In 2019, the majority of the Swiss population (92 %) used the internet. Internet adoption has steadily increased over the period of research. Table 1 shows the proportion of non-users in the Swiss population in the years 2011 to 2019.

1 See working paper at https://www.mediachange.ch/media//pdf/publications/nonuse.pdf for detailed tables on binary logistic regressions of the years 2011–2019 and an extensive list of self-reported main reasons for internet non-use.

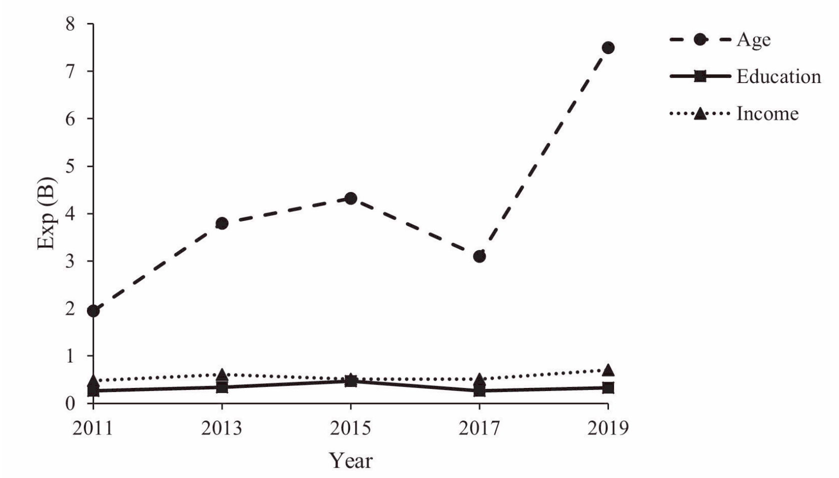
Table 1. Proportion of non-users of the internet in the population of Switzerland 2011–2019. N_{2011}=1,104; N_{2013}=1,114; N_{2015}=1,121; N_{2017}=1,120; N_{2019}=1,120.

	Year				
	2011	2013	2015	2017	2019
Gender					
Male	21 %	13 %	8 %	6 %	6 %
Female	25 %	17 %	17 %	13 %	9 %
Age (in years)					
14–19	27 %	2 %	1 %	0 %	0 %
20–29	12 %	4 %	0 %	2 %	0 %
30–49	11 %	5 %	4 %	3 %	0 %
50–69	23 %	17 %	17 %	13 %	7 %
70+	63 %	53 %	48 %	34 %	40 %
Education					
Lower	49 %	30 %	22 %	21 %	17 %
Intermediate	25 %	16 %	15 %	11 %	9 %
Higher	8 %	6 %	4 %	2 %	2 %
Income					
Low	73 %	52 %	54 %	44 %	39 %
Medium	16 %	11 %	9 %	11 %	5 %
High	5 %	6 %	2 %	0 %	8 %
Total	23 %	15 %	13 %	10 %	8 %

In 2019, two-fifths of those aged 70 and over were internet non-users while there were no non-users in the Swiss population aged 49 and under. Altogether, the highest proportions of non-users were found among the older, the less educated and those with lower household income. The descriptive data shows that internet penetration has increased since 2011. Hence, non-users have become fewer.

To test these discernible trends, binary logistic regressions on the probability of being a non-user were calculated for each of the five years under examination. Figure 1 illustrates the evolution of the effects from 2011 to 2019.

Figure 1. Binary logistic regression: probability of not using the internet 2011–2019. N_{2011}=1,104; N_{2013}=1,114; N_{2015}=1,121; N_{2017}=1,120; N_{2019}=1,120. Exp(B)=odds ratio. Only significant effects at the level of p<.01 are shown.



The results indicate that education, income and age influenced the likelihood of not using the internet significantly during the whole period under examination. Lower education and income as well as higher age significantly predicted internet non-use from 2011 onwards. Thus, the higher a person's level of educational attainment, the greater their household income, and the lower their age, the lower the likelihood of them being non-users. Through the years, the effects of education (e.g., $Exp(B)_{2011}$=.262, $Exp(B)_{2019}$=.330) and income (e.g., $Exp(B)_{2011}$=.483, $Exp(B)_{2019}$=.707) remained relatively stable. The effect of age has grown over the years (e.g., $Exp(B)_{2011}$=1.953; $Exp(B)_{2019}$=7.497). Compared with education and income, age had a consistently greater and growing effect on the probability of not using the internet. Over the whole period examined, gender did not relate to the likelihood of being a non-user.

5.2 Self-reported reasons for non-use

In 2019, the reason most non-users regarded as most important for their non-use was a lack of interest or not finding the internet useful (38 %). Feeling too old to use the internet (16 %) as well as lack of knowledge and being confused by technology (12 %) were further relevant reasons reported by non-users. Over the examined period, lack of interest and knowledge were among the most important reasons for non-use, thus indicating critical barriers to internet use. Recently, cost and physical access have become peripheral problems (6 % and 2 % respectively in 2019).

5.3 Intended future internet use and benefitting from the internet indirectly through proxy-use

Even though most non-users (96 %) use offline media (such as newspapers, magazines, television, radio, or books) for information purposes, some non-users additionally seek to benefit from the internet indirectly through proxy-use. The number of proxy-users has risen slightly in recent years (2011: 36 %, 2013: 48 %, 2015: 40 %, 2017: 51 %, 2019: 40 %), although the development is not consistent. In 2019, most of the proxy-users were over 65 years (87 %) and belonged to the group with low household incomes (83 %), a majority were female (61 %) and had a lower (35 %) or intermediate (58 %) levels of educational attainment. In 2019, the most common fields for proxy-use were e-commerce (41 %) and finding information online (39 %). Entertainment (25 %) and socializing (19 %) were less prominent purposes of proxy-use. Proxy-users mainly asked their (grand-)children (51 %) to help them. Asking one's partner (23 %), a friend (14 %) or someone else (20 %) was less common. The younger generation thus provides an important gateway to the benefits of the internet for the group of non-users, which predominantly consists of people who reached the age of retirement. From 2015 onwards, being a proxy-user significantly correlated with an increased willingness to use the internet in the future (2011: r=.053, p>.05, 2013: r=.156, p>.05, 2015: r=.284, p<.001, 2017: r=.260, p<.01, 2019: r=.277, p<.05). Thus, indirect contact with benefits of the internet through proxy-use is associated with an increased willingness to start using the internet. At the same time, non-users' intention to use the internet in the future has fallen in recent years. While in 2011 three in ten non-users (28 %) said that they would like to use the internet, only one in ten did so in 2019.

To qualify the relevance of this digital divide, we will now look at how integrated internet non-users feel in today's information society.

5.4 Inclusion in the information society

Being a non-user correlated significantly negatively (p<.001 for all years) with the feeling of inclusion in all the years examined (2011: r=-.445; 2013: r=-.376; 2015: r=-.328; 2017: r=-.282; 2019: r=-.280). The share of people who feel integrated into today's information society is thus greater among users than among non-users. This indicates that digital and societal exclusion are closely linked.

6. Discussion

This chapter has addressed the evolution of the first-level digital divide in the highly digitized Swiss society, applying a longitudinal perspective. Our results show that even at this high level of internet penetration – in 2019, 92 % of all Swiss used the internet – a person's sociodemographic and socioeconomic background still influences their likelihood of internet non-use. Over the last years, societal groups that have traditionally been disadvantaged were constantly more likely to be digitally excluded. The stratification of internet use that we observed implies that the knowledge gap hypothesis (Tichenor et al., 1970) still applies to internet penetration in Switzerland. Indeed, a Matthew effect can be observed: while the rich get richer, the already disadvantaged become even more so.

Our results also reveal a lack of interest and a perceived lack of knowledge as the main reasons for non-use. This implies that a basic level of media literacy as a communicative competence is required for internet use. Furthermore, we see a stable share of proxy-users among non-users and a decline in the intention to use the internet. Taken together, this points towards an increasing saturation in internet adoption, while at the same time, internet use has been shown to become increasingly stratified. Thus, even in a highly digitized country like Switzerland, where the internet is regarded a universal service and access is granted to every citizen (ComCom, 2019), traditionally disadvantaged societal groups are at greater risk of digital exclusion.

As the internet gains ever-more relevance for everyday life, not using it becomes increasingly detrimental. Therefore, the shrinking but increasingly disadvantaged group of non-users (600,000 people in Switzerland in 2019) warrants political attention. Increasing internet adoption on a societal level is central to advance social inclusion. While governmental actions like providing necessary infrastructure as well as affordable access and promoting required knowledge are central to this endeavor, the industry can help by providing easily accessible technologies that facilitate adoption (van Dijk, 2020), especially for the elderly who constitute the biggest share of non-users. As has been shown, lack of interest, feeling too old and perceived lack of knowledge are important barriers to using the internet. Policy makers should focus on these when designing policies aimed at increasing the internet adoption. Highlighting the opportunities that the internet offers to non-users specifically is promising. Another promoting factor for internet adoption intention is proxy-use. So-called warm experts, i.e., people close to the non-user that are familiar with using the internet (Bakardjieva, 2005), or peer experts (Doh et al., 2015) may encourage recognition of the usefulness of the internet and thus increase the wish to use the internet.

Finally, the present situation of the covid-19 pandemic highlights that besides market developments and policy measures, unforeseen external events can have a decisive impact on the diffusion and use of a technology. Nationwide lockdowns in numerous countries have influenced internet use hugely. Indeed, the motivation to go online might have grown as dependence on digital tools for working (from home), satisfying informational and consumer needs, or interacting with others has increased to an unprecedented level (Nguyen et al., 2020).

7. *Conclusion*

To conclude, in today's information society, internet use increasingly entails advantages that can hardly be achieved otherwise. This study shows that internet use has become increasingly socially stratified and that internet non-users feel less integrated into today's information society than internet users do. Especially for people who are at greater risk of being socially excluded, i.e., the elderly, the less well-educated and the less affluent, internet use would provide opportunities for greater inclusion. Because of the positive effects that internet use can entail, it should be promoted especially among these vulnerable groups.

While research increasingly focuses on second- and third-level divides and digital inequalities among internet users, this study has shown that a basic digital divide in access to and use of the internet still prevails – even in a highly digitized society. Indeed, internet use remains stratified. This signifies that as long as the digital divide is not bridged, critical services (e.g., governmental; Reisdorf & Groselj, 2018) should not be provided digitally per default, as this would reinforce existing social exclusion. Also, while initiatives to promote internet skills among the population are commendable, there is a danger that increasingly vulnerable groups are left behind and – at some point – will no longer be able to catch up. This digital exclusion can lead to real-life, tangible disadvantages, that must be prevented in an inclusive, digitized society.

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Article III

How Long and What For? Tracking a Nationally Representative Sample to Quantify Internet Use

Noemi Festic, Moritz Büchi & Michael Latzer

Abstract

Testing communication theories requires a valid empirical basis, yet especially for usage time measures, retrospective self-reports have shown to be biased. This study draws on a unique data set of 923 Swiss internet users who had their internet use tracked for at least 30 days on mobile and desktop devices and took part in a survey covering internet usage as well as person-level background variables. The analysis focuses on active usage time overall and on the major services Google Search, YouTube, WhatsApp, Instagram, Facebook, and the online newspaper 20 Minuten. The results showed that overall internet usage time was lower for older and higher-educated users based on both the tracking and survey data, and the reported usage time was consistently higher than the tracked usage time. The tracking data further revealed that internet users in all social groups spent the majority of their time online on a mobile device. The number of users of the major services varied mainly between age groups. These differences were less pronounced when it came to the time users spent engaging with these services. Over the course of a day, the major services varied in their frequency of use: for example, messaging peaked before noon and in the late afternoon, whereas online news use was comparably constant at a lower level.

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How Long and What For? Tracking a Nationally Representative Sample to Quantify Internet Use

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Testing communication theories requires a valid empirical basis, yet especially for usage time measures, retrospective self-reports have shown to be biased. This study draws on a unique data set of 923 Swiss internet users who had their internet use tracked for at least 30 days on mobile and desktop devices and took part in a survey covering internet usage as well as person-level background variables. The analysis focuses on active usage time overall and on the major services Google Search, YouTube, WhatsApp, Instagram, Facebook, and the online newspaper 20 Minuten. The results showed that overall internet usage time was lower for older and higher-educated users based on both the tracking and survey data, and the reported usage time was consistently higher than the tracked usage time. The tracking data further revealed that internet users in all social groups spent the majority of their time online on a mobile device. The number of users of the major services varied mainly between age groups. These differences were less pronounced when it came to the time users spent engaging with these services. Over the course of a day, the major services varied in their frequency of use: for example, messaging peaked before noon and in the late afternoon, whereas online news use was comparably constant at a lower level.

Keywords: internet usage, tracking data, self-reports, survey, digital traces

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Introduction: On the Importance of Measuring Internet Usage with Tracking Data

The way people use digital media and the internet has changed significantly in the past decade (see Latzer et al., 2020 for Switzerland). The internet is increasingly used across multiple devices, often on the go, and this use is very much integrated into everyday activities rather than being a discrete event with a clear beginning and end point. These usage habits have implications for measuring media use (for instance in terms of frequency and time), which has become more challenging as a consequence.

At the same time, theoretical questions of communication processes are increasingly addressed with sophisticated modeling techniques given the growing acknowledgement that cross-sectional regressions cannot support causal claims. However, basic descriptive knowledge about the prevalence of an empirical phenomenon that helps to contextualize specific findings and to know where to look closer in future research is often still scarce: Whether we are interested in the prevalence of filter bubbles (e.g., Dubois & Blank, 2018), want to know what the perils of being online for adolescents are (e.g., Smahel et al., 2020), or care about internet users' privacy protection behaviors (e.g., Boerman et al., 2018), addressing these questions and advancing media and communication theories requires solid empirical evidence on internet use and a foundational understanding of the scale of use in everyday life.

Therefore, this article addresses the following research questions: *How much time do people spend online and using specific services? How does this usage time differ according to sociodemographic characteristics (gender, age, education)?* The results are intended to contribute descriptive knowledge that is not just intuitively interesting, but also necessary for subsequent theorizing of the causes and consequences of these observable patterns. This study relies on a combination of tracking and survey data to answer these questions. The following sections substantiate the reasons for this methodological choice.

Internet usage data has so far mainly been collected through people self-reporting their behavior in face-to-face, phone or web-based interviews. Recently, internet use tracking has emerged as a new option to gather such data. While there are unique challenges to logging people's internet use, it is a promising and complementary new measurement approach. In addition to technological advances that have made tracking usage possible, the academic application of this new way of data collection was mainly motivated by biases in survey data, which is usually self-reported and retrospective. Although a recent meta-study attests self-reported data on media exposure a moderate reliability and a high stability (Scharkow, 2019), it is clear that answering questions like *"How much time do you spend online on an average day?"* is difficult and error-prone. When it comes to the use of specific services, it is likely that internet users find it even more challenging to recall exactly how many times they, for instance, scrolled through their Instagram feed and how much time they spent on the platform.

A combination of tracking data and traditional survey measures—albeit being subject to its own specific challenges (see e.g., Stier et al., 2019)—appears to be the most viable solution to circumvent methods-specific biases (see p. 4) and provide a valid description of people's everyday internet use linked with person-level background variables. Particularly given the research interest of this article—describing internet use in different social groups—including self-reported demographic and socioeconomic variables is vital (and they must be accurate). In existing big data research, such user characteristics are often inferred from user behavior such as clickstreams or consumer purchasing data (e.g., for personalized advertisements).

Such a combination of tracking and survey data has, for instance, been used to study echo-chambers in online news consumption (Cardenal et al., 2019). One of the earlier studies linking survey and tracking data (Dvir-Gvirsman et al., 2016) examined how frequently people were exposed to like-minded content and found that this occurred less often than internet users assumed. Guess et al. (2019) linked tracked Facebook sharing activity data with survey responses and demonstrate how this unique combination leads to the result that users share misinformation a lot less frequently than commonly assumed. Vraga and Tully (2020) demonstrated how fundamentally self-reported news exposure can differ from tracked news exposure and point to individual and contextual characteristics explaining these disparities. Aiming at measuring the implications of using recommender systems, Loecherbach and Trilling (2020) developed an online news environment that allows researchers to experiment with settings and to include user surveys. Such simulated approaches circumvent the challenge of gathering tracking data but limit external validity.

A number of studies have specifically compared self-reported and tracked internet use in terms of frequency, amount or types of use. Based on a large sample of Facebook users, Ernala et al. (2020) revealed that compared to Facebook's server log data, users significantly overestimate the time spent on the platform, while underestimating how often they access the site. For a non-representative sample of 690 Dutch internet users, Araujo et al. (2017) found that self-reported internet use time is higher in comparison with tracked data on time spent online. These differences were partially explained by both internet-use related and contextual factors. Similarly, Scharkow (2016) found that for a large random sample of internet users, the correlation between self-reported and logged internet use was low. Further, internet usage time and frequency were among those measures that were particularly overreported. These results are limited to internet use on home computers. Naab et al.'s (2019) study compared self-reported measures of internet use with results from mobile experience sampling for a sample of students. They found that the participants consistently reported spending more time on Facebook, WhatsApp and YouTube than was found through the in-situ reports that were collected for a duration of two weeks.

Especially relevant in this context are not only comparisons between usage times, but relationships with other relevant variables. For a sample of college students and MTurk workers, Jones-Jang et al. (2020) found that correlations between self-reported usage data and relevant outcomes were lower than between logged usage data and these outcomes, indicating that not only media usage (see section above), but also media usage *effects* may often be underestimated rather than overestimated.

These empirical results relying on a combination of survey and tracking data suggest that given the methodological advances and changed usage habits, very basic questions on internet usage time in different social groups need to be readdressed since there are empirically founded concerns about the accuracy of self-reports. The overview of existing literature presented above reveals several research gaps concerning the quantitative description of internet usage time with survey and tracking data: there is a lack of *representative data* that was collected in a *natural usage situation* and that *includes mobile use*. This article employs an innovative methodological approach introduced below and aims to contribute to filling these research gaps.

Method

Data Collection

The data collection for this article consisted of two main parts: (1) All participants were already part of a mobile (*smartphone or tablet*) tracking panel (see p. 6 for a more detailed description of the sample). To gather tracking data for not only mobile but also desktop devices, the participants received installation instructions for a passive metering software for their *desktop or laptop* device at the start of the field phase. However, not all participants of the study used a desktop device or installed the passive metering software despite maybe owning such a device. Therefore, the proportion of mobile usage time may be slightly overestimated compared to the general population. Between November 2018 and January 2019, we collected tracking data through the passive metering software on private mobile and (if the participants opted in) desktop or laptop devices. The collected variables were the URL of a visited webpage (desktop and mobile) or name of a used app (mobile only), duration and time of the visit, device, and operating system used. (2) At the end of this phase, the participants were advised to uninstall the passive metering software from their desktop or laptop devices and were invited to complete a survey questionnaire.

The survey took 30 minutes on average and included questions on personal background, internet use, risk awareness online, and various internet-use related attitudes.

The participants received a small pecuniary incentive for their participation in the tracking and survey. All participants in the tracking and survey gave informed consent on their participation and the research design was approved by the University of Zurich's ethics review board.

Sample

The independent market and social research company *LINK* recruited and sampled the participants from an existing internet panel. For the desktop and laptop tracking data, we relied on a passive metering solution by *Wakoopa*. The internet panel is actively recruited, which is important in order to reduce the likelihood of a self-selection bias where people with lower privacy concerns would be more likely to select themselves into such a sample. The initial sample of 1'202 respondents is representative by age, gender, region, household size, and employment status for Swiss internet users aged 16 and over. While the overall survey sample is representative for the Swiss internet user population, the tracking sample somewhat overrepresents middle-aged users (aged around 40) and slightly underrepresents the oldest group (70–85). Comparing the survey and tracking samples in terms of other key sociodemographic variables, all proportions were within a single percentage point difference.

The data required preprocessing before analysis. At the level of tracked events (i.e., a site visit), we removed all events with 0 seconds of usage time ($N_{tracked\ events}$ = 233'675) because these reflect automatic redirects and were not part of the participants' actual internet usage; the passive metering software recorded any visited URL regardless of the time spent on it. At the level of participants, we excluded those participants ($N_{participants}$ = 51) who were tracked for fewer than the thirty days planned in the study design. Further, we excluded extreme outliers who reported more than 17 hours of internet usage per day for reasons of plausibility ($N_{participants}$ = 2). The resulting final sample ($N_{participants}$ = 923, $N_{tracked\ events}$ = 13’252’235) formed the basis for the reported results in this article.

Measures

The analyses in this article rely on a combination of the tracking (usage time for the internet and major services) and the survey data (self-reported use for the internet in total and major services, demographic and socioeconomic variables).

Self-reported usage time (*survey*). We asked the respondents to assess their overall usage time of the internet by answering the following question: “For how many hours in total do you use the internet on an average day? Please think of all your internet use (at home, at work, on the road, etc.). Please give us the number in hours, e.g., 15 minutes = 0.25 hours.”

Self-reported usage of major services (*survey*). The respondents were asked to indicate which of the following services they used at least occasionally (multiple responses possible): Google Search, YouTube, WhatsApp, 20 Minuten (most popular free online newspaper in Switzerland), Facebook and Instagram.

Social background variables (*survey*). Since the goal of this article is to compare internet usage in different social groups, the survey included various demographic and socioeconomic variables. In particular, the respondents were asked to report their gender (female, male) as well as their age in years, which was recoded into four groups (16–29, 30–49, 50–69, 70–85). They also reported their completed levels of educational attainment, which were recoded into three levels: individuals whose highest completed education level was the compulsory school were assigned the value *low* and those with tertiary qualifications (university degree or similar) were assigned the value *high*.

Usage time: Internet total (*tracking*). The passive metering software logged the time the users spent on every website or app. We summed up these usage times for every participant and divided this sum by the number of days for which the respective participant's internet use was tracked (this varied between 30 and 120 days).

Usage time: Major services (*tracking*). The measure for the use of major services was calculated by filtering the tracking data for the occurrence of these apps and websites, and extracting these cases from the data set. Analogous to the measure for total internet usage time, we summed up these usage times for every participant who reported using the respective service in the survey and divided this sum by the number of days for which the respective participant's internet use was tracked.

It is important to note that the tracking software measured *active use* of applications or websites, meaning the app or browser window was in the foreground. Therefore, our use data corresponds to the time that users spent on these respective apps or websites but does not reflect, for example, the time the participants were available to receive a message or a call on WhatsApp.

Data Analysis

Data analysis relied on descriptive statistics and particularly on mean score comparisons between different social groups in *R*.[1]

Results

The time Swiss internet users spend online every day was measured both through the tracking and the survey.

[1] The R script for the analysis and the detailed results are available at: https://osf.io/j5mhn/?view_only=7e82e560f19945d4bbbae168cbbcde3e

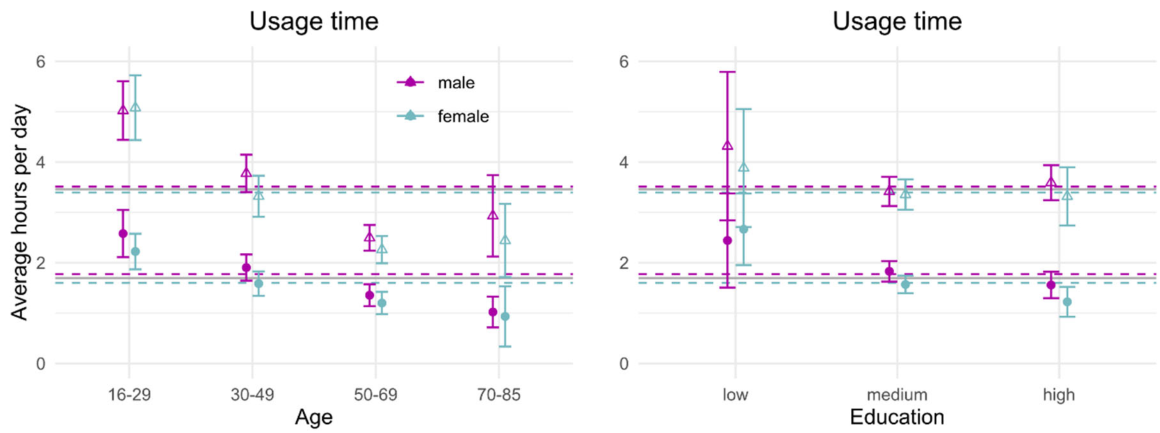

Figure 1. Total daily internet usage (desktop and mobile) by gender, age and education.

Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (hours per day). Lines with points as markers are for tracking data, those with triangles for survey data. Markers are offset for visual reasons, not because they occupy a different space on the X-axis; this pertains to all other figures. $N = 923$ internet users.

Figure 1 depicts differences in daily average tracked and self-reported usage time between different social groups. The results from the tracking and survey data revealed that—with some differences—younger internet users and those with lower levels of educational attainment tend to spend more time online every day. These differences were particularly pronounced for male members of the youngest age group, who spent 1 hour and 39 minutes more online on average compared to females aged 70 and over based on the tracking data. While male internet users tended to be online longer every day, these differences between the genders were not significant. The tracking data revealed that overall, Swiss internet users spent less than two hours on the internet every day. The self-reports were consistently higher in all age and educational groups and across both genders. The mean time that internet users spent online was 1.70 hours based on the tracking data and 3.45 hours based on the survey data. These measures were weakly correlated: $r(933) = .24$, $p < .001$.

Based on the tracking data, the majority of this total internet usage time was spent on mobile devices (M = 1.34 hours per day). The proportion of internet usage time that was through mobile devices tended to be lower for older individuals: while females aged 16 to 29 spent 80% of their time online on a mobile device, this proportion was only at 56% for females aged 70 and over. There were no significant differences between education groups or between the genders. Internet users across all age and education groups and across both genders spent the majority of their time online on a mobile device.

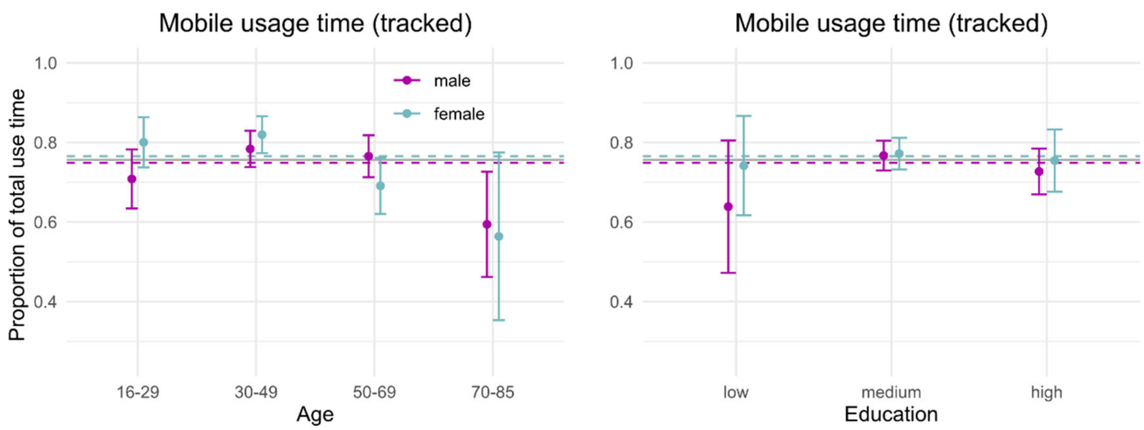

Figure 2. Mobile usage time as a proportion of total usage time by gender, age and education.

Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (hours per day). N = 923 internet users.

In addition to these global results on total internet use, this article specifically aims at empirically investigating the use of certain popular services. As the results in Table 1 reveal, virtually all Swiss internet users reported (*survey*) using WhatsApp and Google Search. A clear majority also used YouTube and Facebook, while 20 Minuten was used by half and Instagram was used by around a third.

These six services accounted for more than a quarter (26.77%) of total internet use in terms of tracked events (*tracking*). WhatsApp was the service that Swiss internet users spent the most time using on average (messages and calls), although the variance was also very high. There were also differences regarding the devices with which the internet users accessed the services. While WhatsApp, Instagram and the newspaper 20 Minuten were almost exclusively used through mobile devices (92–99% mobile accesses), the ratio between mobile and desktop accesses was more balanced for Facebook, Google Search and YouTube. The latter was the only service that was more commonly used on desktop devices.

Table 1. Descriptive overview: user groups, proportions of mobile accesses and usage times.

	User group	% mobile accesses	*M* usage time (minutes per day)	*SD* usage time (minutes per day)
WhatsApp	97.51 % (*N* = 900)	98.64% (*N* = 1’252'757)	13.23	34.53
Google Search	96.10% (*N* = 887)	51.62% (N = 474’614)	3.28	8.65
YouTube	87.87% (*N* = 811)	45.06% (*N* = 183'510)	11.91	32.55
Facebook	69.34% (*N* = 640)	60.81% (*N* = 353'720)	9.42	26.37
20 Minuten	51.44% (*N* = 475)	91.92% (*N* = 124’545)	3.46	10.17
Instagram	38.79% (*N* = 358)	93.37% (*N* = 219'499)	5.08	14.66

Note. User group depicts the share of internet users who reported using the service (*survey*). % mobile accesses shows the share of tracked events for the respective service that were through mobile devices. The last two columns show the mean and standard deviation for the tracked time spent on these services (*tracking*).

When looking at how common using these services is in the Swiss internet user population, there were particularly significant differences across age groups (see Figure 3). While the use of WhatsApp and Google Search was almost uniformly distributed in the Swiss internet user population, there was a slight tendency for older internet users to use these services less. The same trend was found for YouTube and—even more pronounced—

for Facebook and Instagram. 20 Minuten was the only service that was more widespread among older age groups.

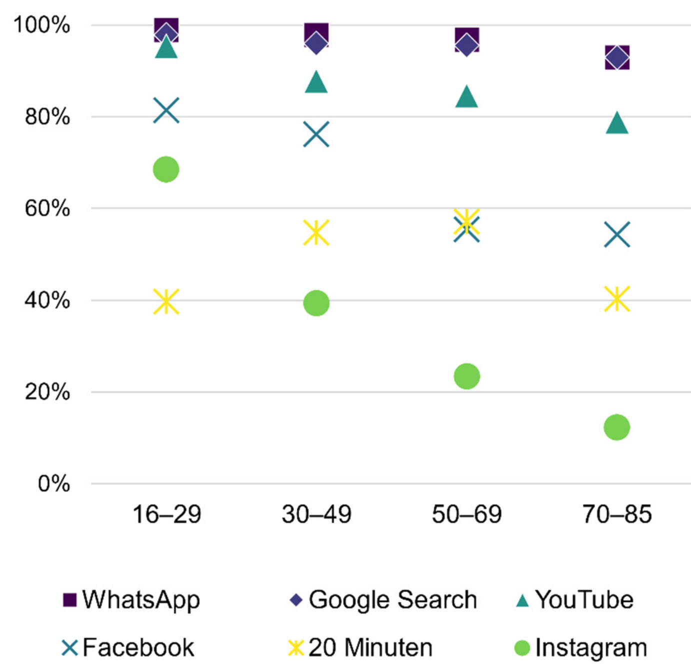

Figure 3. User group of the services by age.

Note. The percentages depict the shares of the respondents who reported using a service in the *survey*. $N = 923$ internet users.

Further, among those internet users who reported using a certain service, we investigated whether the time spent using these services differs between age and educational groups as well as between the genders. Figure 4 shows how the daily time spent using Google Search varied between different social groups.

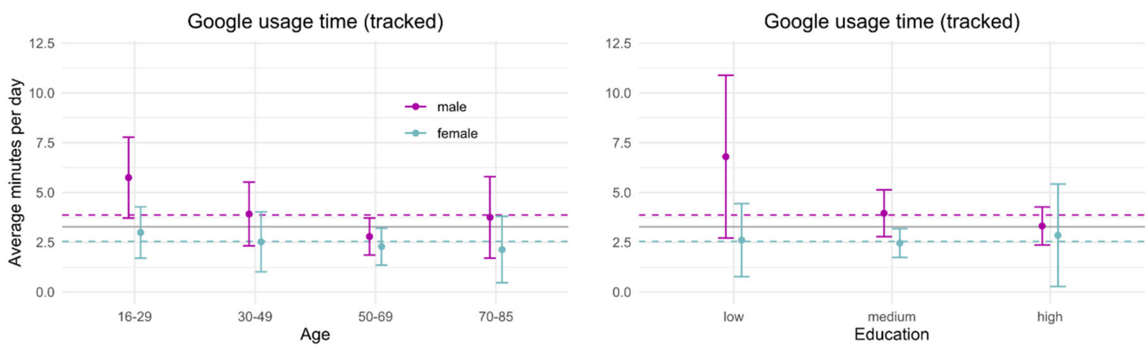

Figure 4. Daily average Google Search usage by gender, age and education.
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 887 Google Search users.

The relationship between age and time spent on Google Search was U-shaped, particularly for men: those aged between 50 and 69 spent less time on Google Search than the younger and older groups. Female internet users tended to spend less time on Google Search: while male internet users aged 16 to 29 spent 5.75 minutes per day on Google Search, this number was significantly lower at 2.13 minutes for females aged 50 to 69.

There were no significant differences between the educational groups regarding the time spent on Google Search. Male internet users with a low level of educational attainment had the highest mean Google Search usage time.

Figure 5 reveals the results for the same comparisons for the online newspaper 20 Minuten. There were no significant differences between age and educational groups as well as across both genders for the time spent using 20 Minuten.

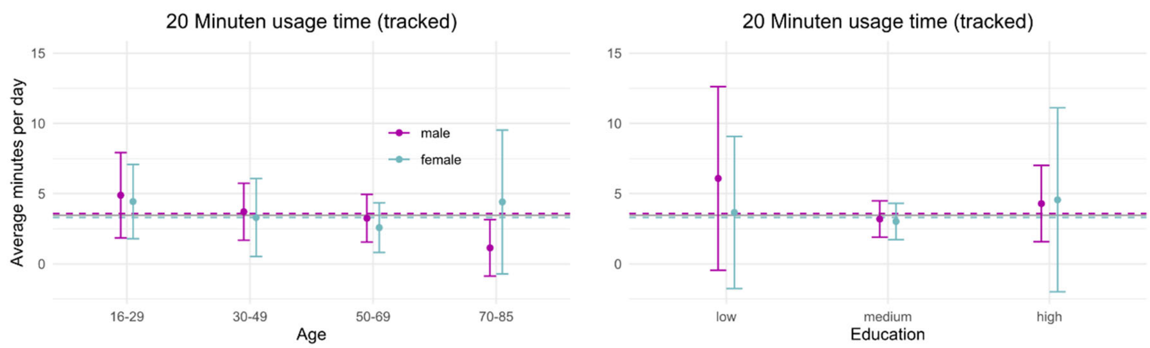

Figure 5. Daily average 20 Minuten usage by gender, age and education.
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 475 users of 20 Minuten.

Figure 6 presents the differences in usage time for WhatsApp. Among female WhatsApp users, there was no difference in usage time between age and educational groups. However, male WhatsApp users in the youngest age group (16–29) used WhatsApp significantly longer every day than those aged between 50 and 69. Those aged between 16 and 29 were the only group with a significant gender difference: young male WhatsApp users spent a lot more time on the direct messaging service (M = 25.6, SD = 40.4) than their female peers (M = 11.6, SD = 24.3).

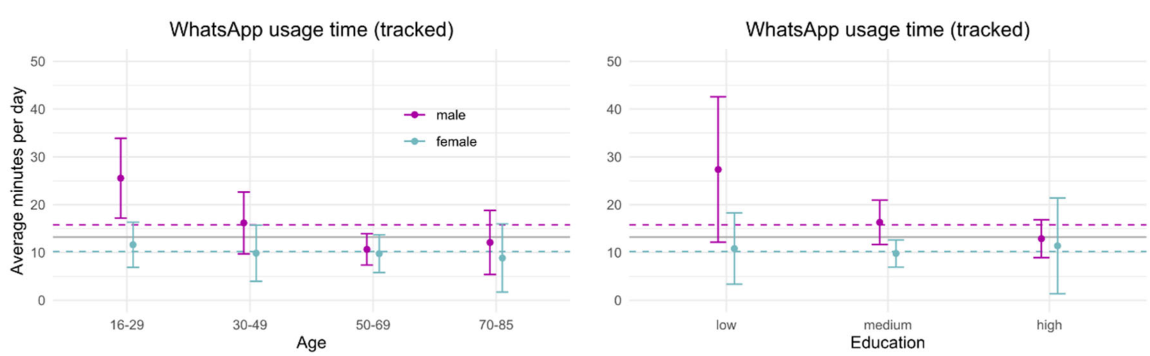

Figure 6. Daily average WhatsApp usage by gender, age and education.
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 900 WhatsApp users.

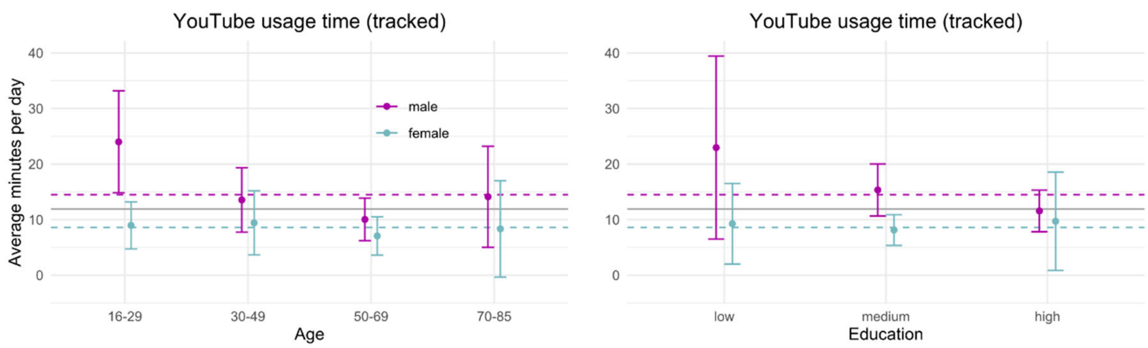

Figure 7. Daily average YouTube usage by gender, age and education.
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 811 YouTube users.

For YouTube usage time, Figure 7 depicts the differences between social groups. Male internet users in the youngest age group or with low educational attainment were the groups that spent the most time on YouTube (24 and 23 minutes, respectively). Among those aged 16 to 29 was the only significant difference between the genders where females spent significantly less time on YouTube. In general, time spent on YouTube decreased with age, although those aged 70 and over use YouTube longer every day than those between 30 and 69. There were no significant differences between educational groups, but especially for men, time spent on YouTube tended to be higher for those with lower educational attainment.

Figure 8 presents differences in usage time for Facebook use. For the time spent using Facebook, there were no significant differences between age and educational groups or across the genders. The time spent on Facebook tended to have a U-shaped relationship with age and male Facebook users tended to use the service longer every day.

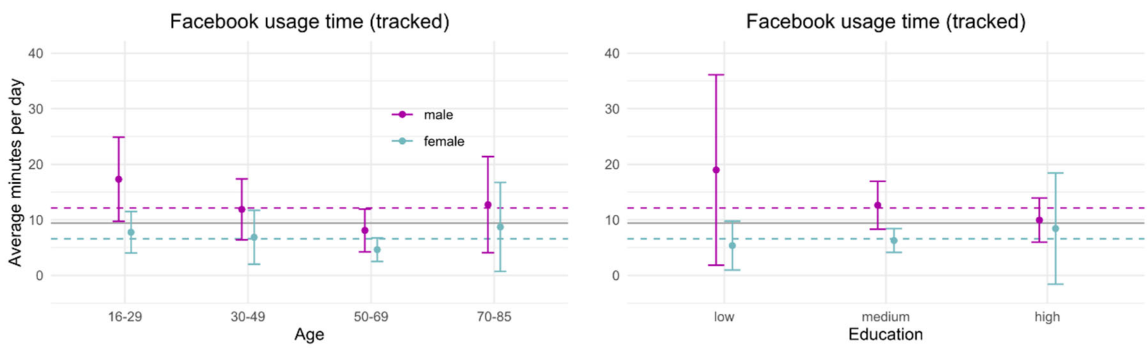

Figure 8. Daily average Facebook usage by gender, age and education.
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). *N* = 640 Facebook users.

Figure 9 shows the mean time spent using Instagram for different groups. Males and females did not systematically differ in the time they spent using Instagram. Younger internet users generally spent more time on Instagram every day. Between educational groups, there were no significant differences. It must be noted that in the oldest age group, there were only 3 male and 4 female Instagram users in the sample. Therefore, the mean for this group should only be interpreted cautiously. For females with high levels of educational attainment, both the mean time spent using Instagram and the variation in time spent were very high (*M* = 8.10, *SD* = 28.30).

Figure 10 depicts how many tracked events our sample contained across the course of a day. Regarding internet use in total, the amount of tracked events steadily increased from the early hours of the morning (about 6 am) and showed a clear peak between 4 and 5 pm. Thereafter, internet use started to decrease again. The daily usage pattern for the major services was similar in that there were less tracked events during the night and the use of these services started to increase at around 6 am in the morning.

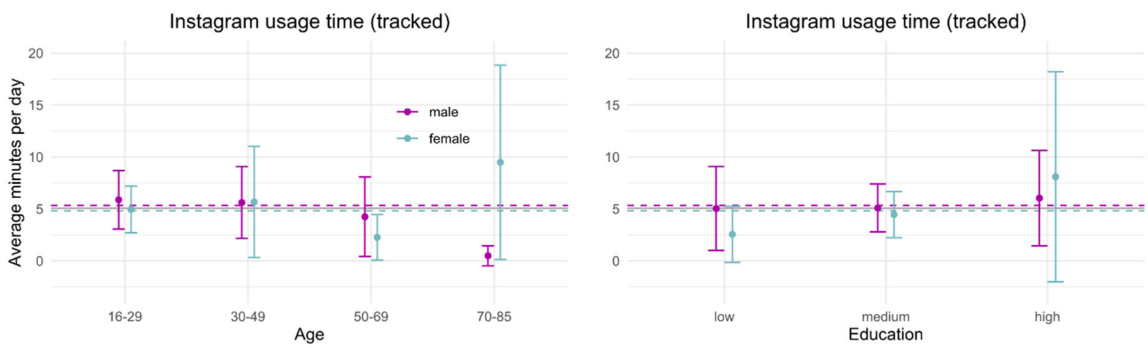

Figure 9. Daily average Instagram usage by gender, age and education.
Note. Vertical bars represent 95% confidence intervals; Horizontal lines represent overall (solid) and group means (dashed). Y-axis indicates means on a continuous scale (minutes per day). N = 358 Instagram users.

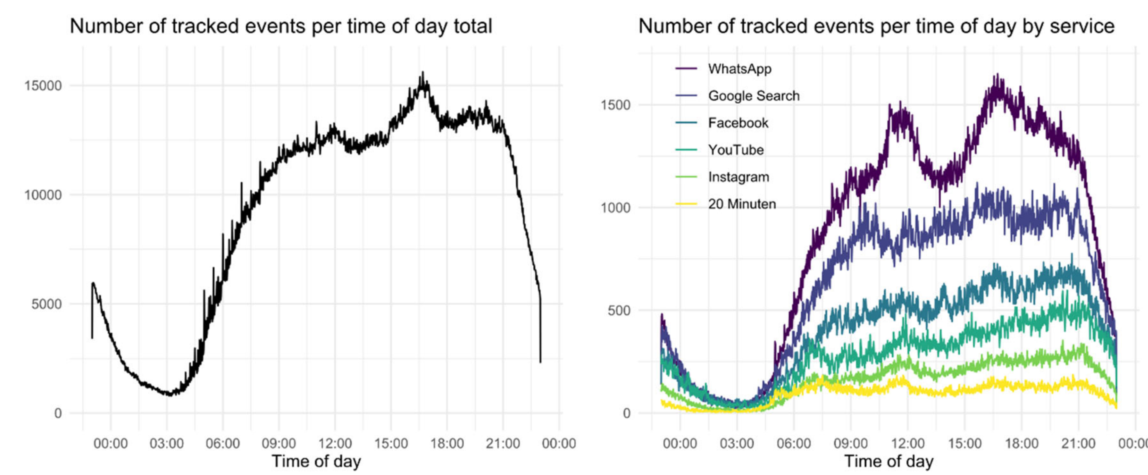

Figure 10. Number of tracked internet usage events per time of day.
Note. N = 923 internet users for the *left panel*; N = user groups of the respective services (see Table 1) for the *right panel*.

There were a few differences between the services we investigated. For WhatsApp, most uses occurred just before 12 pm and at 5 pm, with less activity on the app in the morning and during the afternoon. Internet users used Google Search, Facebook, YouTube and Instagram most heavily in the evening (around 9 pm), although there were also smaller peaks in the morning (e.g., at around 7 am for YouTube). The use of the online newspaper

20 Minuten was relatively uniformly distributed across the course of the day, except for smaller numbers of tracked events during the night.

Discussion and Conclusion

Relying on a combination of tracking and survey data, this article aimed at describing how much time internet users in different social groups (gender, age, education) spend online and using different services.

Both the tracking and survey results on usage time presented a consistent picture in terms of differences across social groups: while there were no significant differences between genders, younger people and those with lower levels of educational attainment tended to spend more time on the internet overall. While this is true for both the tracked and self-reported usage measures, we found stark differences in usage time between these two measures. Based on the tracking results, on average, people spend less than two hours a day on apps or websites, which is half the time they self-reported spending on the internet. These differences provided further indication for the importance of combining both methods for a valid empirical measurement of internet use and refinement of measurement strategies (it should not be assumed that tracking measures a ground truth and self-reports are always biased). Jürgens et al. (2019), for instance, identified sampling, selection and response biases that are specific to tracking data and conclude that "tracking data should not by default be considered an unbiased source of 'true' media exposure" (p. 612). Further, the data does not allow us to distinguish between private and professional internet use. While internet use for professional purposes is, therefore, included in the data for those who use their private device for work, this is not the case for those who have separate devices for work. This is particularly true for desktop or laptop devices. There are probably also differences in terms of how likely one is to use a private device for work based on their employer. Additionally, in the survey question, work use was explicitly included in the measure for overall usage time, whereas many participants in the tracking sample likely had additional devices at work that could not be tracked. This may explain parts of this overestimation of internet usage time, which is also in line with existing research (e.g., Araujo et al., 2017; Naab et al., 2019; Scharkow, 2016).

Moreover, our results indicate only small differences between age groups. While we did find differences in adoption rates of specific services, there were generally only small differences in usage time between age groups among the users of a service. In some instances, age differences were larger: for example, in the youngest age group (16–29), male internet users spent more than double the time on WhatsApp as compared to female users.

Also, the participants in all social groups spent the majority of their online time on a mobile device and, for instance, only one in ten visits to the online newspaper 20 Minuten was through a desktop device. It remains an open question whether this mobile–desktop ratio is different for other types of news outlets. However, the predominance of mobile over desktop internet use emphasizes the importance of tracking internet use on mobile devices including apps (previous studies mainly relied on browser plug-ins or tracking software for desktop devices, see e.g., Möller et al., 2019; Scharkow, 2016). The results regarding time of day showed that internet use started to increase in the early hours of the morning, peaked in the later afternoon and decreased thereafter.

A major advantage of the tracking method in this study was that it gathered observational data in a natural internet use situation. Effects of the measurement on participants' behavior were likely small, because after the initial installation, the tracking software did not interfere with participants' everyday internet use. Such an approach allows a more accurate approximation of their internet use. There are, however, still a number of limitations to consider. For research ethical reasons, it was technically possible for participants to temporarily disable tracking at any time—however, we assume social desirability effects are small because the data include widespread use of typically sensitive activities such as pornographic video consumption (1.4% of all tracked events).[2]

Furthermore, there were respondents in the sample who reported using a service, but their tracking data did not include any tracked instances of that service. It is unclear whether this inconsistency can be attributed to the fact that the participants use these services only very rarely and did not happen to use them in the duration of the tracking data collection.

A few methodological conclusions for further studies relying on tracking data can be drawn from the empirical part of this article. Gathering and analyzing tracking-data is resource-intensive in many ways and entails specific challenges. Conducting a tracking study incurs *high cost*, particularly compared with collecting survey data. This is especially the case when the tracking data is collected over a long time span, for a representative sample and for multiple devices. As becomes apparent from the slight difference in representativeness between the tracking and survey sample in this study (see p. 6), motivating participants to participate in tracking studies in order to gather representative data remains a challenge.

Both the data collection and analysis processes tend to be more complex for tracking than for survey data including questions with closed answer categories. The tracking data that was collected for this study required significantly more cleaning and preprocessing prior to substantive analyses than the survey data. Whereas *measuring* what is supposed to be measured (e.g., time spent on an app) may be more error-prone in survey data (e.g., due to self-report biases), *analyzing* what is supposed to be analyzed may be more error-prone in tracking data. That is, were tracking completely unbiased, standard methods training and statistical software would still present practical obstacles to testing

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[2] We calculated this figure by searching the tracking data for strings of the seven most popular pornographic video sites (see https://www.menshealth.com/sex-women/g22481925/most-popular-porn-sites/).

communication theories with this relatively new source of data. In our case, having no pre-defined answer categories, a wide variety of services used and different names for services depending on language settings or the devices used in the tracking data made it challenging to ensure finding all occurrences of a specific service; and there is no standard for doing this yet. It is clear, however, that especially considering these biases, it is extremely important to make the code used for preprocessing and analyzing tracking data openly available.

Taking these challenges and limitations into account, tracking data—especially in combination with self-reported survey data—provides a promising empirical basis for answering various questions about digital media use and consequences in the future, especially when considering that any empirical data is a selective and incomplete depiction of reality. In line with emerging studies in the field (Mangold et al., 2021), our results indicate that generational and social gaps in internet usage time are relatively low and that this very basic question on internet usage differences still requires further research. This article has provided a quantitative description of internet usage time overall and of popular services across devices and social groups. In doing so, we highlighted advantages and challenges of measuring usage time with tracking data.

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Article IV

Digital Inequalities in Online Privacy Protection: Effects of Age, Education, and Gender

Moritz Büchi, Noemi Festic, Natascha Just & Michael Latzer

Abstract

Datafication entails discussions about adequate privacy and data governance and the role of user self-help in it. This study examined online privacy protection from a digital inequality perspective and analyzed which factors directly and indirectly predict online privacy protection at the individual level. A nationally representative survey was carried out in Switzerland (*N* = 1121) with multiple-indicator measures of online privacy protection and attitudes, privacy breaches experienced, internet skills, and the amount of internet use. Path modeling revealed that pro-privacy attitudes, experiences of privacy breaches, the amount of internet use, and general internet skills are all related to increased privacy-protective behaviors. Internet skills and the amount of use were heavily dependent on age and education, with gender differences being less pronounced. Additionally, lower age and higher education were directly associated with a higher frequency of privacy protection. This study finds that overall, low-use and low-skilled older internet users represent a social group that is particularly vulnerable to negative internet outcomes.

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Digital Inequalities in Online Privacy Protection: Effects of Age, Education, and Gender

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Repeated data-breach revelations like the 2018 *Cambridge Analytica* scandal go hand in hand with increasing concerns about the protection of personal data on the Internet and discussions about adequate privacy and data governance. Contemporary information societies are marked by datafication (van Dijck, 2014) and combine a set of distinctive features, among them big data as a new asset class and new algorithmic methods of extracting economic and social value from it (Latzer, Hollnbuchner, Just, & Saurwein, 2016). The volume and scope of data collection is continuously expanding, and small and big personal data are increasingly at the core of various business models. They are being traded on a large scale and have essentially become a currency in multi-sided Internet platform markets with which users pay—knowingly or unknowingly—for zero-priced goods (Just, 2018). This unprecedented availability of data and the sophisticated methods of harnessing it result both in calls to get over privacy by proclaiming a post-privacy era (Heller, 2011) and claims to provide adequate levels of data and privacy protection. From an institutional perspective the governance of privacy or data comprises a mix of interwoven actors and instruments (Bennett & Raab, 2003; Latzer, Just, Saurwein, & Slominski, 2003). This mix ranges from *top-down* command-and-control regulation at the one end, like the EU General Data Protection Regulation (Regulation (EU) 2016/679), to *bottom-up* user self-help at the other end. The latter refers, for example, to ways of generally and deliberately limiting the disclosure of personal data or of actively managing this disclosure with a myriad of PETs—privacy enhancing technologies—or by using fake identities (Preibusch, 2015).

The impotence of the state to guarantee full-fledged protection in global online networks in general (Roßnagel, 1997), and the legacy of the conventional liberal privacy paradigm with focus on individualistic conceptions of privacy in particular (Bennett & Raab, 2003; Regan, 1995), both suggest a more prominent role for user self-help in this governance mix.

In fact, being online has become a societal standard and prerequisite for functioning in society by facilitating, among other things, social interactions and relationship building

(Ellison, Vitak, Steinfield, Gray, & Lampe, 2011). A complete refusal of data disclosure is therefore not an option in this new data-driven age (Hargittai & Marwick, 2016), especially if Internet users wish to profit from the various advantages of using the Internet. As a consequence, the individual balancing of the benefits and risks of disclosing personal data as well as self-protection become more important. While some empirical studies show that active privacy protection varies from one person to another (Latzer, Büchi, & Just, 2015a), a digital-inequality perspective on the wider distribution of privacy protection across societies is largely missing. In particular, work has not explored digital inequalities in the extent to which people actively protect their privacy online, and the factors that explain the different dimensions of privacy self-help protection on the individual level. Such an understanding is necessary, however, to comprehend better who gets what level of data protection, and to identify whether or not there are systematically disadvantaged and vulnerable social groups. Such knowledge may, in turn, feed back into policy-making with the aim of remedying structural inequalities—a consideration that has not received adequate attention in data or privacy protection policies thus far.

This chapter contributes to a more nuanced understanding of differences in self-help privacy protection based on nationally representative survey data and includes Internet skills as an important digital inequality variable. Individuals' self-help is only one means of privacy governance among many, and uncovering its specifics says little about the overall extent of privacy protection that is accorded to a particular person or society at large. However, by conceptually analyzing online privacy as a social value (instead of mainly as an individual one) within a digital inequalities framework, and by empirically exposing sociodemographic and Internet-usage-related predictors of self-help privacy protection, one is able to locate digital inequalities with regard to active online privacy protection, and to uncover the factors that inhibit or facilitate adequate self-protection.

In line with digital inequality research, it is likely that disadvantaged Internet users with lower digital skills or education in general are more vulnerable to privacy violations. At the same time questions have been raised as to whether a privacy divide will necessarily map neatly into a digital divide (Bennett & Raab, 2003), as those who are socioeconomically better off may be presumed to be particularly vulnerable to data extraction and profiling for economic reasons. Little research has been done on (sociodemographic) predictors of online privacy protection, particularly drawing on population-level data. This chapter contributes to closing this gap and empirically addresses the following questions: What explains variance in individuals' privacy protection behavior online? How is individuals' privacy protection behavior influenced by sociodemographic attributes, by the amount of people's overall Internet use and their Internet skills, as well as by their attitudes towards personal information and past privacy breaches?

This chapter first provides a brief overview of existing research on online privacy with a focus on protective behavior. It then outlines the relevance of researching online privacy protection from a digital inequalities perspective. Privacy is fundamentally seen as a common, public and collective value (Regan, 1995) whose unequal distribution may be a societal problem. Its protection and social distribution are therefore not only a regulatory issue but essentially an issue of social policy (Bennett & Raab, 2003). The empirical part describes the methods and results. A discussion of the findings and their implications concludes the chapter.

Protection of Online Privacy

The expectation that Internet use yields personal, economic or social advantages is often complemented by important assumptions about its opposite effects (van den Hoven, 2008). Experiencing privacy breaches first-hand can have real-life consequences. These can take the form of tangible outcomes like job loss or feelings of embarrassment due to personal information becoming publicly available against one's will. But even the perception of or potential for insufficient privacy protection, for instance due to the mere possibility of surveillance, can have negative effects in that people may be deterred from exercising their freedoms online – a phenomenon also described as chilling effects (e.g., Penney, 2017). Such incidents or feelings are sometimes presumed to induce stress or to affect an individual's subjective well-being negatively (Reinecke & Oliver, 2017). Negative privacy experiences and general awareness about the importance of privacy online appear, however, in discord with actual privacy protection behavior, and evidence of its predictors and their strength varies.

Inconsistent user behavior regarding online privacy has, for example, been extensively and repeatedly researched, in particular for social media, within the framework of the *privacy paradox* (e.g., Barnes, 2006; Norberg, Horne, & Horne, 2007; Taddicken, 2014). This holds that Internet users tend to share large amounts of personal information online, despite simultaneously claiming to care or be worried about the security of their data. Hargittai and Marwick (2016) summarize three main causes for this phenomenon reported in existing literature: a general lack of understanding of possible risks or dangers, deficits regarding appropriate skills to protect personal privacy, and the social relevance of sharing information, among other things, for socialization or employment purposes. In focus group interviews with 40 young adults, their own research shows how feelings of resignation and pragmatic, cynical attitudes provide further explanations for why Internet users' privacy concerns do not immediately translate into protective behavior or less disclosure (Hargittai & Marwick, 2016). Similarly, *privacy fatigue*, conceptualized by Choi, Park, and Jung (2018) as composed of emotional exhaustion and cynicism, was shown to result in a greater intention to provide personal information and to be a more important predictor of privacy behavior than privacy concerns for a sample of 324 Internet users.

Research reveals that people are not generally ignorant, but that they continuously and actively negotiate the scope and amount of personal information they share in order to protect and express themselves against variables that affect their privacy (Young & Quan-Haase, 2013). For example, in a longitudinal panel study of 5076 early adopters, Facebook users expanded their privacy-seeking behavior and withheld increasing amounts of personal data over time, sharing less with "stranger" profiles in the network (Stutzman, Gross, & Acquisti, 2012). At the same time, they tended to share increasing amounts of personal information with profiles that were connected to their own, which meant that they also, and potentially unknowingly, shared increasing amounts of data with "silent listeners" such as Facebook, third parties and advertisers.

Altogether, existing literature on online privacy has predominantly revealed privacy concerns and attitudes as well as experienced privacy breaches as predictors of privacy protection (Baruh, Secinti, & Cemalcilar, 2017). Drawing on the same data set as this chapter, Büchi, Just and Latzer (2017) showed, for example, that past experiences with privacy breaches strongly predicted current protective behavior. Also, in accordance with privacy paradox research, caring about privacy, i.e. strong privacy attitudes, did not automatically lead to strong self-protection. The main result, however, was that general Internet skills were a key predictor of users' privacy behavior.

The mixed and sometimes contradicting results of existing research can be attributed to differing definitions or operationalizations of privacy concerns and protective behaviors (Kokolakis, 2017). For instance, privacy behavior is commonly measured through the amount or scope of information that individuals disclose online rather than actual protection measures they actively pursue. Privacy must therefore always be viewed against specific contexts and varies greatly with changing circumstances (Acquisti, Brandimarte, & Loewenstein, 2015).

Digital inequalities in privacy protection

From its inception, the idea of privacy protection has been predicated on a liberal democratic model, essentially on an individualistic conception of privacy as a special type of "right to be let alone" (Warren & Brandeis, 1890, p. 193). While this individualist privacy paradigm is increasingly being questioned in research, among other things, with a recognition of its social value (Regan, 1995; Bennett & Raab, 2003; Nissenbaum, 2010; Solove, 2015), there is still a tendency in policy-making and regulation to remain loyal to this legacy. An example of this is the above-mentioned EU data-protection regulation, which came into effect in May 2018. It particularly aims at allowing citizens better control of their data by introducing, among other things, a new right to data portability or strengthened rights to request the erasure of data. However, privacy in general, and the risks and harms incurred by privacy violations in particular, affect people differently as individual privacy needs vary by social identity and situation—an issue that this new regulation, for example, does not account for. While it contains comprehensive obligations regarding reciprocal communication between the various stakeholders involved in data protection, the encouragement of awareness-raising activities, codes of conduct and certification mechanisms, there is no provision that accounts for scrutinizing likely disparities among the people this regulation is intended to protect. Such knowledge, however, could assist in detecting inequalities in privacy and data protection and allow adjusting public policies accordingly.

To discuss online privacy protection in line with digital-inequality scholarship is therefore precisely to rethink this traditional conception of privacy (protection): from a primary emphasis on its importance to individuals to an acknowledgement of its broader importance to societies at large and the likely consequences this entails for policy-making.

Systematically or structurally marginalized groups can be assumed to experience privacy (protection) differently from privileged groups within a society (Marwick & boyd, 2018; Matzner et al., 2016). Increasingly, individuals are required to provide personal data as a precondition for employment, the receipt of social services, or the avoidance of negative financial consequences (Marwick & boyd, 2018). For example, automated assessment methods are increasingly used to determine the "employability" of job candidates (O'Neil, 2016). Their social media data is used to calculate their fit for a specific position based on personality type analyses from likes and shares on social media profiles or the assessment of a candidate's network connections to determine their social capital (Madden, Gilman, Levy, & Marwick, 2017).

Various studies have started investigating online privacy for such disadvantaged groups. For instance, privacy concerns have been found to be among the top five reasons for Internet nonuse among members of disadvantaged public housing communities in a major US city—a pattern that is in contrast with general population data that report such concerns as the least-mentioned reason (Li, Chen, & Straubhaar, 2018). Further, for Internet users in these communities, age was the only sociodemographic factor significantly and negatively related to digital privacy-protection skills and to the conduct of digital activities that can compromise privacy (i.e., activities like online purchases, online banking, or the use of social online networks that involve self-disclosure of personal information and that enhance quality of life).

It is particularly these disadvantaged groups that are most dependent on the decisions made based on their data and who are likely to be unaware of data-collection practices (Matzner et al., 2016) or have inadequate skills to manage their own information disclosure on the Internet (Li et al., 2018). Older individuals and women have been shown to have lower levels of technical skills of privacy control, whereas education had no effect (Park, 2013). Park's (2013) analysis of a probability sample of 419 American Internet users surveyed in 2008 revealed age as the most important sociodemographic predictor of information control behavior, suggesting that older users are a particularly vulnerable group in connection with privacy online. Also, men tended to have higher technical privacy skills and have greater confidence in their own privacy protection behavior (Park, 2015). For a representative sample of 3000 American adults, Madden et al. (2017) detected low-income individuals as a specifically vulnerable group that reports being unconfident about their understanding of privacy policies, their ability to manage privacy settings, and report difficulties in finding tools and strategies that would help them protect their data online. These results are particularly alarming, because such vulnerable population groups are specifically targeted by data-driven surveillance practices. Such disadvantaged groups are then also particularly vulnerable to potential errors or biases embedded in data-driven, algorithmic systems that make automated decisions.

Privacy protection behavior has also been (implicitly) researched in relation to digital inequalities and the privacy paradox. This has often been regarded as a generational particularity, distinguishing young people's behavior. Recent research, however, suggests that if such a privacy paradox exists, generational divides or differences do not suffice to explain it (Hargittai & Marwick, 2016; Madden, Lenhart, Cortesi, & Gasser, 2013). Drawing on a sample of American college students surveyed about their privacy practices on Facebook, Tufekci (2012) found that negative experiences and general concerns drive self-protective measures.

This chapter now scrutinizes what inhibits privacy protection and thereby focuses on the amount of Internet use, general Internet skills, privacy attitudes, and experienced privacy breaches as predictors for self-help protection behavior and specifically investigates differences based on sociodemographic variables (age, gender, education).

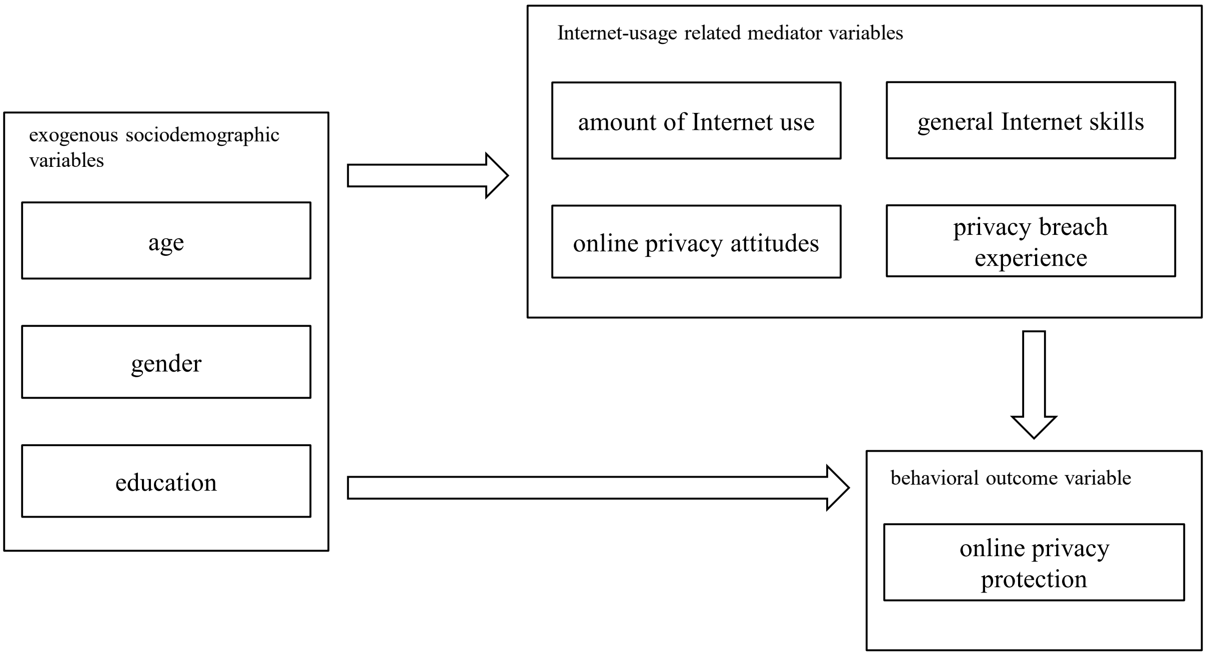

Figure 1. Conceptual model to explain online privacy protection.

The model shown in Figure 1 conceptualizes online privacy protection as dependent on two groups of variables. First, to explain privacy-related behavior, *experience* with privacy violations and *attitudes* regarding the protection of potentially sensitive personal data are considered relevant (Chen, Beaudoin, & Hong, 2016; Kokolakis, 2017). Besides these variables that are directly related to privacy, more general measures at the level of Internet usage, *skills* and *amount*, are expected to influence online privacy protection behavior (Park, 2013; Litt & Hargittai, 2014). Second, sociodemographic variables potentially affect the level of self-help online privacy protection as well as its Internet-usage-related predictors. The conceptual model specifically indicates that online privacy is sensitive to inequalities. Variables such as education have traditionally been associated with digital disadvantage; for example, less educated users have been shown to have lower Internet skills (Hargittai, 2008;

Van Deursen & Van Dijk, 2010). Such socially determined differences in skills then potentially assert themselves in manifold outcomes, not least in the level of online privacy.

The basic relationships proposed in the model combined with existing empirical work reviewed above leads us to test the following hypotheses. The first set concerns the relationship between privacy-protection behavior and Internet-use-related variables:

Online privacy protection is positively predicted by:

H1a: Privacy breach experiences

H1b: Online privacy attitudes

H1c: General Internet skills

H1d: Amount of Internet use

Further, based on research on digitally disadvantaged groups:

H2a: Age negatively predicts amount of Internet use and general Internet skills.

H2b: Being female negatively predicts amount of Internet use and general Internet skills.

H2c: Higher levels of education positively predict amount of Internet use and general Internet skills.

Additionally, the sociodemographic variables are expected to directly influence privacy protection consistent with digital inequality:

Higher levels of online privacy protection will be associated with:

H3a: Lower age

H3b: Higher education

H3c: Being male

Method

Representative Survey Data

We collected nationally-representative survey data (N=1121) in 2015 as part of the World Internet Project – Switzerland survey. This survey measures various aspects of Internet use and in 2015 included a module on privacy-related questions to test the proposed hypotheses of this study. Respondents were interviewed via landline or mobile phones. In this general Swiss population survey, to ensure representativeness, we constructed sampling quotas based on age, gender, region, and employment status (Latzer et al., 2015a). Analyses reported below exclude non-users of the Internet, resulting in an effective sample of 970

Internet users. This sample comprised 48% women, 36% had a tertiary education degree, and the median age was 45 years.

Data Analyses

The conceptual model presented in Figure 1 was translated into a statistical model comprising exogenous variables, mediators, and an outcome variable. The analysis thus relied on path modeling. The analytical procedure towards testing the tenability of the hypotheses was first to estimate a saturated version of the model, i.e., all exogenous variables predicted all mediators and the outcome, and all mediators predicted the outcome. In a second step, non-significant paths were removed in favor of model parsimony. We used the lavaan package in the statistical software R (Rosseel, 2012) with robust maximum likelihood estimation. We tested the adequacy of the multi-item measures with confirmatory factor analysis and assessed model fit conventional criteria in the structural equation modeling literature (Schermelleh-Engel, Moosbrugger, & Müller, 2003; Hu & Bentler, 1999).

Measures

In addition to the variables individually described below, respondents indicated their age and gender. Education was recorded using five categories. The variable was subsequently recoded into three categories, with low education serving as reference group: low (primary or secondary school), medium (vocational school, A levels degree or high school graduation), and high education (university, university of applied sciences). All other measures used multiple items (see appendix, Table A2). For online privacy protection, privacy-breach experience, online privacy attitudes and general Internet skills, we calculated mean indices for use in the path model.

Online privacy protection. The measure for individual self-help privacy protection on the Internet was constructed by adapting four items from the Pew Research Center's Internet & American Life Project (Rainie, Kiesler, Kang, & Madden, 2013) and a Eurobarometer survey on data protection (European Commission, 2011). Respondents answered on a four-point frequency scale ranging from 1 = *never* to 4 = *frequently* as to how regularly they change privacy settings, provide fake information about themselves online, manage cookies or monitor which information is available about them online. Managing cookies was the most prevalent online privacy protection measure.

Privacy breach experience. To determine whether respondents had suffered privacy violations, they were directly asked whether their privacy had been violated, their data had been abused, they had received abusive e-mails, or had been asked for banking or personal details in the past year. All four questions were answered on a binary scale where 0 = *no* and 1 = *yes*. Male Internet users reported having been subject to privacy breaches more often than female respondents. Overall, being asked for banking or personal details online was the most common privacy breach experience in the sample, with 36% of the respondents reporting this negative experience.

Online privacy attitudes. To measure individuals' privacy attitudes, we adapted four items from the Pew Research Center's Internet & American Life Project (Rainie et al., 2013). Respondents were asked about how important they think it is that only they or those they have authorized know the search queries they perform online, their location when they use the Internet, the websites they visit, and their communication partners on the Internet. The information deemed most sensitive by respondents was the identity of their interlocutor.

General Internet skills. Internet skills were measured applying a validated survey instrument for general populations (Van Deursen, Helsper, & Eynon, 2014). Originally, five different types of Internet skills were included: operational, information navigation, social, creative, and mobile. Respondents were asked to rate their ability to perform five Internet-use-related tasks by rating their agreement with statements on a five-point Likert scale (see appendix, Table A2). For operational skills (being able to open downloaded files), 73% of the sample indicated the highest level of agreement, indicating very little variation and a ceiling effect. This item was thus excluded from subsequent analyses and we proceeded with a four-item measure of general Internet skills.

Amount of Internet use. A composite variable for the amount of Internet use (Blank & Groselj, 2014) was constructed by summing the frequency (6-point scale) of engaging with a set of 37 diverse Internet applications such as checking facts, playing games, reading news, comparing products, or messaging (see Latzer, Büchi, & Just, 2015b for details on the different uses surveyed). The theoretical range of the variable was 0–185; the empirical range was 3–132 ($M = 51$, $SD = 20$).

Results

CFA of the latent multi-item measures for general Internet skills, online privacy attitudes, privacy breach experience, and online privacy protection produced a well-fitting model with (see appendix, Figure A1). Bivariate correlations among the Internet-use-related variables revealed that skills and privacy-breach experience are positively associated with use (see appendix, Table A1).

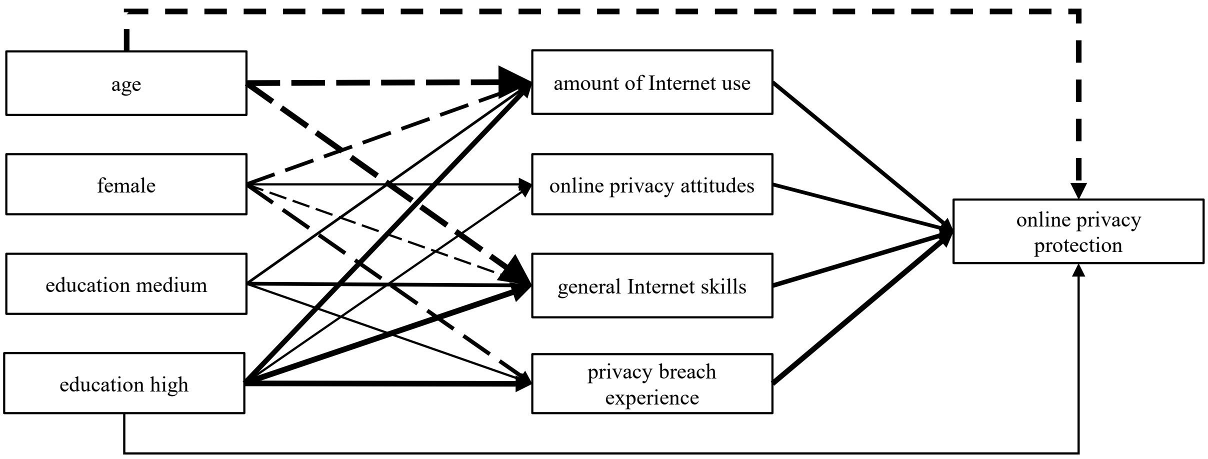

Figure 2. Path model (empirical test of the conceptual model in Figure 1). Solid lines indicate positive significant regression coefficients; dashed lines indicate negative significant regression coefficients. Line width is scaled to the standardized regression estimate, i.e. thicker lines indicate stronger effects. Covariances among the exogenous variables and among the mediators are not shown but were also modeled. See Table 1 for full model results.

The paths specified in the statistical model, derived from the conceptual model developed above, fit the empirical relationships among the variables very well. Figure 2 provides a graphic representation of the main estimated paths and Table 1 lists all parameter estimates. Based on these results, we evaluate the hypotheses.

The first set of hypotheses held that privacy protection would be positively predicted by four Internet-use-related variables. The model lends clear support to these hypotheses: privacy-breach experience (*H1a*), online privacy attitudes (*H1b*), general Internet skills (*H1c*), and amount of Internet use (*H1d*) all had significant and positive effects. For example, an increase of one on the 5-point Internet skills scale was associated with a .15 increase in the level of self-help privacy protection on a 4-point scale (see Table 1).

The third set of hypotheses pertained to the direct effects of socio-demographic variables on the frequency of performing privacy protective actions. *H3a* was supported with age negatively affecting online privacy protection. *H3b* was only partially supported; high education had a weak but significant effect, whereas the coefficient for medium education was not significant. *H3c* was rejected because gender was not directly associated with online privacy protection (see Table 1).

Table 1

Parameter Estimates of the Path Model

		Unstandardized	SE	*z*	*p*	Standardized
Regressions						
protection	←					
	use	0.006**	0.001	5.217	<.001	0.179
	attitudes	0.111**	0.016	6.895	<.001	0.171
	skills	0.15**	0.024	6.147	<.001	0.201
	experience	0.158**	0.018	8.583	<.001	0.237
	age	-0.01**	0.001	-8.26	<.001	-0.247
	educ.high	0.085*	0.038	2.228	0.026	0.057
use	←					
	age	-0.573**	0.031	-18.614	<.001	-0.5
	female	-6.841**	1.114	-6.138	<.001	-0.169
	educ.med	4.982**	1.666	2.99	0.003	0.123
	educ.high	9.613**	1.793	5.362	<.001	0.231
attitudes	←					
	female	0.173*	0.071	2.418	0.016	0.077
	educ.high	0.203**	0.073	2.789	0.005	0.088
skills	←					
	age	-0.027**	0.002	-16.583	<.001	-0.479
	female	-0.179**	0.056	-3.216	0.001	-0.092
	educ.med	0.338**	0.082	4.114	<.001	0.173
	educ.high	0.625**	0.085	7.38	<.001	0.31
experience	←					
	female	-0.381**	0.067	-5.646	<.001	-0.175
	educ.med	0.221*	0.098	2.248	0.025	0.101
	educ.high	0.552**	0.103	5.379	<.001	0.246
Covariances						
use	↔					
	skills	6.653**	0.541	12.294	<.001	0.448
	experience	4.555**	0.616	7.392	<.001	0.25
	attitudes	1.945**	0.647	3.007	0.003	0.101
skills	↔					
	experience	0.147**	0.028	5.255	<.001	0.163
attitudes	↔					
	skills	0.083*	0.033	2.536	0.011	0.087
	experience	0.186**	0.036	5.187	<.001	0.159

Note. χ^2 (5, N = 970) = 6.00, p = 0.307, χ^2 / df = 1.20, CFI = .999, TLI = .996, RMSEA = .014, SRMR = .010. See Figure 2 for graphic representation. * p < .05. ** p < .01.

Additionally, the following paths that we had not explicitly hypothesized were retained in the path model given their significant estimates. Online privacy attitudes were positively predicted by being female and having high education. Experiencing privacy breaches was predicted positively by education and being male.

At 40%, the variance (R^2) explained in the outcome variable (online privacy protection) was very high. The general Internet usage variables (amount and skills) were strongly dependent on sociodemographics (R^2 of 26% and 23%, respectively), whereas the explained variance in the privacy-related mediators was comparably low (R^2 of 7% for privacy breach experience and 1% for privacy attitudes).

Discussion and Conclusion

Understanding what factors inhibit privacy protection may provide a basis for improvements in privacy practice and policy. To this end, this chapter uniquely conceptualized online privacy from a digital inequality perspective. It provides nationally representative data from Switzerland for an explanatory model of self-help online privacy protection. Using multi-indicator variables and path modeling, the results reveal distinct pathways to online privacy relevant for digital inequality and corresponding policies. The results show that pro-privacy attitudes, experiences of privacy breaches, the amount of Internet use, and general Internet skills all related to increased privacy-protective behaviors. Amount of use and skills were themselves highly dependent on sociodemographic attributes with younger, male, and more educated users reporting higher values. Additionally, lower age and higher education were directly associated with higher frequency of privacy protection. Older age was directly linked to lower self-help privacy protection. Age also exhibited a strong indirect negative relationship with privacy protection via amount of Internet use and Internet skills. Low-use and low-skilled older Internet users thus represent a social group particularly vulnerable to experiencing negative Internet outcomes.

While educational reforms have started to include digital skills development in schools—for example by addressing safe social network site use—skills training for older Internet users remains challenging, and informal social support plays a major role (Courtois & Verdegem, 2016; König, Seifert, & Doh, 2018). Furthermore, and independent of age, digital inequalities in online privacy are also salient with regards to Internet skills and level of education.

To the extent that self-help measures of online privacy protection prove effective, the analysis shows that digital inequalities in Internet use carry over to relevant outcomes, in this case the protection of personal data. Because privacy and control over one's personal data relate to social power and discrimination, inequalities emerging from online behavior on top of long-standing forms of social inequality are problematic. In addition to deeply rooted social inequalities, digital inequalities, in particular in Internet skills, warrant attention. Privacy breaches are one important way in which Internet use and related variables can negatively affect individuals' well-being and ultimately feed back into life chances and social stratification. Accordingly, it is an area where existing inequalities are of concern and need to be addressed both by policy and future research.

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Appendix

Table A1

Means, standard deviations, and zero-order correlations of the variables in the path model

Variable	*M*	*SD*	1	2	3	4	5	6	7	8
1. age	44.39	17.62								
2. female	0.48	0.50	-.01							
3. education high	0.38	0.49	.18**	-.10**						
4. education medium	0.47	0.50	.01	.10**	-.73**					
5. amount of Internet use	51.30	20.29	-.46**	-.17**	.07*	-.06*				
6. online privacy attitudes	3.77	1.12	-.01	.07*	.08*	-.04	.09**			
7. general Internet skills	3.70	0.98	-.42**	-.10**	.10**	-.07*	.58**	.09**		
8. privacy breach experience	1.07	1.09	.02	-.19**	.19**	-.09**	.26**	.16**	.19**	
9. online privacy protection	2.01	0.73	-.40**	-.08*	.10**	-.07*	.49**	.25**	.47**	.35**

Note. * $p < .05$. ** $p < .01$.

Table A2

Measurement item details

Latent variable	Item	Wording	Scale	M (SD)
General Internet Skills	infnavskill	*I find it easy to decide on the best keywords for web search.*	5-point	3.9 (1.0)
	creativeskill	*I know how to create and upload content.*	5-point	3.0 (1.6)
	mobileskill	*I know how to download apps to a mobile device.*	5-point	3.9 (1.5)
	socialskill	*I know how to change who I share content with.*	5-point	3.4 (1.5)
Online Privacy Attitudes	searchhist	*How important is it for you that only you or people you authorize know which search queries you perform?*	5-point	3.5 (1.4)
	location	*…where you are located when using the Internet?*	5-point	3.6 (1.4)
	visit	*…which websites you visit?*	5-point	3.7 (1.4)
	emailto	*…with whom you communicate over the Internet?*	5-point	3.9 (1.4)
Privacy Breach Experience	infabuse	*Thinking of the past year, did you feel that your personal data was passed on or abused?*	binary	0.31 (0.46)
	abusemail	*…have you ever received obscene or abusive e-mails?*	binary	0.29 (0.45)
	netscam	*…been contacted by someone online asking for bank or personal details in the past year*	binary	0.36 (0.48)
	breach	*Have you ever had your privacy violated online?*	binary	0.11 (0.31)
Online Privacy Protection	settings	*Do you change settings so that content is only visible to specific people?*	4-point	1.9 (1.2)
	fakename	*Do you use fake information online such as a fake name?*	4-point	1.5 (0.90)
	cookies	*Do you block, delete, or deactivate cookies?*	4-point	2.7 (1.2)
	monitor	*Do you monitor which information is available about you online?*	4-point	2.0 (0.98)

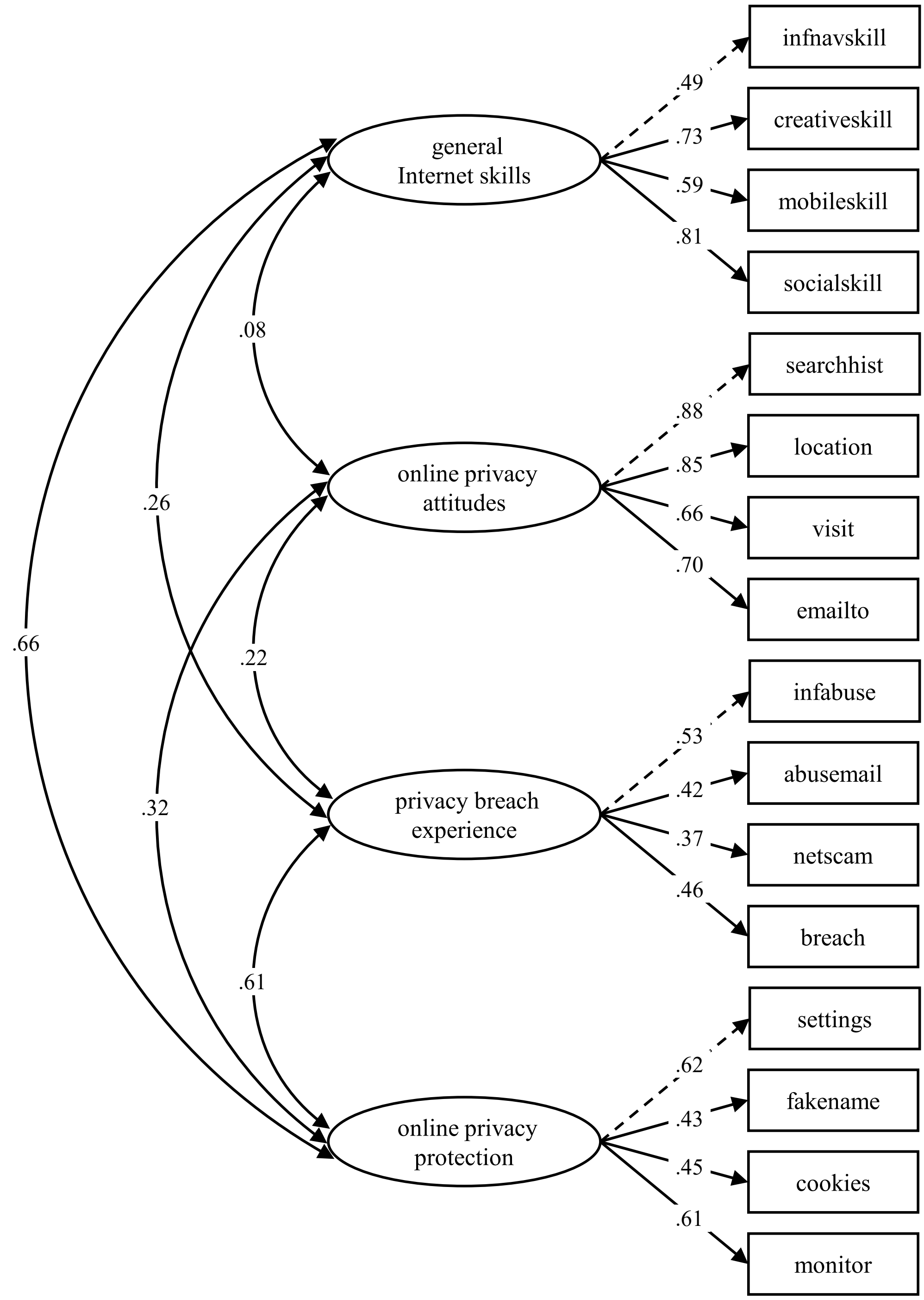

Figure A1. Confirmatory factor analysis for the correlated four-factor latent measurement model. See Table A2 for item details. Standardized coefficients are shown; dashed lines indicate reference items (unstandardized factor loading fixed to 1). Model fit: χ^2 (98, N = 970) = 180.81, $p < 0.001$, χ^2 / df = 1.85, CFI = .976, TLI = .971, RMSEA = .030, SRMR = .032.

Article V

How Social Well-Being Is Affected by Digital Inequalities

Moritz Büchi, Noemi Festic & Michael Latzer

Abstract

Digital inequalities have real consequences for individuals' everyday lives—this basic assumption drives digital inequality research. Recent efforts have focused on tangible benefits of online engagement, yet subjective quality of life measures also matter as internet outcomes. This article contributes to closing this gap. First, it theoretically introduces subjective social well-being—the appraisal of one's functioning in society—as a consequence of digital participation, potential, and perception differences. Second, it tests the dependence of social well-being on these three dimensions using structural equation modeling with nationally representative survey data. Results reveal that the perception of digital belongingness directly increases social well-being, and internet skills as digital potential do so indirectly. The net effect of digital participation is insignificant. These findings lead to recommendations for policies targeting digital inequalities and future research directions.

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How Social Well-Being Is Affected by Digital Inequalities

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Digital inequalities have real consequences for individuals' everyday lives—this basic assumption drives digital inequality research. Recent efforts have focused on tangible benefits of online engagement, yet subjective quality of life measures also matter as Internet outcomes. This article contributes to closing this gap. First, it theoretically introduces subjective social well-being—the appraisal of one's functioning in society—as a consequence of digital participation, potential, and perception differences. Second, it tests the dependence of social well-being on these three dimensions using structural equation modeling with nationally representative survey data. Results reveal that the perception of digital belongingness directly increases social well-being, and Internet skills as digital potential do so indirectly. The net effect of digital participation is insignificant. These findings lead to recommendations for policies targeting digital inequalities and future research directions.

Keywords: digital inequality, digital divide, Internet use, skills, well-being, information society, Internet outcomes, social inequality

With the diffusion of the Internet in modern societies came a plethora of research on differences in Internet access and use. Although much research has been conducted on sociodemographic differences concerning Internet access, digital skills, and specific uses of the Internet (e.g., Robinson et al., 2015), the societal consequences of these digital inequalities have been much less explored. The significance of digital inequality research lies in the often implicit assumption that participation in the information society requires effective Internet use and yields personal, social, and economic advantages. Even if everyone used the Internet, differences in achieving individually meaningful positive outcomes would remain as a social problem (Newman & Gurstein, 2016; Siefer, 2016). This results in the essential challenge of identifying relevant outcomes of socially differentiated Internet use in everyday life. This article argues for the inclusion of subjective well-being as a key outcome, not least because it contains potential as an object and basis of public policies.

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The study makes three main contributions to the research on the consequences of digital inequalities. First, it theoretically develops subjective (social) well-being as an addition to existing, predominantly tangible digital inequality outcome measures. Second, its empirical results allow reliable and nationally generalizable statements. They also have value for other social democracies where the Internet is crucial for everyday functioning. The data used for the empirical analysis are representative for Switzerland, a country with high Internet penetration, and include nonusers of the Internet as a baseline. So far, research on the effects of the Internet on subjective well-being has lacked studies that are based on population-level data and include validated measures. Third, the model includes users' Internet skills, which is essential because insufficient skills seem to prevent users from engaging in beneficial online activities (e.g., Büchi, Just, & Latzer, 2017; Hargittai, 2010; Hargittai & Shaw, 2013; Nimrod, 2013, 2014).

This study's contributions are equally theoretical and empirical: A relevant outcome measure for digital inequality scholarship is developed by combining subjective well-being theory with digital inequality and Internet use research, and we provide a first empirical assessment of the relationship between variables related to digital inequality and social well-being as an outcome. Results show that Internet skills as a measure of the potential to participate in the information society positively influence both actual Internet use and belongingness to the information society. The perception of digital belongingness increases social well-being.

This article first introduces the concept of digital inequality and its consequences in information societies. Then, social well-being is defined and introduced as an addition to existing measures of digital inequality outcomes. The presumed effects of digital participation, potential, and perception on social well-being are theoretically developed. The empirical section then presents the methods and results before discussing the implications of the findings.

Theoretical Considerations for the Integration of Subjective Well-Being Into Digital Inequality Research

Digital Inequalities and Their Consequences in Information Societies

The diffusion of the Internet has given rise to questions of digital inequality. This line of research has predominantly addressed how socioeconomic characteristics like gender, age, level of education, employment, and income are related to Internet use and non-use (DiMaggio, Hargittai, Celeste, & Shafer, 2004; Robinson et al., 2015; Zillien & Hargittai, 2009). Although Internet access and Internet usage inequalities have been extensively researched, including in multicountry comparative studies (e.g., Büchi, Just, & Latzer, 2016; Galperin, 2017; Ono & Zavodny, 2007), the consequences of these existing digital inequalities for individuals' subjective well-being remain largely unclear. The assumption of digital inequality research that Internet use is beneficial overall serves as a starting point for this study.

Research on the consequences of digital inequalities assumes that even if access to the Internet and sufficient usage skills are given, people differ in their abilities to convert their digital resources into specific (offline) objectives. Furthermore, it can be expected that Internet users who are able to continuously achieve high offline returns through their Internet use additionally benefit from feedback effects: Higher economic, cultural, and social capital allows them to further improve their Internet skills, which in turn are likely to have a positive effect on their future offline outcomes (Van Deursen, Helsper, Eynon, & van Dijk, 2017). Although studies on divides in terms of access and use are clearly relevant, it is especially these digital inequality outcomes that ultimately affect life chances and reveal how individuals' Internet use relates to their social functioning (Lissitsa & Chachashvili-Bolotin, 2016).

So far, digital inequality outcomes have mainly been understood as manifest outcomes in economic, social, political, institutional, or educational life domains (Blank & Lutz, 2018; Van Deursen & Helsper, 2018). General findings show that individuals with lower social status seem to gain fewer advantages from digital engagement, indicating an exacerbation of existing inequalities. Although Internet outcomes like finding a job or making new friends online are clearly relevant, we argue that additional, more latent and subjective outcomes of Internet use also matter: How does individuals' Internet use or nonuse make them feel about themselves as a part of the larger society, and how does this ultimately affect their mental health? Nonusers of the Internet may feel left out and stigmatized while explaining their Internet avoidance with a perceived lack of usefulness of the Internet (Reisdorf, Axelsson, & Söderholm, 2012). We argue for subjective well-being in general as an important and necessary addition to existing outcome measures in digital inequality research. So far, *social* well-being has been the least studied component of subjective well-being (Keyes, 2014), although it is precisely this concept that seems highly relevant in relation to the Internet because it focuses on the individual's functioning in society. Information and communication opportunities for social orientation and a high level of interactivity are key affordances of the Internet. This study therefore develops social well-being as a consequence of digital inequalities.

The Internet affects subjective well-being through its growing role in virtually all domains of everyday life. It is clear, however, that there are also more salient predictors of general well-being, such as physical health (e.g., Helliwell & Putnam, 2004; Lissitsa & Chachashvili-Bolotin, 2016). The societal importance of the Internet, however, is still growing, and if there are already significant overall effects in a general population sample, this outcome measure requires increased attention. The main research question this study seeks to answer is, therefore, *How is social well-being affected by digital inequalities?*

Subjective Social Well-Being as a Consequence of Digital Inequalities

Various indicators aim at measuring quality of life or well-being at the individual or societal level, ultimately all dealing with the pursuit of a "good life" (Ryan & Deci, 2001). Figure 1 shows an overview of prominent quality of life indicators identified in the literature. These indicators represent approaches to measuring quality of life and are conceptually distinct, yet empirically interrelated. The focus of the present study is on social well-being as a consequence of digital inequalities. In the past, the focus of both academia and policy makers has been mostly on economic indicators like gross domestic product (Organisation for Economic Co-operation and Development [OECD], 2013). Other macro conditions, like safety, access to education, or legal and political factors, can also serve as indicators of well-being. Although such measures provide important indications at the population level, inferring an individual's mental state is inaccurate (Keyes & Shapiro, 2004).

An individual's physical and mental health in a clinical sense also play an important role in this context. The desire to measure mental health more generally has given rise to an interdisciplinary research tradition concerned with conceptions of well-being going beyond economic or medical definitions. Subjective well-being can be understood as an approach to measuring mental health as a part of quality of life at the individual level (Diener, Oishi, & Tay, 2018). Contrary to clinical diagnosis, for example, it is a self-assessment of an individual's well-being in various life domains (Keyes, 2014). Two dominant research branches can be distinguished, which differ with regard to their underlying philosophical assumptions (see Figure 1). The *hedonic* definition of subjective well-being focuses on a balance between positive and negative affect and mainly regards pleasure and life satisfaction as constituents of a happy life (Bradburn, 1969; Diener, 1984; Kahneman, Diener, & Schwarz, 2003). Whereas hedonic approaches generally define subjective well-being in terms of the absence of negative mood or mental illness (Ryan & Deci, 2001), the *eudaimonic* approach argues that subjective well-being is reflected not only in the absence of negative factors (e.g., pain) but also in the presence of positive functioning. Individuals who do not suffer from mental health problems or disease do not automatically experience high subjective well-being. Accordingly, positive affect is not the opposite of negative affect (Keyes & Shapiro, 2004; Ryan & Deci, 2001; Ryff & Keyes, 1995). Therefore, the eudaimonic definition of subjective well-being does not rely on happiness as the single decisive factor for well-being. Rather, it includes indicators like purpose in life, personal growth, or self-acceptance (Jahoda, 1958).

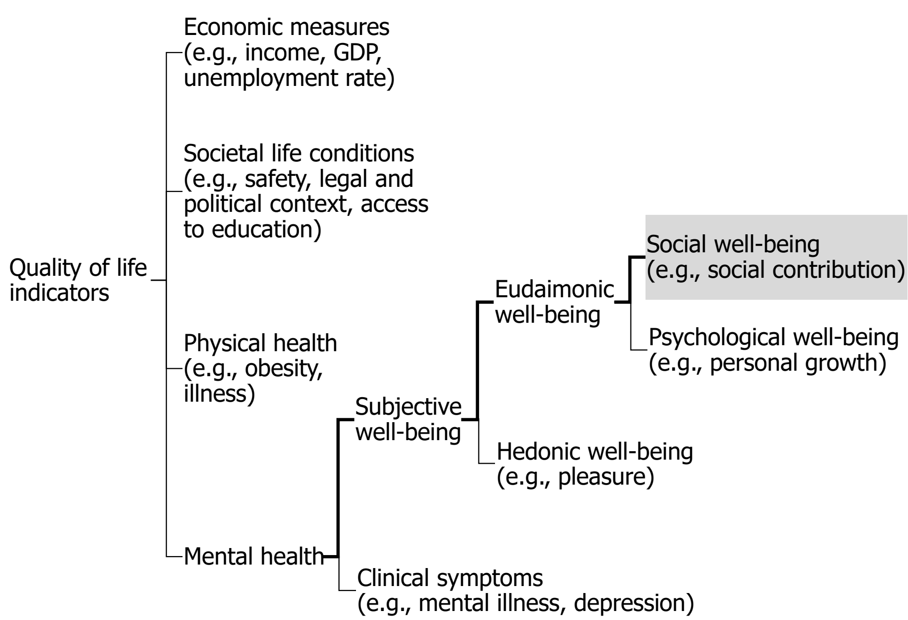

Figure 1. Social well-being as a quality of life indicator.

The eudaimonic definition of subjective well-being can be subdivided into psychological well-being and social well-being. The former deals with self-acceptance, purpose in life, environmental mastery, positive relationships, autonomy, and personal growth (Ryff, 1995). *Psychological* well-being is the aspect of an individual's subjective well-being that relates to private life. *Social* well-being, on the other hand, is a primarily public phenomenon, which is concerned with the challenges an individual faces while being embedded in social structures and communities (Keyes, 2014).

Keyes (1998) defined social well-being as "the appraisal of one's circumstance and functioning in society" (p. 122). The concept deals with the quality of people's relations to society as well as their individual functioning in society and other social groups, and reflects "positive social health" (Keyes, 1998); therefore, it is an important measure of quality of life overall (Keyes & Shapiro, 2004). To date, the health of individuals reflected in their ability to function within society and social groups has only been sparsely researched (Keyes, 2014) even though humans primarily satisfy their needs through the fulfillment of social roles. Also, the functioning of individuals in society is necessary for the functioning of society as a whole.

Social well-being is a multidimensional concept, comprising five social challenges that individuals face in their everyday lives (Keyes, 1998). *Social integration* corresponds to the assessment of the quality of one's relationships to society and other communities like neighborhoods, families, or friend groups. *Social contribution* is the self-report of one's social value and includes the feeling of having something to give to society and being an important member thereof. *Social actualization* is concerned with the assessment of the potential and progress of society as a whole. *Social coherence* deals with the perception of the quality, organization, and functioning of the social world and includes interest in knowledge about the world. *Social acceptance*, finally, measures the perception of society through the character and the qualities of other people as a general category (Keyes, 1998).

Overall, high social well-being means that an individual can successfully deal with the social challenges in his or her life. According to Keyes (1998), education is particularly predictive of resources and self-conceptions, and therefore social well-being; higher education positively influences one's income, quality of housing, and neighborhood. Lower socioeconomic status, however, is associated with lower physical and mental health. The effect of age on social well-being is inconsistent (Keyes, 1998). As a general sociological concept, social well-being measurement does not refer to the information society; it is predominantly predicted by other offline measures. In this study of digital inequalities, the overall effects are therefore presumably small, but relevant nonetheless. These digital inequalities are assessed in three dimensions: digital participation, potential, and perception.

Digital Influences on Social Well-Being

This article views Internet use (digital participation), Internet skills (digital potential), and a feeling of belongingness to the information society (digital perception) as potential digital-inequality-related influences on social well-being. Existing research in the field has mostly considered other measures for quality of life, like psychological well-being and life satisfaction, or related concepts like social capital and social cohesion. In this context, it is important to note that different dimensions of subjective well-being are understood as complementary rather than competing functions (Huta, 2015; Ryan & Deci, 2001). The following sections build on existing findings and theoretical considerations to expand the understanding of the consequences of the Internet for mental health by focusing on the distinctly social aspects of well-being.

Digital Participation: Internet Use. The Internet constitutes a key infrastructure of information societies. Using the Internet frequently for everyday tasks of communication and information-seeking thus corresponds with being an active part of the information society. Internet use is a prominent dimension of digital inequality, with research showing clear socioeconomic differences (e.g., Büchi et al., 2016; Zillien & Hargittai, 2009). Early studies already saw that media like television or telephones allow people to participate in the broader social and cultural world practically and symbolically (e.g., Haddon, 2000; Tubella, 2005). Compared with traditional media, the Internet is characterized by manifold individual opportunities for use, which makes the examination of its effects more complex.

To the best of our knowledge, the only study so far that has directly considered the impact of Internet use on *social* well-being as proposed by Keyes (1998) examined how well-being changed in a sample of psychology students after participants began using the Internet (Contarello & Sarrica, 2007). The results showed that adoption of the Internet made the students feel that they were more integrated into communities, that they had more to contribute to society, and that it was easier to understand how society works. Since the second half of the 1990s, research on the relationship between Internet use and well-being in general has intensified. Initial utopic scenarios predicted that the Internet would decrease social inequalities by empowering socially disadvantaged groups. Already in 2002, a study in three Chinese cities revealed the Internet as the most important medium for improving quality of life (P. Lee, Leung, Lo, & Xiong, 2008).

In an online survey of 1,210 Dutch teenagers, Valkenburg and Peter (2007a) found Internet use to positively affect quality of life by increasing the time spent with existing friends. Further, online communication had a positive effect on life satisfaction by promoting the feeling of closeness to friends (Valkenburg & Peter, 2007b). Internet use thus promotes social relationships—or in Keyes' (1998) theory, social integration—and thereby has a positive effect on well-being. A major subset of studies that suggest a positive effect of Internet use on subjective well-being focuses on older adults, for whom Internet use can be instrumental in maintaining or establishing social connections (e.g., Choi, Kong, & Jung, 2012; Cotten, Anderson, & McCullough, 2013; Szabo, Allen, Stephens, & Alpass, 2018).

Although there is a lack of research on social well-being as a consequence of digital inequalities, the related concept of social capital has been more intensely studied in relation to the Internet. The pioneer study "Netville" (Hampton & Wellman, 2003) found that online interactions supplemented offline forms, and a general routinization of Internet use in everyday life leads to many positive and negative effects occurring simultaneously (Wellman, Quan-Haase, Witte, & Hampton, 2001). In a survey of heavy Internet users in 100 households, those with a larger number of bridging social ties showed stronger social engagement and used the Internet more frequently for social purposes, which increased their subjective quality of life (Kavanaugh, Reese, Caroll, & Rosson, 2005). A positive relationship between social capital and mental well-being was found in a meta-study for adults over the age of 50, drawing on 11 studies with large samples (Nyqvist, Forsman, Giuntoli, & Cattan, 2013). Internet use has also been shown to improve one's self-image and self-confidence in qualitative (Fokkema & Knipscheer, 2007) and quantitative research (Valkenburg, Peter, & Schouten, 2006). It enables users to communicate anonymously and control interactions to a large extent (Amichai-Hamburger & Furnham, 2007). Nimrod's (2013) results from a survey of 631 users of online depression communities showed that heavy participation in such communities increased benefits like emotional support and led to offline improvements. Connecting with like-minded people and having the opportunity to choose interactions is likely to improve the way in which other people are perceived. More generally, Internet-enabled selective communication offers a plethora of opportunities to connect and socially interact with people who have similar interests or attitudes across time and space.

Although the Internet's potential to increase sociability is well established, research has also pointed to specific negative effects. In a study by Caplan (2003), valuing online social interaction more than face-to-face interaction was more likely among lonely users, which in turn led to more negative outcomes. Recent research has also proposed that positive and negative consequences of Internet use occur simultaneously; the balance for an individual user is affected by factors such as amount of use, skills, and attitudes (Blank & Lutz, 2018; Büchi, Festic, Just, & Latzer, 2018; Van Deursen & Helsper, 2018). Taken together, these various mechanisms nonetheless suggest a positive effect of more frequent Internet use for information and communication on overall social well-being.

Digital Potential: Internet Skills. In the literature on digital inequality, Internet skills play an important role (see Litt, 2013) because information and communication technology (ICT) innovations pose a threat for those who do not have the abilities to cope with the digitization of various life domains (e.g., Helsper, 2008). Even for young people, the development of Internet skills is highly dependent on existing resources rather than a matter of course (Eynon & Geniets, 2016; Robinson, 2009). However, basic Internet skills are a prerequisite for the meaningful use of various online applications enmeshed in everyday communication (Katz & Gonzalez, 2016). Digital potential and the ability to use digital media in an autonomous, deliberate, and strategic way therefore become increasingly important to enable citizens to participate in the information society (Büchi & Vogler, 2017; Hargittai & Shaw, 2013; Helsper & Eynon, 2013).

In addition to a lack of time resources and formal education, insufficient skills are a factor that keeps people from maximizing the benefits of their Internet use (B. Lee, Chen, & Hewitt, 2011) or keeps them offline entirely (Reisdorf et al., 2012). The Internet can only be leveraged in an informed and selective way, and thereby increase personal well-being, if users possess the necessary Internet skills (Leist, 2013). In comparison with other media, this especially applies to the Internet because it requires users to control, filter, and autonomously acquire content (Park, 2012). Theoretical considerations on how Internet use can promote (social) well-being are therefore conditioned on users possessing relevant skills. For example, an individual can only maintain contact to other people via online communication and foster social integration when he or she is able to use such services—on a technical level but also strategically in the sense that use is consistent with personal goals.

The promotion of Internet skills that enable people to take part in society is a key factor in preventing social exclusion (Facer & Furlong, 2001). In contemporary information society, Internet skills represent such abilities (also see Duff, 2011; Gurstein, 2015), which are particularly relevant for older adults who can compensate for potential declines in well-being when ageing. Internet skills are thus an important source of social integration in the information society. Abilities or potential can also influence individual well-being independent of concrete Internet uses: The attainment of new abilities and the command of new technologies can increase the feeling of being able to act, of personal growth and autonomy, and of purpose in life (Nimrod, 2014). The acquisition and possession of Internet skills has an empowering effect (Fuglsang, 2005), increases the feeling of independence (Haddon, 2000), and therefore supports a feeling of social value or contribution.

In a nationally representative survey (Büchi et al., 2017), Internet skills were the strongest predictor of self-help measures against harmful online outcomes, in this case privacy infringements. Experiencing privacy breaches or other negative consequences on the Internet may lead to a perception that other people are malicious. On the flip side, Internet skills that help prevent negative experiences can improve how Internet users see other people and thereby promote social acceptance. Internet skills can also enable individuals to play an active part in how they are affected by communication (Potter, 2010).

Digital Perception: Belongingness. Belongingness, finally, is an individual's perception and feeling of being part of the information society. This is a related but separate dimension of digital inequality, because even without extensive and skilled Internet use, it is possible to feel belongingness. Alongside such digital potential and participation, perceptions also matter. That is, it may be relevant for well-being not only how individuals can and do use the Internet, but also how they perceive their belonging to modern society.

There is a strong relationship between the feeling of societal belongingness and the physical and mental health of individuals (Baumeister & Leary, 1995). Digital belongingness reflects collective identity and taps into the sense of oneself as a member not of a specific community or a society in general, but specifically of the modern, networked information society (see Tubella, 2005). Turkle (1995) noted that "people look at technology and see beyond it to a constellation of cultural associations" (p. 61). This article thus proposes that people have a relatively unconscious sense of how strongly they are part of modern societal developments characterized by an ever-increasing role of information and communication technologies in social, political, and economic processes.

Ahn and Shin (2013) showed that the need for (social) relatedness partly mediated the positive relationship between the use of social networking sites and subjective well-being. The innate human need for relatedness also influenced how individuals used Facebook for social interaction purposes to fulfill this need and thereby increased their subjective well-being (Lin, 2015). More generally, salient features of the societal environment such as an increasing reliance on and relevance of ICTs impact social identity; in cases where such social change aligns well with one's existing identity, belongingness is increased and tends to have positive consequences for well-being (see Haslam, Jetten, Postmes, & Haslam, 2009). The extent to which someone feels that they belong to the information society thus is likely to affect aspects of subjective well-being concerned with the appraisal of one's functioning in a larger collective, that is, social well-being.

Combining the theoretical considerations and existing empirical studies presented earlier, this article seeks to test the effect of different dimensions of digital inequality on social well-being as a measure of quality of life. In summary, Internet skills are expected to affect both Internet use, a relatively objective measure of participation in the information society, and belongingness, a subjective measure of participation in the information society. Internet skills are theoretically interpreted as the potential to benefit from digital communication in the information society. They represent a necessary but not sufficient condition to use the Internet in functional ways and to feel a sense of belonging to the information society. Skills as the ability to act influence both what is actually done and how one feels.

Empirical Assessment of Digital Inequality Effects on Social Well-Being

Procedure and Participants

To our knowledge, Contarello and Sarrica (2007) is the only study to use Keyes' (1998) measure of social well-being in conjunction with Internet use. An important limitation of that study, however, is that respondents were asked to judge the impact of their Internet use on their well-being themselves. Here, we aim to statistically establish the relationship between dimensions of digital inequality and social well-being to strengthen the empirical basis of theoretical explanations. For this study, survey data representative for Switzerland (N = 1,060) were collected in 2015 through an independent market research institute. Participants were interviewed via landline and cell phones (computer-assisted telephone interviews) to reach a representative sample that also included nonusers of the Internet as a comparison group when investigating ICT use and perceptions. A total of 86% of the sample were Internet users (n = 910), and 14% reported not using the Internet (n = 150); 50.8% were female, and the mean age was 49.09 (SD = 17.46), ranging from 18 to 84.

Data Analysis

To first test the effect of Internet use versus nonuse on social well-being, we employed multivariate regression analysis drawing on the full sample. Second, we relied on structural equation modeling (SEM) to empirically address the question of how Internet-related variables predict social well-being. For this part of the analysis, we relied solely on adult users of the Internet. The SEM approach makes it possible to combine latent variable measurement and structural path analysis in a single modeling framework and global fit assessment (see Bagozzi & Yi, 2012). We employed SEM with the *lavaan* package in *R* (Rosseel, 2012) using maximum likelihood estimation, robust Huber–White standard errors, and full-information maximum likelihood estimation for missing values (all variables had less than 5% missing values). Indirect paths—that is, mediated effects—were also estimated in *lavaan*. The fit between the model-implied relationships between variables and their empirical covariances was evaluated based on two types of fit indices (Hu & Bentler, 1999; Schermelleh-Engel, Moosbrugger, & Müller, 2003): the comparative fit index (*CFI*) and Tucker–Lewis index (*TLI*) where 1 indicates a perfect fit, and two estimates where 0 indicates a perfect fit, the root mean square error of approximation (*RMSEA*) and the standardized root mean square residual (*SRMR*). Robust estimates of the respective measures are reported. For the measurement models, confirmatory factor analysis (CFA) was conducted in *lavaan*.

Measures

Social well-being. To assess individuals' subjective social well-being, we adopted Keyes' (2009) short-form measure consisting of five items. Respondents were asked to rate their agreement on a 5-point

Likert scale with the statements that they belong to a community (social integration), that they have something valuable to give to the world (social contribution), that the way our world works makes sense to them (social coherence), that the world is becoming a better place (social actualization), and that people are basically good (social acceptance). The first item was responsible for a poor CFA fit and did not load substantively onto the social well-being factor. Thus, excluding the social integration item drastically improved the model fit to $\chi^2(2, N = 910) = 3.03$ ($p = .220$), $\chi^2 / df = 1.52$, $CFI = .996$, $TLI = .988$, $RMSEA = .024$, $SRMR = .014$, indicating a very close fit. The analysis of the structural paths that follow therefore used this four-item latent factor for social well-being. Standardized factor loadings ranged from .37 to .71 (all $p < .001$).

Internet use (digital participation). Internet use as a measure of actually participating in the information society was also modeled as a latent variable. That is, rather than conceptualizing use as a binary measure, or using total usage time, we propose that the most popular online activities reflect a relevant Internet use factor. From a number of activities included in the survey (Latzer, Büchi, & Just, 2015), the top activities were selected: Respondents reported their frequency of checking e-mails, using search engines, looking for news online, and using online encyclopedias on a 6-point scale ranging from 0 = *never* to 5 = *multiple times per day*. Looking up a term online was also among the most popular online uses but did not fit the proposed usage factor. The four other items had factor loadings between .52 and .82 (all $p < .001$) and reflected a very well-fitting Internet use factor: $\chi^2(2, N = 910) = 3.02$ ($p = .220$), $\chi^2 / df = 1.51$, $CFI = .998$, $TLI = .994$, $RMSEA = .025$, $SRMR = .011$.

Internet skills (digital potential). The measurement of general Internet skills as the potential to participate in the information society relied on a validated survey instrument for general populations (Van Deursen, Helsper, & Eynon, 2016). Respondents were asked to rate their agreement with five statements on a 5-point Likert scale about being able to perform five Internet-use related tasks (open downloaded files, find suitable search terms, change sharing settings, create and upload content, and install mobile applications). CFA of the model for a one-factor latent Internet skills measurement indicated that the item on social skill (change sharing settings) and the item on creative skill (create and upload content) were correlated beyond their common variance accounted for by the Internet skills factor. The measurement model with this covariance freely estimated instead of constraining it to zero subsequently fit the data well: $\chi^2(4, N = 910) = 20.35$ ($p < .001$), $\chi^2 / df = 5.09$, $CFI = .982$, $TLI = .954$, $RMSEA = .067$, $SRMR = .023$. Standardized factor loadings ranged from .57 to .67 (all $p < .001$).

Belongingness (digital perception). The personal perception of belongingness was assessed with a single question. Toward the end of the survey, respondents were asked, “You have answered many questions about media, the Internet and new communication technologies—do you feel you belong to this new information society?” The item was measured on a 5-point Likert scale ranging from 1 = *not at all* to 5 = *strongly* ($M = 3.51$, $SD = 1.16$).

Results

A first test of the basic question of whether digital inequalities impact social well-being compared users of the Internet with nonusers; all five dimensions of social well-being were predicted in multiple regressions with age, education, gender, and a dummy variable indicating whether a respondent used the Internet or not. For three of the well-being items, Internet use had no significant effect, and for two items, it had very small and opposite effects (see Table 1). In sum, users and nonusers of the Internet did not differ systematically in their social well-being. That is, at least cross-sectionally, the mere fact of having bridged the access divide does not have a positive or negative outcome at the subjective level of well-being. However, in an analogous regression model, digital belongingness was affected by being an Internet user (b = .69, β = .20, p < .001, R^2 = .14). We then tested the effects of further dimensions of digital inequalities on well-being in more complex models. How do the participation in, the potential for, and the perception of Internet use influence social well-being?

Table 1. The Effect of Using the Internet on the Five Dimensions of Social Well-Being.

	Effect of Internet use (binary)		
Social well-being dimension	*b*	*SE*	β
Social integration	.42 (p = .006)	.16	.09
F(4, 1034) = 7.56, p < .001, R^2 = .02			
Social contribution	.21 (p = .092)	.12	.06
F(4, 1024) = 1.88, p = .111, R^2 = .003			
Social coherence	.04 (p = .726)	.11	.01
F(4, 1007) = 4.18, p = .002, R^2 = .01			
Social actualization	-.32 (p = .004)	.11	-.10
F(4, 1000) = 2.26, p = .061, R^2 = .005			
Social acceptance	.02 (p = .862)	.11	.01
F(4, 1027) = .37, p = .828, R^2 =- .002			

Note. A series of multivariate regression models estimated the effect of using versus not using the Internet on dimensions of well-being. The models predicted dimensions of social well-being with Internet use while controlling for gender, age, and education.

Latent variable structural equation models tested the effects of Internet use, Internet skills, and the feeling of belongingness to the information society on social well-being in the sample of Internet users. First, a model controlling for sociodemographic variables was estimated: Model 1: χ^2(106, N = 910) = 286.84 (p < .001), χ^2 / df = 2.71, *CFI* = .940, *TLI* = .925, *RMSEA* = .043, *SRMR* = .034. The model fit was relatively low regarding *CFI* and TLI. Model 2 was then specified more parsimoniously, retaining only the variables of theoretical interest (i.e., excluding control variables) and fit the data very well: χ^2(71, N = 910) = 127.07 (p < .001), χ^2 / df = 1.79, *CFI* = .979, *TLI* = .973, *RMSEA* = .029, *SRMR* = .026 (see the appendix for the latent variable measures). A comparison of the structural path estimates of the controlled model with those of the simpler second model showed no substantive differences (see Table 2). This indicated that sociodemographic variables, although they may affect the level of the other variables, did not influence the relationships among the theoretical constructs relevant to the research question. In the interest of model parsimony and closer fit to the data (Kline, 2011), we report the results of this second model. In Figure 2, standardized estimates are reported: *ns*: non-significant (p > .05); * denotes p < .001 (see Table 2 for unstandardized estimates).

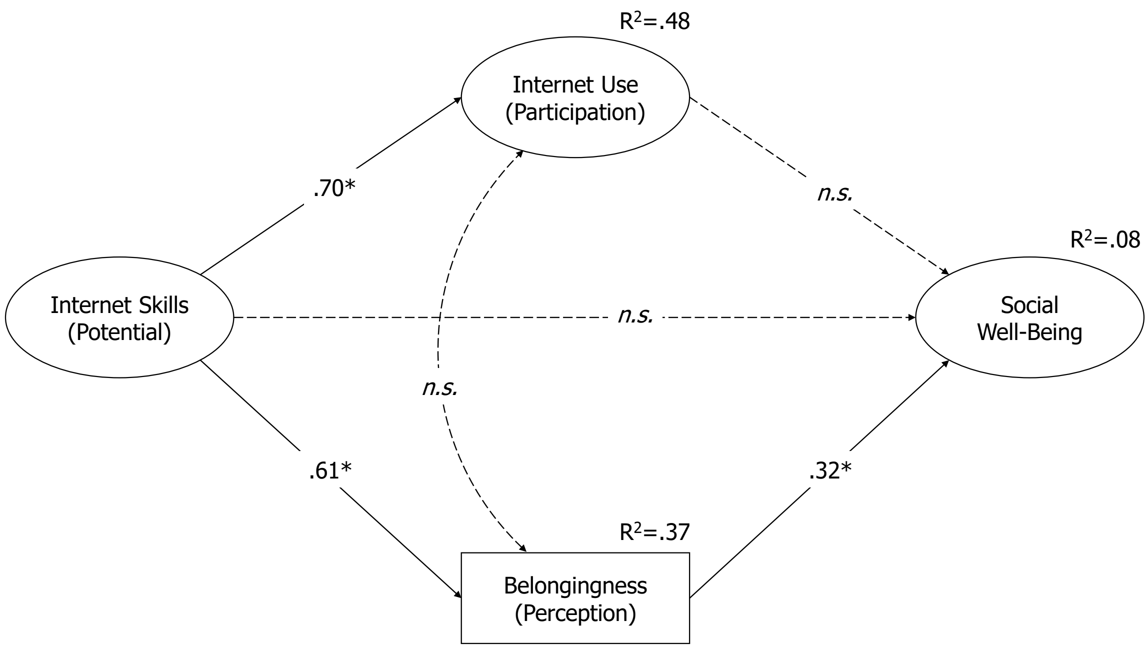

Figure 2. Structural equation modeling results (Model 2).

Table 2. Structural Equation Model Unstandardized Path Estimates.

Structural paths	Model 1	Model 2
Internet use ← Internet skills	.91*	.92*
Belongingness ← Internet skills	1.12*	.99*
Internet use ↔ Belongingness	.06 (*p* = .077, *ns*)	.06 (*p* = .092, *ns*)
Social well-being ← Internet skills	.07 (*p* = .558, *ns*)	-.03 (*p* = .753, *ns*)
Social well-being ← Internet use	-.05 (*p* = .412, *ns*)	-.04 (*p* = .583, *ns*)
Social well-being ← Belongingness	.20*	.22*

As noted, two structural equation models were estimated. Model 1 included control variables (only their significant relationships were ultimately retained in the model). Age, gender, and education were entered as controls. Model 2 included no control variables. Single-headed arrows indicate regression effects, and double-headed arrows indicate covariances. Comparing Model 1 and Model 2 shows that there are no substantive effect differences. The more parsimonious and thus better fitting Model 2 is therefore retained.

Participating in the information society through engaging with the most common online activities did not affect social well-being positively or negatively (see Figure 2 and Table 2). Respondents' digital potential in the form of Internet skills did not directly influence social well-being either. However, Internet skills very strongly and positively predicted Internet use and belongingness. This perception of belonging to the information society in turn positively and substantively affected social well-being. The standardized estimate for the indirect effect of Internet skills on social well-being via belongingness was .19 ($p < .001$), meaning that skills positively affect well-being by promoting belongingness to the information society. This model, comprising three digital inequality-related predictors, accounts for 8% of the variance in general social well-being.

Discussion

The results show that *perceptions*—how people feel they belong to the contemporary information society and assess their own digital skills—influence social well-being much more than *behavior* in the sense of manifest digital participation. Overall, at a population level, general Internet effects on social well-being were expectedly small. Nonetheless, the results point to consequences of digital inequalities for social well-being in the form of positive effects of digital potential (Internet skills) and perception (belongingness to information society; see Figure 2). A main insight of this study is therefore that belongingness, the personal perception of being part of modern developments and societal change characterized by the ubiquitous relevance of ICTs, is a key resource of social well-being. This feeling of belongingness, in turn, depends strongly on one's digital potential in the form of general Internet skills, a major dimension of digital inequality. Internet skills had a strong indirect effect on general offline well-being. Such skills have been shown to align with existing social inequalities, meaning that advantaged population groups possess higher skills (e.g., Hargittai, 2010).

We found that overall, existing digital inequalities translated to relevant outcome measures of quality of life. Users, as compared with nonusers, and especially those with ample online experience, are more likely to feel a sense of belonging to the information society, which then contributes to general social well-being. It is important to emphasize that Keyes' (2009) measure of social well-being is conceptually not related to a notion of information society or the role of the Internet, which strengthens the theoretical significance of the relationship found between digital potential and social well-being. This is the first study that demonstrates consequences of digital inequalities for social well-being; future research could also integrate hedonic and psychological well-being toward a model of "digital flourishing" (see Figure 1; see Keyes, 2014). While this article introduced the concept of social well-being into research on digital inequalities and their consequences, an expansion to other branches of quality of life indicators (see Figure 1) in relation to the Internet is desirable to produce a broader picture of the interplay between digital inequalities and individuals' well-being.

In future research, the role of Internet skills, use, and belongingness may also be investigated for different age groups. It seems plausible to assume that different mechanisms are in play in distinct life stages; positive effects of Internet-related variables may dominate in one group, whereas negative outcomes may be more prevalent in others, ultimately changing the total effect on subjective well-being. Furthermore, the benefits attainable through different Internet uses may vary according to one's personal needs, motivations, and attitudes. In the model presented, the direct path between Internet use (digital participation) and social well-being was not significant. Rather than concluding that participation in the information society is in fact irrelevant for well-being, it appears plausible that the zero net effect of Internet use (see Figure 2 and Table 2) is the result of competing mechanisms. To better understand the effect of Internet use on the appraisal of functioning in society, positive and negative effects should be studied in more detail in future research. While the theoretical background for this study suggested that Internet use connects individuals to information and communication relevant for their social lives with minimal transaction costs and thus impacts one's social well-being positively, recent research has also described digital overuse (Gui, Fasoli, & Carradore, 2017) and perceptions of feeling overwhelmed (Stephens et al., 2017) as an emerging social phenomenon. Gui et al. (2017) argued that the overabundance of information and social relationships in everyday life, combined with the social pressure to function digitally, can impair well-being. This means that our model may be moderated by specific digital well-being skills distinct from general Internet skills: Only under the condition that individuals have specialized capacities to manage the potential negative side effects of their digital participation, and thus avoid feeling overburdened, could their use be considered functional or beneficial for well-being. A further investigation of this possibility seems highly relevant to digital inequality research because overuse and its related concepts (specific coping skills and social pressure) are likely to be unequally distributed along socioeconomic fault lines.

This article is also relevant to the current academic debate on subjective well-being because it focuses on its social component, which has been neglected thus far. As indicated, there are strong theoretical arguments for a relationship between Internet-related variables and social integration. However, we had to exclude that very item from our model because of low factor loading and an unsatisfactory model fit. We assume that this measurement problem stems from the wording of the social integration item that concerned a feeling of integration in communities like neighborhoods (Keyes, 1998). In the country of study, family or friend groups seem to be more relevant communities in which people attain a sense of integration. Based on this limitation, the operationalization of social well-being may need to be updated and adjusted to the specific sociocultural contexts in future research.

Nonetheless, the results of this study not only illustrate the consequences of existing digital inequalities, but also have policy implications because they contribute to the empirical basis of evidence-based policy making regarding the promotion of Internet use and skills development. Public policies are often geared toward promoting adoption of new technologies but rarely assess longer term impacts of integrating them into everyday life, particularly on the level of subjective quality of life indicators. Underlining previous research (Büchi et al., 2017; Hargittai, 2008; Helsper & Eynon, 2013), the conclusion is that general, transferable digital skills represent a worthwhile target for digital inclusion policy and that a new category of digital well-being skills needs attention. Although the OECD (2017), for example, shows continued effort to measure well-being in information societies as a basis for policy, the roles of digital skills, participation, and perception remain underappreciated. Overall, we argue for the continued consideration of subjective aspects of well-being in the study of digital inequalities and the consequences of ICTs for quality of life more generally.

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Appendix

Latent Variable Factor Loadings and Summary Statistics

Latent factor	Measurement item	Factor loading	*M*	*SD*
Social well-being	Social contribution	.44*	3.15	1.23
	Social coherence	.55*	3.28	1.08
	Social actualization	.61*	2.59	1.07
	Social acceptance	.43*	3.40	1.12
Internet skills (potential)	Operational skills	.64*	4.51	1.01
	Navigation skills	.59*	3.89	1.03
	Social skills	.62*	3.41	1.49
	Creative skills	.57*	3.00	1.56
	Mobile skills	.65*	4.00	1.52
Internet use (participation)	Look for news	.56*	3.05	1.59
	Search-engine use	.75*	4.05	1.07
	Check e-mails	.54*	4.20	1.01
	Use online encyclopedia	.58*	2.45	1.29

Note. Standardized estimates from Model 2 are reported. * $p < .001$.

Article VI

Digital Overuse and Subjective Well-Being in a Digitized Society

Moritz Büchi, Noemi Festic & Michael Latzer

Abstract

In modern everyday life, individuals experience an abundance of digital information and communication options, and pressure to use them effectively and constantly. While there are many benefits attainable through the use of digital information and communication technologies (ICTs), digital overuse needs to be explored as it may impair individual well-being. A nationally representative survey explored the extent of perceived digital overuse (PDO) and tested its relation to social digital pressure, digital coping skills, and, to assess everyday offline relevance, to individual subjective well-being. Results indicated that 28% of Swiss Internet users perceived digital overuse, which was strongly and negatively associated with well-being. Social pressure was positively related to overuse. Differences in experiencing and dealing with digital overabundance are highly relevant to general well-being and need to be further researched in light of social change and ICT innovations.

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Digital Overuse and Subjective Well-Being in a Digitized Society

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Abstract

In modern everyday life, individuals experience an abundance of digital information and communication options, and pressure to use them effectively and constantly. While there are many benefits attainable through the use of digital information and communication technologies (ICTs), digital overuse needs to be explored as it may impair individual well-being. A nationally representative survey explored the extent of perceived digital overuse (PDO) and tested its relation to social digital pressure, digital coping skills, and, to assess everyday offline relevance, to individual subjective well-being. Results indicated that 28% of Swiss Internet users pereived digital overuse, which was strongly and negatively associated with well-being. Social pressure was positively related to overuse. Differences in experiencing and dealing with digital overabundance are highly relevant to general well-being and need to be further researched in light of social change and ICT innovations.

Keywords

well-being, digital overuse, structural equation modeling, digital skills, digital pressure

Introduction: Abundance of Digital Information and Communication

Digital information and communication technologies (ICTs) are the default infrastructure for societal participation in many countries, be it for information seeking, socializing, or entertainment (Graham & Dutton, 2014). Various forms of partaking in the digitized society are beneficial for well-being (see, for example, Amichai-Hamburger, 2007; Lissitsa & Chachashvili-Bolotin, 2016). However, the overabundance of Internet-based digital information and communication options also presents a potential impairment to personal well-being (Gui, Fasoli, & Carradore, 2017). The main contribution of this article is the conceptualization and empirical assessment of perceived digital overuse (PDO) in relation to subjective well-being (SWB).

This does not imply that the Internet is a harmful medium per se; there are undeniably many valuable information and communication options online. Rather, it appears that those who manage to derive positive life outcomes from their use minimize the potential negative effects (Salo, Pirkkalainen, & Koskelainen, 2017). Accordingly, specific skills in coping with digital overabundance and in managing potential negative side effects of their digital participation may help users to maintain high well-being. In this process, the social context, understood as the everyday relevance of Internet use, likely matters, too: both PDO and the need for mitigating coping skills are assumed to be more salient in social settings where the pressure to function digitally is high. Individuals who are constantly confronted with expectations and norms regarding their "digital functioning" as a form of social pressure may experience more overuse and would need particularly high coping skills.

The global digital divide narrative was put forward under the assumption that Internet access and use inevitably produce benefits. Limitations to the "the more the better" account have been problematic Internet use (Caplan, 2002; Tokunaga & Rains, 2016; Yellowlees & Marks, 2007) and Internet or smartphone addiction (Brand, Laier, & Young, 2014; Chóliz, 2010; Griffiths, 1996), mostly understood as clinically defined minority phenomena. And, more recently, neuroscientific (He, Turel, Brevers, & Bechara, 2017) and public health research (Domoff, Borgen, Foley, & Maffett, 2019) has started to examine the effects of excessive digital media use. However, public and academic discourse has also identified potential individual and societal harms apart

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from psychiatric diagnoses. In fact, research has pointed to perceptions of digital overuse as an impairment to well-being that affects larger parts of the population: in a large survey in the United Kingdom, 41% of Internet users agreed with the statement "I spend too much time online" (Ofcom, 2016, p. 32).

To take advantage of the Internet as a positive resource in everyday life, users frequently need to manage the overabundance of digital information and communication options. The point of departure for the present study is that Internet use can provide people with relevant information, entertainment, services, and social connections that are beneficial for well-being (Helsper & van Deursen, 2015)—but that a negative personal impact is expected when its use is experienced as too much. Although Internet users frequently experience a general sense of overuse, there is a gap in research on its prevalence, predictors, and consequences. The article focuses on PDO and SWB at the user level and contributes to the broader debate on how various facets of Internet use relate to happiness.

The Experience of Digital Overuse

Unlike problematic, compulsive, or excessive Internet use as a pathologic and thus minority condition, perceiving general digital overuse is an emerging social issue; it is less severe but much more common (Gui & Büchi, 2019). The ubiquity of the Internet and social media has set constant availability as a new societal standard. This is partly due to the emergence of algorithmic selection applications that recommend new entertainment content, compile personalized news feeds, or select relevant posts for infinite scrolling (Willson, 2017). Features like push notifications have the capacity to enable anytime and anywhere communication and availability, often by interrupting other ongoing (offline) activities. Social media firms have dedicated teams that try to make their services as "addictive" as possible (Leslie, 2016). By personalizing content combined with automated recommendations (e.g., YouTube, Facebook) and tailoring services specifically to the users' interests, these social media platforms aim at maximizing the time people spend engaging with them, and their profits. Consequently, the question arises whether users feel overburdened by this vast array of available communication and information options and how they manage their Internet use and social pressure. Digital overuse is thus a general and broad latent phenomenon that occurs when everyday Internet use surpasses an individual standard or vague sense of a personal optimum. This perception crosses different life domains, devices, and applications, and can therefore be seen as an accumulated, abstracted consequence of the interplay between specific usage patterns and technology push.

Importantly, this concept is subjective and relative—we do not imply that a specific threshold value for the amount of use is harmful. For instance, digital-screen engagement as an "objective" amount of use variable did not correlate with adolescent well-being with any practical significance (Orben & Przybylski, 2019a), supporting our rationale of conceptualizing overuse as an individual experience if it is to be relevant for well-being. We thus define PDO as the positive difference between the extents of practiced and desired Internet use, that is, the perceived excess of time allocated to Internet use in absolute, relative, and synchronistic terms. While the related but separate concepts of problematic Internet use or addiction rely on cutoff scoring (Kardefelt-Winther et al., 2017)—that is, the "desired" extent is exogenously defined by experts such as psychiatrists—PDO depends entirely on the individual and context: one person's overuse is another's lifeblood (see Bawden & Robinson, 2009, p. 187). Because the personally desired extent of Internet use is presumably a latent dimension of which users themselves may not be cognizant, the measurement needs to rely on indirect manifestations. Individuals can express when their use becomes overuse, without thinking about specific numbers, when it overall feels like too much, displaces other valued activities, or causes cognitive overload (also see Gui & Büchi, 2019; Gui et al., 2017).

We identify three concrete manifestations of PDO. First, a general feeling of spending too much *absolute* time online is the most straightforward indicator of overuse (Ofcom, 2016). While people may have difficulties in reporting accurate total time or frequency estimates (Scharkow, 2019), they are the experts on their own attitudes and perceptions. A second indicator of digital overuse is the feeling that Internet use regularly and perhaps subtly pushes other—and according to one's personal ideals, more important—things aside (see Hall, Johnson, & Ross, 2019). The concept of PDO thus foregrounds conflicts in the *relative* importance of everyday activities competing for time. This overallocation of time to Internet use relative to other valued activities also taps into deficient self-regulation associated with a tendency to procrastinate (Reinecke et al., 2018). Third, PDO likely manifests itself in negatively evaluated *synchronicity* of multiple online stimuli and feelings of overload (LaRose, Connolly, Lee, Li, & Hales, 2014; Yeykelis, Cummings, & Reeves, 2014). Overuse is thus reflected in the feeling that one is trying to do too many things at the same time online.

Given the public and academic debate about using "too much" technology, we first ask how users themselves assess their use, or more precisely, what proportion of Swiss Internet users feels they overuse the Internet. Thus far, studies are limited to understanding digital overuse as pathological, typically assessed in student populations (see Tokunaga & Rains, 2016). However, it is crucial to assess how widespread the perception of digital overuse as a societal phenomenon is, that is, in representative population-level surveys. To explore this, we formulate the following research question:

> **Research Question 1:** To what extent do Internet users self-report digital overuse?

A Link to Theories of the Good Life: Subjective Well-Being

News reports on Internet overuse, generally focusing on social media or smartphones, often propose negative effects on individuals' mental health (e.g., Booth, 2019; Cornish, 2017; Klass, 2019). To assess whether digital overuse is relevant for well-being, we first need to determine the appropriate measurement of well-being. Both academia and policy makers have long pursued the goal of measuring the "good life" of individuals and societies, using various indicators to determine quality of life (Miao, Koo, & Oishi, 2013). While economic, political, or social macro conditions were previously regarded as the best indicators, SWB has recently received more attention as a way of measuring individual mental health. It is one important aspect of quality of life among other factors like physical health, societal living conditions, and economic measures (Michalos, 2014). SWB is a self-assessment of an individual's well-being in different life domains (for an overview, see Diener, Oishi, & Tay, 2018). Early research described a happy person as a "young, healthy, well-educated, well-paid, extroverted, optimistic, worry-free, religious, married person with high self-esteem, high job morale, modest aspirations, of either sex and of a wide range of intelligence" (Wilson, 1967, p. 294); this was reassessed, leading to the finding that a happy person has a "positive temperament, tends to look on the bright side of things, and does not ruminate excessively about bad events, and lives in an economically developed society, has social confidants and possesses adequate resources for making progress toward valued goals" (Diener, Suh, Lucas, & Smith, 1999, p. 295).

The role of media and communication is absent or implicit in this literature. However, SWB has recently received increasing attention from communication research (e.g., Amichai-Hamburger, 2007; Burke & Kraut, 2016; Chan, 2015; Reinecke & Oliver, 2017; Valkenburg & Peter, 2007). Often, such research derives causal mechanisms regarding communication effects on well-being from the affordances of ICTs. A mostly separate line of scholarship using a digital inequality framework has primarily been concerned with social differences in Internet access and use (e.g., Brandtzæg, Heim, & Karahasanović, 2011; Büchi, Just, & Latzer, 2016). A crucial but under-researched addition here is the analysis of differential consequences of Internet use (Büchi, Festic, & Latzer, 2018; Van Deursen & Helsper, 2018). Thus far, outcomes of Internet use have particularly been studied in terms of tangible, concrete outcomes like finding a job or making friends online (Helsper & van Deursen, 2015). With the realization that such outcomes of Internet use can equally be of a subjective or mental nature (Büchi et al., 2018; Huang, 2010), adding SWB measures as an outcome is a step toward empirically assessing the social impact of the Internet more holistically by consolidating theoretical arguments from both lines of research.

Existing studies on the implications of usage differences generally show that individuals of higher social status seem to be taking greater offline advantage from their digital engagement, resulting in an amplification of existing inequalities (Hargittai & Hsieh, 2013). The digital inequality framework assumes that skilled Internet use can be personally, socially, and economically advantageous (Robinson et al., 2015). However, empirical studies show mixed results, likely due to a wide variety of operationalizations, and do not give a clear answer as to whether the Internet positively affects well-being in society (Çikrıkci, 2016; Huang, 2010, 2017). In research on Internet effects on social well-being with a representative sample for the Swiss population, digital participation through online information seeking or communication had no significant direct effect, although the perception of digital belongingness was directly related to social well-being, and Internet skills were indirectly related (Büchi et al., 2018). A reason for the absence of a net digital participation effect may be that positive and negative outcomes of Internet use occur simultaneously (Blank & Lutz, 2018). In a large survey of US teens, of which 95% have access to a smartphone, 45% believe social media has neither a positive nor negative effect on young people (Anderson & Jiang, 2018).

Internet use is multifaceted, and we need to further disaggregate it to reveal the effects of online engagement on well-being. While some amount of Internet use is a social requirement in the digital age, we argue that overuse can impair well-being. For instance, in a large-scale study of adolescents, Przybylski and Weinstein (2017) found a quadratic relationship between digital-screen time and mental well-being, albeit with small effect sizes, indicating that moderate use is most advantageous. Previous work has shown that differentiating between types of Internet use does not sufficiently disentangle the uncertain effects of Internet use on SWB (Büchi et al., 2018). Rather, it appears crucial to study a different dimension, namely perceptions of overuse, which arises from the adapted circumstances of Internet use in digitized societies.

Potential negative effects of Internet-enabled information and communication abundance such as Internet overuse have been identified (Gui et al., 2017; Stephens et al., 2017). In their theoretical work, Gui et al. (2017) identified the abundance of information and communication options in everyday life as a surplus that is difficult to manage, and its overuse can impair well-being; these dynamics have even evoked a somewhat overdrawn but in parts valid analogy to overconsuming food (Johnson, 2015). In related research, technostress has been linked to exhaustion, mental strain, and reduced productivity, as well as problems regarding concentration, sleep, identity, and social relations (Kushlev & Dunn, 2015; Salo et al., 2017). Sbarra, Briskin, and Slatcher (2019) compiled evidence on how smartphone and social networking site use negatively impact well-being through disruption of cognitive and relationship processes. In the workplace, perceptions of information, communication, and system feature overload were found to contribute to productivity losses (Karr-Wisniewski & Lu, 2010). Overall, there is an ongoing debate on the existence and magnitude of negative effects of digital ICT uses on well-being, often fueled by research on adolescents (Bell, Bishop, & Przybylski, 2015; Livingstone, 2018; Orben & Przybylski, 2019b).

Drawing on representative data from the United Kingdom, the *Communications Market Report* (Ofcom, 2016) revealed that over 40% of the population feel they spend too much time online. A large proportion of these individuals further confirmed that their personal or professional life had suffered from that. Frequently mentioned consequences were missing out on sleep, interrupted face-to-face communication, less time spent with family and friends, or being late for work (Ofcom, 2016). We hypothesize that PDO is negatively related to individuals' personal well-being as an Internet-unrelated measure of quality of life.

Hypothesis 1: PDO is negatively associated with SWB.

Additional Contextual and Individual Factors

When investigating the relationship between PDO and SWB, other variables that concern an individual's social setting as well as their ability to cope with the challenges they face in their everyday Internet use must be considered.

Social Digital Pressure (SDP)

Usage patterns of ICTs are interrelated with existing social norms. For example, a couple of decades ago, "new owners of telephone answering machines were commonly concerned about obligations to monitor their machines constantly and return calls expeditiously" (Mick & Fournier, 1998, p. 137). Today, this "soft coercion" (Ling, 2016) includes expectations regarding online responsiveness, skills, and social presence (Gui & Büchi, 2019). Social digital pressure (SDP) thus reflects the norm or perceived societal expectation to function digitally and to be able to manage everyday challenges of digital media. As a context variable, it concerns the practical relevance of digital overabundance to one's everyday life. Depending on people's job situation and social setting, the degree to which they are expected to deal with new technologies varies greatly. Individuals who face higher pressure to function digitally in their everyday lives are at a higher risk of perceiving Internet overuse.

Hypothesis 2: SDP is positively associated with PDO.

Digital Coping Skills (DCS)

Digital communication abundance does not necessarily or automatically degrade well-being. We propose that specific DCS, which enable Internet users to manage potential negative side effects of digital participation and avoid feeling overburdened, enable functional and personally beneficial Internet use. While there has been some research on potential organizational mitigating mechanisms to combat technology overuse, little attention has been paid to how users cope with the risk of digital overuse (Salo et al., 2017).

Internet users generally cope with risks through self-help, for instance, privacy protection (Park, 2013) or trying to influence algorithms (Bucher, 2017; van der Nagel, 2018). Fraser and Kitchin (2017) summarize these actions individuals take to "oppose, evade, alter, or otherwise navigate their way around emerging problems" (p. 3) as "slow computing." In countering the risk of digital overuse, the relevant skills concern selective and goal-oriented use. Analogously to Bawden's theorization of information overload (Bawden, Holtham, & Courtney, 1999; Bawden & Robinson, 2009), some users have the competence to avoid feelings of powerlessness against the technological push and take control of their use. Gui et al. (2017) note that "they [users of digital media] increasingly need specific skills to channel digital stimuli towards personal goals and benefit, avoiding excessive multi-tasking, fragmentation of daily time and overconsumption of new media" (p. 155).

Hypothesis 3: DCS are negatively associated with PDO.

DCS are not only presumed to have a mitigating effect on digital overuse, but we also argue that this specific set of skills is positively associated with SWB (Leung, 2010). Acquiring new skills can induce a sense of achievement by being able to cope with new technologies and handle-associated challenges well (Nimrod, 2014). DCS may increase a feeling of autonomy, competence, and self-efficacy and are therefore expected to have a positive relationship with SWB.

Hypothesis 4: DCS are positively associated with SWB.

The relevance of these coping skills is likely to be context-dependent: we expect them to be more important in social settings where the pressure to function digitally is generally high. When the pressure to respond to messages quickly or be able to use various Internet applications is high in an individual's environment, they are exposed to a higher risk of feeling overburdened and experiencing perceived overuse. They therefore need to master specific skills to mitigate this possibility. In settings where this pressure is low, Internet users need fewer coping skills and are less susceptible to overuse and its effects on well-being.

Hypothesis 5: The association between DCS and SWB is moderated by SDP (such that the positive association between DCS and SWB is stronger for users who experience higher SDP).

Our theoretical arguments and review of existing studies have not led to any hypotheses regarding the relationship between SDP and SWB and the relationship between SDP and digital coping skills (DCS).

Covariates

Sociodemographic characteristics like sex, age, and education have long been shown to correlate with measures of how the Internet is used (e.g., Brandtzæg et al., 2011; Büchi et al., 2016). In addition, given that we are looking at perceived overuse, the amount of actual use may also be relevant. How the actual amount of Internet use relates to individual well-being is an empirically unsolved question and highly dependent on the operationalization of both variables (e.g., Huang, 2010; Przybylski & Weinstein, 2017). In this study, we see individuals' amount of Internet use and standard sociodemographic characteristics as control variables to consider when detecting the relationship between overuse on well-being.

Method

Nationally Representative Survey Data

The analysis uses original data from a nationally representative computer-assisted telephone survey conducted in 2017 in Switzerland (N=1,120). It included a module on digital well-being to address the research question and hypotheses of this study. Using random digit dialing, respondents were contacted and interviewed through landline (80%) or mobile phone (20%). In this general population survey, to ensure representativeness, sampling quota were constructed based on age, sex, and region (Latzer, Büchi, Festic, & Just, 2017). Analyses reported below exclude non-users of the Internet, resulting in an effective sample of N=1,011 Internet users. This sample comprised 50% women and the median age was 46 years (range: 14–93). A total of 34% had a tertiary education degree and 68% were employed full time or part-time; 19% were students and 12% were retired.

Missing values were rare and mainly concerned the Internet activity items used to construct the measure of the amount of use. The highest percentage of missing values (1.48%) was identified for the item asking respondents how frequently they consumed erotic content online. Multiple imputation by chained equations was used to obtain a complete data set (Azur, Stuart, Frangakis, & Leaf, 2011; van Buuren & Groothuis-Oudshoorn, 2011). Comparisons between summary statistics of the original and the imputed data set columns showed no significant differences.

Measures

Perceived digital overuse. The items for PDO were newly developed in a larger project on digital well-being, pretested in a student sample, and cross-validated in a large, population-level survey in a second country (see Gui & Büchi, 2019). Respondents were asked to what extent they agreed with the following three statements (1=*completely disagree*, 5=*completely agree*) about how they personally evaluate their Internet use: "I spend more time on the Internet than I would like," "I often try to do too many things at the same time when I am online," and "When I use the Internet, I lose time for more important things." The initial items for overuse also draw on the *Communications Market Report* (Ofcom, 2016), which asked about neglecting other aspects of life to make time for online activities and the feeling of spending too much time online, as well as on the theoretical work by Gui et al. (2017). To keep PDO viable as an instrument in larger surveys, it was limited to three items.

Subjective well-being. SWB was measured using the Warwick–Edinburgh Mental Well-Being Scale (WEMWBS), which was developed for population surveys (Stewart-Brown et al., 2011; Tennant et al., 2007). It covers the hedonic and eudaimonic aspects and central indicators of SWB (positive affect, psychological functioning, and interpersonal relationships). The short-form scale consisting of seven items was used, asking respondents to pick the category that best represented their experience in the last 2 weeks in response to the following statements (1=*none of the time*, 2=*rarely*, 3=*some of the time*, 4=*often*, 5=*all of the time*): "I've been feeling optimistic about the future," "I've been feeling useful," "I've been feeling close to other people," "I've been feeling relaxed," "I've been dealing with problems well," "I've been thinking clearly," and "I've been able to make up my own mind about things."

Social digital pressure. The users' context, the social pressure regarding the use of the Internet, that is, SDP, was measured by asking respondents to what extent they agreed with the following three statements (1=completely disagree, 5=completely agree): "In my everyday life, people expect that I am capable of using various Internet applications," "In my everyday life, people expect that I reply quickly to messages," and "In my everyday life, people expect me to be active on social networking sites." These items build on previous work on perceived norms (Fishbein & Ajzen, 2011); for instance, the communication norm or expectation that one is constantly available (Ling, 2016; Reinecke et al., 2017).

Digital coping skills. To measure people's DCS, we asked respondents to rate their agreement with the following three statements (1=*completely disagree*, 5=*completely agree*): "I am able to selectively choose people or information sources to follow online," "I am able to set up my Internet devices or services so that they do not disturb me," and "I am able to distinguish Internet activities that are important for me from those that are not."

Amount of Internet use. A measure for the amount of Internet use was constructed by summing the frequencies (0=*never*, 5=*several times a day*) of using 35 diverse Internet applications (e.g., online messaging, checking facts, streaming videos, or social media use; see Blank & Groselj, 2014 for a discussion of this measure). The theoretical range was 0–175, the empirical range was 1–111 (M=51.12, median=51, SD=19.62).

Sociodemographic variables. Respondents' level of education, employment status, age (in years), and sex (0=*male*, 1=*female*) were measured. Education was recorded using

Table 1. Analytical Strategy.

	Descriptive statistics	(Moderated) regression analysis	Structural equation model
Research Question 1	•		
Hypothesis 1		•	•
Hypothesis 2			•
Hypothesis 3			•
Hypothesis 4		•	•
Hypothesis 5		•	

five categories. The variable was subsequently recoded into three categories: low (primary or secondary school), medium (vocational school, A-levels or high-school graduation), and high education (university, university of applied sciences). Employment status was recorded as currently employed full time, part-time, or unemployed.

Analytical Strategy

First, we report descriptive statistics to answer Research Question 1. Confirmatory factor analysis (CFA) tested the measurements of the latent variables. The multivariate statistical methods then included regression and moderation analysis to test Hypotheses 1, 4, and 5, including control variables and structural equation modeling (SEM) to address Hypotheses 2 and 3 and to retest the nomological network of latent variables in light of the regression analysis results (see Table 1). All analyses were performed in the software *R*; the *lavaan* package (Rosseel, 2012) was used for CFA and SEM, with unweighted least squares (ULS) estimation and polychoric correlations given the ordinal measurement of the indicator items (Forero, Maydeu-Olivares, & Gallardo-Pujol, 2009). Models were assessed using conventional cutoffs from the CFA and SEM literature (Hu & Bentler, 1999; Schermelleh-Engel, Moosbrugger, & Müller, 2003).

Results

Descriptive Statistics

To answer Research Question 1, the descriptive statistics of the three indicators of PDO are reported. The mean for the question about spending too much time online (absolute PDO) was 2.51; for doing too many things at the same time (synchronistic PDO), it was 2.27, and 2.64 for losing time for more important things (relative PDO).

These values were just below the middle of the answer scale. The most prevalent feeling of digital overuse thus concerned relative time allocation, but the means for the other two items were fairly similar. Calculating the mean of the three indicators for each respondent revealed that 28% experienced overuse in that they scored higher than the scale middle of 3. Figure 1 shows the distribution of responses: the modal response category was 1 for all three items, indicating generally low overuse. At the other end, we do see that sizable proportions of the population express digital overuse—between 20% and 28% *agree* (4) or *completely agree* (5) with the statements. Furthermore, if we take the maximum response value for any of the three items for each individual and again combine agreement values 4 and 5, 46% report overuse. That is, nearly half of Internet users agree with at least one of the three statements about overuse. Don't know answers or refusals were very rare (0.6%).

Measurement Model

A combined CFA was performed with the four multi-item measures as a precondition to extract factor scores for regression analysis and to use latent variables in SEM (see Supplemental Figure A1). The proposed structure of loadings was well supported by the data, $\chi^2(97, N=1{,}011)=335.71$, $\chi^2/df=3.46$, CFI = .964, TLI = .955, RMSEA = .049, SRMR = .049, with only one minor modification (a freely estimated covariance between the residual variances of two items of the SWB factor was added, see Online Appendix). Hence, the empirical pattern of salient and non-salient factor loadings validates our items proposed to measure the four latent variables of theoretical interest.

Regression and Moderation Analysis

Factor scores were predicted and saved from the CFA for subsequent regression and moderation analysis. The model regressed SWB as the dependent variable on PDO, DCS, SDP, the product of DCS and SDP, amount of use, age, employment, education, and sex (Table 2).

PDO had a negative effect on SWB, $b=-.35$, $t(999)=-15.45$, $p<.001$. DCS had a positive effect, similar in absolute effect size, $b=.41$, $t(999)=17.28$, $p<.001$. None of the demographic control variables nor the amount of Internet use had significant effects on well-being. The effect of SDP was small but positive and significant, $b=.16$, $t(999)=5.02$, $p<.001$. The interaction term between SDP and DCS was positive, but not significant, $b=.06$, $t(999)=1.66$, $p=.097$. That is, the estimated coefficient for the effect of DCS on SWB is greater for higher values of SDP: for example, it is .46 for above-average SDP of 1 compared with .34 for below-average SDP of –1, but given the sparsity of data for very low or very high values of SDP, the 95% confidence interval for the coefficient estimation includes the point estimate for the mean level of SDP, that is, 0 ($b=.41$) (see Table 2).

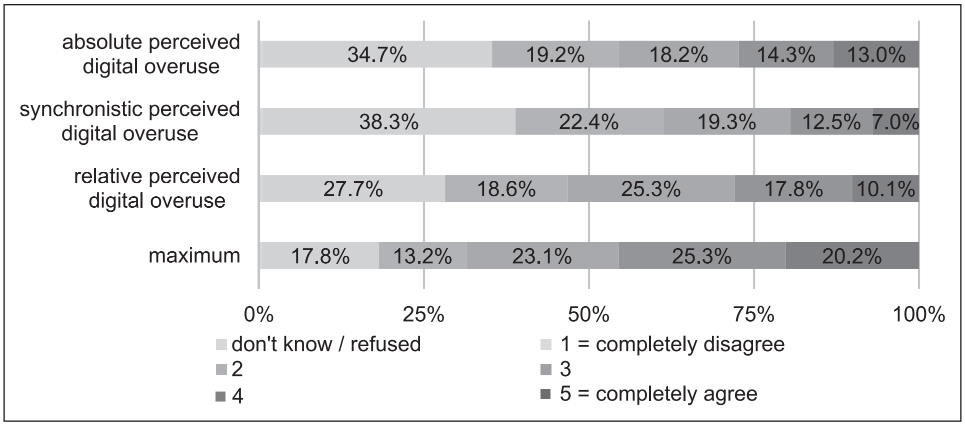

Figure 1. Distribution of indicators of perceived digital overuse.
Maximum refers to the proportion of the highest response to any of the three indicators.

Table 2. Moderated Regression Analysis of SWB.

	Unstd. *b*	*SE*	*t*	*p*	Std. *b*
(Intercept)	–.063	.071	–0.89	.374	.000
PDO	–.354*	.023	–15.45	.000	–.507
DCS	.406*	.024	17.28	.000	.474
SDP	.161*	.032	5.02	.000	.170
DCS × SDP	.055	.033	1.66	.097	.039
Amount of use	.0003	.001	0.39	.700	.012
Age	.0006	.001	0.72	.472	.021
Part-time employed	–.027	.030	–0.91	.364	–.025
Full-time employed	.018	.030	0.64	.524	.019
Medium education level	.011	.028	0.39	.697	.010
High education level	–.020	.020	–1.02	.306	–.025
Female	.024	.026	0.914	.361	.024

SE: standard error; PDO: perceived digital overuse; DCS: digital coping skills; SDP: social digital pressure.
$F(11, 999) = 85.83$, $p < .001$, adjusted $R^2 = .48$. Omitted categories: unemployed, low education level, male
*$p < .001$.

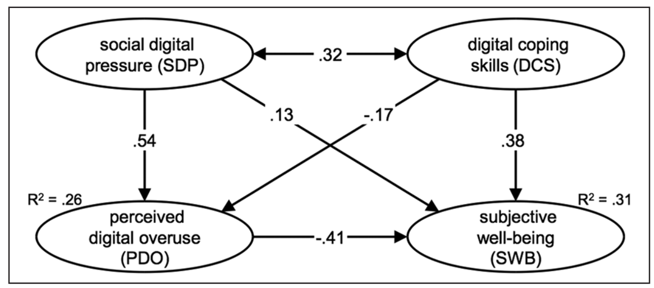

Figure 2. Structural equation model.
Standardized regression estimates are shown. See Table 3 for full model results.

A very high proportion of the variance in SWB was explained by the predictors, $F(11, 999) = 85.83$, $p < .001$, $R^2 = .48$. Omitting the non-significant interaction term in an updated regression model resulted in virtually identical parameter estimates and fit, $F(10, 1{,}000) = 93.97$, $p < .001$, $R^2 = .48$. In summary, the regression analysis provided strong support for Hypotheses 1 and 4, whereas Hypothesis 5 was rejected.

Structural Equation Model

First, we evaluated the global fit and found that the proposed model fit the empirical covariance matrix well: χ^2 $(97, N = 1{,}011) = 335.71$, $\chi^2/df = 3.46$, CFI = .964, TLI = .955, RMSEA = .049 (95% CI = [.044, .055]), SRMR = .049. Given that the SEM and the four-factor CFA measurement model were both saturated including the same set of latent and manifest variables, the global fit measures were identical; however, the structural path estimates still differed, given the assumption of endogeneity for PDO and SWB in the SEM. Figure 2 shows a graphical representation of the model with standardized estimates and Table 3 provides all estimates.

The path estimates (all $p < .001$ unless otherwise noted) show that PDO had a substantial negative effect on SWB, while DCS had a nearly equal but positive effect. Again, SDP weakly and positively predicted well-being, in this model, non-significantly ($p = .054$). In the SEM, PDO was modeled as a mediator: SDP very strongly and positively affected overuse and DCS affected it weakly and negatively. SDP and DCS correlated positively.

The results from the SEM approach confirm the regression analysis as they support Hypotheses 1 and 4. In addition, treating PDO as an endogenous variable in SEM made it possible to test Hypotheses 2 and 3, which were both supported.

Model Robustness Checks

The results of the structural equation model were cross-checked with different estimators, different standard error calculations and control variables. The results reported above used ULS estimation and bootstrapped standard errors with 10,000 draws, which we deemed most appropriate for the

Table 3. Parameter Estimates of the Structural Equation Model.

		Unstd.	SE^a	Z	p	Std.	R^2
Regressions							
SWB	←						.308
	PDO	–.282*	.042	–6.72	.000	–.409	
	DCS	.300*	.053	5.65	.000	.380	
	SDP	.121	.063	1.93	.054	.133	
PDO	←						.259
	SDP	.704*	.077	9.16	.000	.538	
	DCS	–.197*	.062	–3.19	.001	–.174	
Covariances							
DCS	↔						
	SDP	.146*	.027	5.34	.000	.324	
useful	↔						
	feelclose	.241*	.040	6.08	.000	.317	
Latent variables							
SWB	→						
swb1	future	1[b]				.568	.322
swb2	useful	.960*	.083	11.62	.000	.545	.297
swb3	feelclose	.732*	.080	9.12	.000	.415	.172
swb4	relaxed	.911*	.072	12.68	.000	.517	.267
swb5	dealwell	1.114*	.080	13.88	.000	.632	.400
swb6	thinkclear	1.190*	.096	12.42	.000	.676	.456
swb7	ownmind	1.106*	.087	12.77	.000	.628	.394
DCS	→						
dcs1	select	1[b]				.719	.518
dcs2	nodistract	.858*	.081	10.60	.000	.617	.381
dcs3	important	.927*	.090	10.29	.000	.667	.444
PDO	→						
pdo1	absolute	1[b]				.817	.667
pdo2	synchronistic	.902*	.055	16.52	.000	.737	.543
pdo3	relative	.866*	.048	18.02	.000	.708	.501
SDP	→						
sdp1	expquick	1[b]				.624	.389
sdp2	expskills	1.267*	.106	11.91	.000	.790	.625
sdp3	expsns	.946*	.076	12.44	.000	.590	.348

SE: standard error; SWB: subjective well-being; PDO: perceived digital overuse; DCS: digital coping skills; SDP: social digital pressure.
Single-headed arrows indicate regressions; double-headed arrows indicate covariances.
χ^2 (97, N = 1,011) = 335.71, CFI = .964, TLI = .955, RMSEA = .049, SRMR = .049. See Figure 2 for graphic representation.
[a]Standard errors computed with 10,000 bootstrap draws.
[b]Fixed to unity.
*p < .001.

nature of our data; the CFI was .964 and the RMSEA was .049. Maximum likelihood (CFI = .943, RMSEA = .042) and diagonally weighted least squares estimation (CFI = .976, RMSEA = .045) produced similar fit measures. Using robust standard errors instead of bootstrapping consistently yielded larger standard errors in the range of 10%–15% difference. Accordingly, the p-values reported above are on the conservative side. Additional models, including all sociodemographic control variables entered in the regression analysis, or alternatively retaining only those that were significant compared with the model reported above, naturally produced slightly different estimates, but none of the results regarding the tenability of the hypotheses were affected. For example, in a model with all control variables, the standardized effect of PDO on SWB was –.39 (p < .001), compared with –.41 (p < .001) in Figure 2. All of these analyses are documented here: https://osf.io/b74ce/?view_only=7dc61ab2438b43dcbd7e4795f13797fd.

Discussion and Limitations

Many people experience digital overuse—in our study of Swiss Internet users, 28% had a mean score higher than the scale middle. In multivariate analyses, higher PDO was substantially related to lower well-being. DCS were positively associated with well-being and social pressure was positively associated with overuse. The abundance of digital information and communication options in everyday life is a social fact in Switzerland and many other countries (although there remains a shrinking proportion of people who cannot or do not want to use the Internet, see Latzer et al., 2017)—this macro condition impacts individuals' perceptions and actions. In this context, we find that differences in dealing with and experiencing digital overabundance relates to individuals' SWB. The regression and structural equation models were able to explain a very high percentage of the variance in SWB (48% and 31%, respectively). SWB (positive thoughts and feelings relating to one's recent everyday life) as the outcome measure of this study and the Internet-use-related variables (overuse, pressure, and skills) as predictors are very distinct, yet the results revealed strong associations between them. This leads to the conclusion that overuse is not solely relevant on a "digital level." Rather, as the boundaries between an individual's online and offline lifeworld become increasingly blurred, digital overuse will become a more pressing social issue.

It is important to acknowledge the cross-sectional nature of the data in interpreting the results. While the models include directional paths that represent our theoretical assumptions, the empirical results are correlational and cannot rule out omitted-variable bias or reverse causality. Overall, the measures for PDO, SDP, and digital coping would benefit from further validation. For instance, the item asking about the expectation of being active on social networking sites may be problematic as it represents a separate dimension. Agreement to this item may correlate differently with sociodemographic variables than the other SDP items about digital skills and responsiveness. Future operationalizations should therefore reassess the dimensionality of this construct. The items measuring PDO referred to "the Internet," yet respondents' understanding of this term may vary depending on their specific uses and experiences. A challenge for future work will thus involve finding appropriate terminology to capture the digital ICT repertoire to which PDO pertains; perhaps qualitative inquiry would show that such precision is only possible for more narrowly defined populations or applications.

Contrary to our assumption expressed in Hypothesis 5, there was no significant interaction such that the positive effect of DCS on SWB would be stronger for users who experience higher SDP. It may be that the social level is less relevant here and the mechanism is more psychological: if a user needs or wants to use the Internet a lot (but does not necessarily experience the expectation that they do), then DCS become more important for well-being. In future research on overuse involving the effects of social norms, human values and personality traits may be promising additional predictors. Research on media use and well-being has also addressed the role of self-control—avoiding digital overuse may be contingent upon the ability to resist "sweet temptations" (Hofmann, Reinecke, & Meier, 2017).

The results showed a small but positive effect of SDP on SWB; we lack a clear theoretical explanation for this, but it may be that the digital pressure measure is confounded with social connectedness which is positively tied to well-being. In experimental research where social pressure was manipulated, it in fact had a negative effect on well-being by reducing competence in a sample of smartphone users (Halfmann & Rieger, 2019). Presumably, there is also a third variable in play that is associated both with digital pressure and SWB, such as employment or professional engagement. Individuals in more high-performance jobs would perceive higher digital pressure but at the same time reap well-being benefits from their professional achievements (we included employment status in the regression analysis, which showed no effect, but lack more detailed data to explore this possibility further).

This article is aligned with research on the broad question and public debate on how Internet use relates to happiness. We contribute a countrywide, representative analysis of digital well-being beyond a single service or platform. Existing studies have shown positive, negative, or zero effects, depending on the specific operationalizations of Internet use and happiness (Huang, 2017; Leung, 2010; Orben, Dienlin, & Przybylski, 2019). An important novel contribution of the present study is the focus on overuse in this context—after decades of a prevailing "the more the better" narrative. Contrary to more techno-deterministic or prescriptive interpretations of overuse (e.g., Montag & Walla, 2016), the insight is not that intense use necessarily equals overuse and is thus "bad," but rather that ICT innovations and social change require adaptive behavior from individuals intent on maintaining high personal well-being. At the social level, the historically rapid diffusion of the Internet and connected devices has produced a cultural delay, meaning that the modification of social norms that would protect against overuse is lagging behind technological developments (Gui & Büchi, 2019). For digital inequality research, the association between PDO as a second-level variable and SWB as a third-level variable is highly relevant; in combination with the finding that higher levels of education are associated with lower overuse (Gui & Büchi, 2019), future research needs to address the potential causal chain from offline status markers through Internet use variables to differences in well-being. It appears that in some contexts of a digitized society, digital inequality is shifting from scarcity to overabundance.

With the rise of digital, networked, and continuous communication in everyday life, social functioning—an individual's "ability to fulfill their role within environments such as work, social activities, and relationships" (Bosc, 2000, p. 63)—has met significant new challenges. In this vein, the study's results help further develop the notion of digital well-being—understood as a shorthand term for the maintenance of SWB in a social environment characterized by the digitization of all life domains and the constant abundance of digital information and communication options as a default. We need updated theoretical perspectives to grasp the mutual dependencies of ICTs and social life, that is, to explain well-being not as a function of technology itself, but of its ensuing individual and social harms (e.g., overuse, online harassment, manipulation based on digital traces) and benefits (e.g., relevant information, online social capital, economic efficiency). Future theoretical and empirical research can further differentiate and add to these factors, positive and negative.

Conclusion

PDO, a widespread perception among Internet users in a digitized society that is among the happiest in the world (Helliwell, Layard, & Sachs, 2018), is strongly associated with individual well-being. At the same time, we have shown that specific skills in coping with the everyday strains of information and communication abundance can offset its negative impacts. This study points to digital overuse as a social issue and stresses the importance of a new set of skills that is necessary to cope with such challenges of the digital age, both in academic research and policymaking. Further theoretical and empirical research is needed to address the challenge of how individuals can maintain high well-being in a digital society—sometimes despite and sometimes thanks to the pervasiveness of digital ICTs in virtually all life domains.

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Supplemental Material

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Article VII

A Guideline for Understanding and Measuring Algorithmic Governance in Everyday Life

Michael Latzer & Noemi Festic

Abstract

Algorithmic governance affects individuals' reality construction and consequently social order in societies. Vague concepts of algorithmic governance and the lack of comprehensive empirical insights into this kind of institutional steering by software from a user perspective may, however, lead to unrealistic risk assessments and premature policy conclusions. Therefore, this paper offers a theoretical model to measure the significance of algorithmic governance and an empirical mixed-methods approach to test it in different life domains. Applying this guideline should lead to a more nuanced understanding of the actual significance of algorithmic governance, thus contributing to an empirically better-informed risk assessment and governance of algorithms.

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A guideline for understanding and measuring algorithmic governance in everyday life

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Keywords: Algorithmic governance, Policymaking, Reality construction, Everyday life, Mixed-methods

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INTRODUCTION

The growing use, importance and embeddedness of internet-related algorithms in various life domains is widely acknowledged. Academic and public debates focus on a spectrum of implications in everyday life, caused by internet-based applications that apply automated algorithmic selection (AS) for, among other things, searches, recommendations, scorings or forecasts (Latzer, Hollnbuchner, Just, & Saurwein, 2016; Willson, 2017). These discussions are often combined with reflections on growing automation in general and the impact of artificial intelligence (e.g., machine learning) in particular (Larus et al., 2018). Questions emerge as to how to analytically grasp and assess the consequences of the diffusion of algorithmic selections in modern societies, which some observers characterise as *algocracies* (Aneesh, 2009) in an *algorithmic age* (Danaher et al., 2017), marked by growing relevance of informatics and statistics in the governance of societies.

In this paper we provide a guideline for answering these questions. We (1) take a governance perspective and suggest to understand the influence of automated algorithmic selections on daily practices and routines as a form of institutional steering (governance) by technology (software). This institutional approach is combined with practice-related concepts of everyday life, in particular of the daily social and mediated constructions of realities, and embraces the implications of algorithmic governance in selected life domains. Based on these combined approaches, and on a review of empirical algorithmic-governance literature that identifies research gaps, we (2) develop a theoretical model that includes five variables that measure the actual significance of algorithmic governance in everyday life from a user perspective. To examine these variables for different life domains an innovative empirical mixed-methods approach is proposed, which includes qualitative user interviews, an online survey and user tracking.

Results from applying the proposed guideline should contribute to a more nuanced understanding of the significance of algorithmic governance in everyday life and provide empirically informed input for improved risk assessments and policies regarding the governance of algorithms. Accordingly, applying this guideline should help both academics and practitioners to conduct policy analyses and assist them in their policy-making.

A NUANCED UNDERSTANDING OF ALGORITHMIC GOVERNANCE IN EVERYDAY LIFE

In the fast growing academic and non-academic literature on algorithms, their implications in daily life are summarised using a variety of sometimes misleading and only vaguely defined terms, ranging from algocracy and algorithmic selection to algorithmic regulation and algorithmic decision-making. In the following, a nuanced understanding of “algorithmic governance” is developed from an institutional perspective, that can form the basis for policy analyses and policy-making.

Governance can be understood as institutional steering (Schneider & Kenis, 1996), marked by the horizontal and vertical extension of traditional government (Engel, 2001). Governance *by* algorithms, also referred to as *algorithmic governance,* captures the intentional and unintentional steering effects of algorithmic-selection systems in everyday life. Such systems are part of internet-based applications and services, applied by private actors / commercial platforms (e.g., music recommender systems) and political actors (e.g., predictive policing). They include both institutional steering *with* and *by* algorithms in societies, i.e., as tools or as (semi-) autonomous agents, either in new or already established commercial and political governance systems. Our understanding of algorithmic governance in everyday life overlaps with Yeung's (2018) *algorithmic regulation*. But algorithmic governance in everyday life goes far beyond 'intentional attempts to manage risk or alter behaviour in order to achieve some pre-specified goal', and refers not only to 'regulatory governance systems that utilise algorithmic decision making' (Yeung, 2018, p. 3). Unintentional effects of automated algorithmic selections are a major part of algorithmic governance and call for special attention in policy analyses and policy-making.

Danaher et al. (2017) use the terms *algorithmic governance* and *algocracy* largely synonymously, referring to the intertwined trends of (1) growing reliance on algorithms in traditional corporate and bureaucratic decision-making systems, and (2) the outsourcing of decision-making authority to algorithm-based decision-making systems. In accordance with Aneesh (2009) and Danaher (2016), we do not understand algocracy as the final stage of technological singularity 'when humans transcend biology', as foreseen by Google's director of engineering Ray Kurzweil (2005), but rather as a kind of governance system where algorithms govern (i.e., shape, enable and constrain activities) either as intentionless tools of human agents or as non-human agents equipped with a certain autonomy. [1] Together and also as part of other kinds of (traditional) governance systems (e.g., legal systems, self-regulations, cultural norms and traditions), they *co-govern* societies. The extent of the relative importance of algorithmic selections in daily routines and their overall effect on social order in societies, however, is an open research question. Empirically assessing the significance of algorithmic governance is particularly important since accurate assessments of the role of algorithms (e.g., degree of automation and autonomy) and associated risks are a prerequisite for the development of adequate public policies.

Different aspects of algorithmic governance have received attention from various disciplines, leading to a large but fragmented body of research. A comprehensive empirical assessment of the significance of algorithmic selection in daily life requires both concepts of *algorithmic selection* and of *everyday life* that can be operationalised. This article commences with a working definition of algorithmic selection as the automated assignment of relevance to certain selected pieces of information and a focus on internet-based applications that build on algorithmic selection as the basic unit of analysis (Latzer et al., 2016).

ALGORITHMIC SELECTION APPLICATIONS AS UNITS OF ANALYSIS

The emerging field of critical algorithm studies can roughly be grouped into studies that centre on (single) algorithms *per se* as their unit of analysis, and those that focus on the socio-technical context of AS applications. Studies focusing on the algorithm itself show the capabilities of AS and aim to detect an algorithm's inner workings, typically by reverse engineering the code (Diakopoulos, 2015), experimental settings (Jürgens, Stark, & Magin, 2015), or code review (Sandvig, Hamilton, Karahalios, & Langbort, 2014). Often, however, they are not able to determine the overall social power that algorithms exert, because algorithms are studied in isolation and user perceptions and behaviour are not sufficiently accounted for. Generally, a purely technical definition of algorithms as encoded procedures that transform input data into specific output based on calculations (e.g., Kowalski's, 1979, 'algorithm = logic + control') and the mere uncovering of the workings of an algorithm do not reveal much about the risks of their applications and their social implications. Algorithms remain 'meaningless machines' (Gillespie,

2014) or 'mathematical fiction' (Constantiou & Kallinikos, 2015) until they are connected to real-world data (Sandvig et al., 2014). This is accounted for in studies on the socio-technical context of AS, where algorithms are viewed as situated artefacts and generative processes embedded in a complex ecosystem (Beer, 2017; Willson, 2017). As such, algorithms are only one component in a broader socio-technical assemblage (Kitchin, 2017), comprising technical (e.g., software) and human (e.g., uses) components (Willson, 2017). By focusing on internet-based applications that build on algorithmic selection as units of analysis and on the societal functions they perform (see Table 1), this article integrates itself within the second group of research.

Table 1: Functional typology of AS applications (adapted from Latzer et al., 2016)

Types	Examples
Search	General search engines (e.g., Google search, Bing, Baidu) Special search engines (e.g., findmypast.com, Shutterstock, Social Mention) Meta search engines (e.g., Dogpile, Info.com) Semantic search engines (e.g., Yummly) Question and answer services (e.g., Ask.com)
Aggregation	News aggregators (e.g., Google News, nachrichten.de)
Observation/surveillance	Surveillance (e.g., Raytheon's RIOT) Employee monitoring (e.g., Spector, Sonar, Spytec) General monitoring software (e.g., Webwatcher)
Prognosis/forecast	Predictive policing (e.g., PredPol) Predicting developments: success, diffusion etc. (e.g., Sickweather, scoreAhit)
Filtering	Spam filter (e.g., Norton) Child protection filter (e.g., Net Nanny)
Recommendation	Recommender systems (e.g., Spotify, Netflix)
Scoring	Reputation systems: music, film, and so on (e.g., eBay's reputation system) News scoring (e.g., reddit, Digg) Credit scoring (e.g., Kreditech) Social scoring (e.g., PeerIndex, Kred)
Content production	Algorithmic journalism (e.g., Quill, Quakebot)
Allocation	Computational advertising (e.g., Google AdSense, Yahoo!, Bing Network) Algorithmic trading (e.g., Quantopian)

The typology in Table 1 demonstrates how broad the scope of AS applications has become. An approach that focuses on socio-technical and functional aspects is accessible for research into the social, economic and political impact of algorithms (Latzer et al., 2016) and the power algorithms may have as gatekeepers (Jürgens, Jungherr, & Schoen, 2011), agents (Rammert, 2008), ideologies (Mager, 2012) or institutions (Napoli, 2014). The institutional governance perspective, that is applied in this paper, identifies algorithms as norms and rules that affect daily behaviour by limiting activities, influencing choices, and creating new scope for action. They shape how the world is perceived and what realities are constructed. In essence, algorithms co-govern everyday life and impact the daily individual construction of realities—the individual consciousness—and consequently the collective consciousness, which in turn makes them a source and factor of social order, resulting from a shared social reality in a society (Just

& Latzer, 2017).

ALGORITHMS CO-GOVERN DAILY LIFE AS INSTRUMENTS AND ACTORS

The governing role of algorithms needs further analytical specification. As general-purpose technologies (Bresnahan, 2010), algorithms have an impact on a wide range of life domains, and as enabling technologies their impact is contingent on social-use decisions. From a co-evolutionary perspective (Just & Latzer, 2017), algorithmic governance is a complex, interconnected system of distributed agency (Rammert, 2008) between humans and software, a co-evolutionary circle of permanent shaping and being shaped at the same time. Algorithms co-govern what can be found (e.g., algorithmic searches), what is anticipated (e.g., algorithmic forecasts), consumed (e.g., algorithmic recommendations) and seen (e.g., algorithmic filtering), and whether it is considered relevant (e.g., algorithmic scoring) (Just & Latzer, 2017). They thereby contribute to the constitution and mediation of our lives (Beer, 2009). The use of only vaguely defined terms like *algorithmic decision-making* can be misleading regarding the assessment of social consequences of different kinds of algorithmic governance. Various analytical distinctions should be kept in mind when studying algorithmic governance:

Algorithmic selection applications on the internet differ widely in their degree of automation and autonomy. At one end of the spectrum, algorithms are used as instruments with imposed agency to exert power without any autonomy, with predefined and widely predictable outcomes [2]. At the other end, machine-learning algorithms govern with a delegated agency that implies a predefined autonomy, leading to unforeseeable results [3].

To indicate the actual autonomy of algorithmic systems on the internet, a similar classification to that applied for self-driving cars may be helpful, where a labelling from 1 (low) to 5 (full) marks the degree of automation (Bagloee, Tavana, Asadi, & Oliver, 2016). Literature on automated weapons systems provides another instrumental way to categorise the remaining control by humans in automated decision-making systems: humans are classified as being either (1) in-the-loop and fully in control, (2) on-the-loop and able to intervene if felt necessary, or (3) off-the-loop and without any option to intervene (Citron & Pasquale, 2014). This distinction, for example, proves helpful when liabilities for algorithmic governance are evaluated. The term automated decision-making algorithms often refers to decisions by algorithms without human involvement (off-the-loop), and has already led to regulatory interventions. The use of automated decision-making systems with significant legal or social effects is restricted (e.g., fully automated tax assessments), for example, by article 22(1) of the European General Data Protection Regulation (GDPR), whereas the use of other automated decision-making systems—based on non-personal data—is not restricted (Martini & Nink, 2017).

Algorithmic selections as part of internet-based applications are related to everyday human decisions in different ways. In most of the functional categories listed in Table 1, automated algorithmic selections are applied to augment and enhance everyday human decision-making but not to fully replace it. This is predominantly the case for algorithmic recommendations, filtering and scoring results. Nevertheless, it has to be considered that in many cases (e.g., credit scoring, predictions on recidivism, ranking of job candidates) it becomes increasingly problematic for those responsible to ignore or counteract algorithmic results in their decisions, in particular if these algorithmic outputs are accessible to others or to the public. Accordingly, AS applications that are aimed at enhancing human decisions can *de facto* evolve into systems where humans merely remain on-the-loop and will only intervene in exceptional cases.

Further, algorithmic selections vary strongly in their scope of potential consequences (social and economic risks). For instance, there is a significant difference between a simple algorithmic filtering concerning which post from a friend is shown in someone's social media feed and a more meaningful and directly relevant algorithmic scoring of someone's creditworthiness. Accounting for the case-specific scope and context of algorithmic selections is therefore highly relevant for appropriate policy conclusions. For instance, two technologically identical algorithms where one is applied for recommending books and the other for recommending medical treatments call for very different policies due to the disparity of risks of these automated algorithmic selections.

Algorithmic (co-)governance results in opportunities and risks. The advantages of algorithmic governance such as efficiency gains, speed, scalability and adaptability are compromised by risks ranging from bias, manipulation and privacy violations, to social discrimination, heteronomy and the abuse of market power (Latzer et al., 2016), or by efficiency-based (inaccurate decisions) and fairness-based objections (unfair decisions) in algorithmic governance (Zarsky, 2016).

In sum, while algorithms are increasingly active as tools and actors in governance regimes that affect many life domains on a daily basis, the relative importance of algorithmic governance is far from clear. The practice-related approach proposed here aids the empirical assessment and understanding of this significance of algorithmic governance.

A PRACTICE-RELATED APPROACH TO EVERYDAY LIFE

Everyday life as a field of research is rooted in various theoretical traditions (Adler, Adler, & Fontana, 1987), among other things in phenomenological sociology (Schütz, 2016), historical materialism (Heller, 1984) and De Certeau's (1984) anthropology.

As for the area of inquiry, this paper takes a practice-related approach (Pink, 2012). Since the field lacks comprehensive empirical research that goes beyond individual services, this article suggests studying the significance of algorithmic governance for everyday life in a more inclusive manner. In order to derive an executable research design, however, it is necessary to analytically segment 'everyday life'. We focus on four domains of everyday life that span central areas of everyday practice: (a) social and political orientation, (b) recreation, (c) commercial transactions, and (d) socialising. This categorisation is derived from a representative, country-wide CATI survey of internet use in Switzerland. While an infinite number of activities can be performed on the internet, a confirmatory factor analysis revealed four distinct internet usage factors that group the most important internet activities for Swiss internet users (see Büchi, Just, and Latzer, 2016 for an overview of the activities for each domain). Therefore, this categorisation lends itself to an analytical distinction between different life domains in which people engage in online activities and use AS applications in particular. It is important to note that these life domains are obviously closely interrelated and do not necessarily represent the categories in which individuals perceive their everyday lives. Although there is no standard conceptual framework for everyday life, Sztompka (2008), for example, points to its various defining traits, such as that everyday life events include relationships with other people, that they are repeated and not unique, have a temporal duration, and often happen non-reflexively, following internalised habits and routines.

In order to appropriately account for the increasing role of technology, research must go beyond human relationships as one defining characteristic of everyday life. The theory of the social or mediated construction of reality (Berger & Luckmann, 1967; Couldry & Hepp, 2016) is fruitful for the understanding of how social interactions and media technologies shape the perception of the social world. Berger and Luckmann (1967) argue that the social world is constructed through social interactions and underlying processes of reciprocal typification and interpretation of habitualised actions. In this meaningful process, a social world is gradually constructed whose habitualised actions provide orientation, make it possible to predict the actions of others and reduce uncertainty. This leads to an attitude that the world in common is known, a natural attitude of daily life (Schütz & Luckmann, 2003). Accordingly, the resources, interpretations and the common-sense knowledge of routinised practices in everyday life—which increasingly includes AS applications—are seemingly self-evident and remain unquestioned.

This paper particularly aims to expose what is generally left unquestioned and to propose a guideline for the assessment of perceptions and use of AS applications for a wide range of everyday practices in order to better understand their impact, associated risks, and the need for public policies. Willson (2017) emphasises that one of the concerns of studying the everyday is to make the invisible visible and to study the power relations and practices involved. AS applications are seamlessly integrated into the routines of everyday life through domestication (Silverstone, 1994)—the capacity and the process of appropriation—which renders them invisible. Algorithms operate at the level of the 'technological unconscious' (Thrift, 2005) in widely unseen and unknown ways (Beer, 2009). Consequently, the study of algorithms aims to reveal the technological unconscious and to understand how AS applications co-govern everyday online and offline activities. AS applications must be investigated in relation to online and offline alternatives to determine the relative significance of algorithmic governance for everyday life, for example by bearing in mind an individual's media repertoire [4] (Hasebrink & Hepp, 2017). Thus far only a small body of empirical research on AS has emerged with regard to the everyday activities of orientation, recreation, commercial transactions and socialising.

EXISTING EMPIRICAL RESULTS AND RESEARCH GAPS

(a) The significance of algorithmic governance has received the most attention in research on *social and political orientation*. Search applications and news aggregators are understood as intermediaries (Bui, 2010; Newman, Fletcher, Kalogeropoulos, Levy, & Nielsen, 2018) between traditional mass media and individual news consumption. Empirical research suggests that algorithmic selection will become more important for information retrieval in the future (Newman et al., 2018; Shearer & Matsa, 2018). Accompanying these considerations are fears of personalised echo chambers (Sunstein, 2001) or filter bubbles (Pariser, 2011), leading to fragmented, biased perceptions of society (Dylko, 2016). However, recent empirical studies fail to show a coherent picture: there are clear patterns of algorithmically induced, homogenous opinion networks (Bakshy, Messing, & Adamic, 2015; Del Vicario et al., 2016; Dylko et al., 2017), but other studies indicate more opinion diversity despite algorithmic selection and qualify the risk of echo chambers with empirical evidence (Barbera, Jost, Nagler, Tucker, & Bonneau, 2015; Dubois & Blank, 2018; Fletcher & Nielsen, 2017; Heatherly, Lu, & Lee, 2017; Helberger, Bodo, Zuiderveen Borgesius, Irion, & Bastian, 2017; Zuiderveen Borgesius et al., 2016).

(b) AS applications also increasingly shape daily *recreation* (i.e., entertainment and fitness). Recommendation applications have been shown to play a predominant role here. The main concerns are diminishing diversity (Nguyen, Hui, Harper, Terveen, & Konstan, 2014), the algorithmic shaping of culture (Beer, 2013; Hallinan & Striphas, 2016) and the social power of algorithms (Rieder, Matamoros-Fernandez, & Coromina, 2018). Again, there has been no clear empirical evidence for this hypothesis, but rather studies qualifying this risk (Nguyen et al., 2014; Nowak, 2016).

Further, wearables—networked devices equipped with sensors—have entered everyday life.

Empirical studies investigate the perception, use and modes of self-tracking (Lupton, 2016; Rapp & Cena, 2016), and its social and institutional context (Gilmore, 2015). Such wearables have often been disregarded in critical algorithm studies, although they are an important way in which AS governs the perception of the self (Williamson, 2015) and everyday life in general.

(c) For *commercial transactions*, there has been a focus on studying recommender systems focusing on the performance of algorithms (Ur Rehman, Hussain, & Hussain, 2013) or the implementation of new features (Hervas-Drane, 2015). Their impact on consumers is mostly studied by evaluating their perceived usefulness (Li & Karahanna, 2015). Furthermore, allocation algorithms in the form of online behavioural advertising have attracted attention (Boerman, Kruikemeier, & Zuiderveen Borgesius, 2017), revealing inconsistent results on users' perceptions of personalised advertisements (McDonald & Cranor, 2010; Smit, Van Noort, & Voorveld, 2014; Ur, Leon, Cranor, Shay, & Wang, 2012).

(d) For *socialising*, the research focus is on how algorithms curate user interactions on social networking sites and dating platforms (Bucher, 2012; Hitsch, Hortaçsu & Ariely, 2010). These applications raise concerns like social distortion effects or the question of how social connections are adapting to an algorithmically controlled model (Eslami et al., 2015; Rader, 2017; Rader & Gray, 2015; Van Dijck, 2013). So far, there has been no empirical analysis to confirm the relevance of these risks.

Altogether, research on the impact of algorithmic governance on everyday life has produced a plethora of theoretical considerations and fragmented, application-specific empirical findings. To date there has been no comprehensive and systematic empirical investigation of the various central domains of everyday practices. However, generalising policy implications from studies on individual AS services (e.g., Facebook, Twitter or search engines) should be treated with caution. Moreover, existing studies focus on AS applications in relative isolation. Due to this narrow perspective, they are unable to evaluate the power of algorithmic governance in everyday life. Existing work has mostly taken a top-down approach, disregarding the perspective of users. Studies on user perceptions have predominantly relied on self-reported survey measures. While extensive qualitative studies (e.g., Bucher, 2017) offer the basis for a better scientific understanding of the social effects of AS applications, they do not allow generalisable statements at the population level. There is also a lack of empirical work with data on individuals' actual internet use. To the best of our knowledge, there is no empirical study on the population level that uses tracking data on both mobile and desktop devices, a prerequisite to gain a comprehensive picture of individual internet use. Finally, there have been very few nationally representative studies on the use and perception of AS (e.g., Araujo et al., 2018; Fischer & Petersen, 2018). These existing empirical results do not provide a sound basis for policy-making in this area.

The following section proposes a methodological design that is suited to filling the research gaps identified above. It is designed with the objectives of providing a better understanding of how algorithms exert their power over people (Diakopoulos, 2015)—which essentially corresponds to our understanding of algorithmic governance—and to offer useful evidence-based insights for public policy deliberations regarding algorithmic governance and the policy choices for the governance *of* algorithms.

MEASURING ALGORITHMIC GOVERNANCE FROM A USER PERSPECTIVE

This section develops a theoretical model of the variables intended to measure the significance of algorithmic governance for everyday life and form the basis for theory-driven empirical assessments. We then propose a mixed-methods approach to empirically determine the extent to which AS applications govern daily life, since purely theoretically derived risks may lead to premature policy recommendations.

THEORETICAL MODEL OF THE SIGNIFICANCE OF ALGORITHMIC GOVERNANCE IN EVERYDAY LIFE

To empirically grasp the significance of algorithmic governance for everyday life, we develop a theoretical model that accommodates the operationalisation of algorithmic governance and entails five variables that influence the potential and effectiveness of this particular type of governance: usage of AS applications, subjective significance assigned to them, awareness of AS, awareness of associated risks, and practices to cope with these risks.

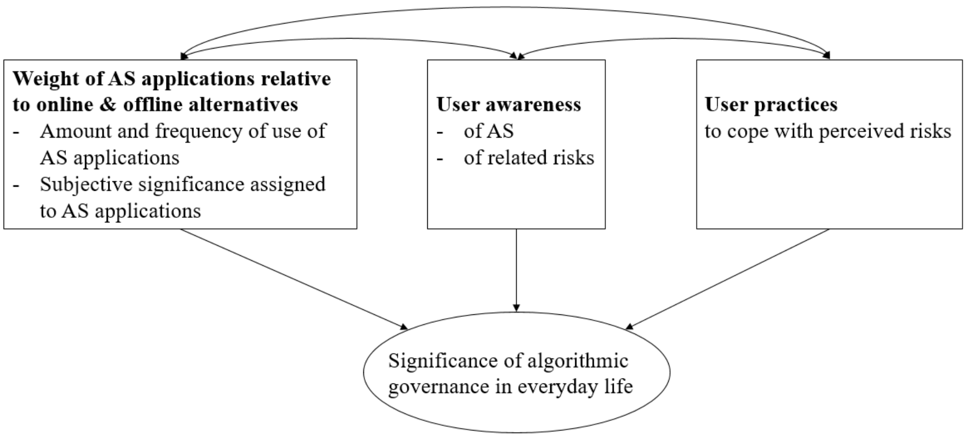

Figure 1: Theoretical model of variables measuring the significance of algorithmic governance in everyday life.

First, in order to determine the governing potential of AS applications in everyday life, their *usage* (extent, frequency) must be measured, particularly compared to their online and offline counterparts. Also, their governing potential is determined by whether and how these applications have changed people's behaviour, for instance with regard to individual information seeking, listening to music, gaming, or dating. Second, the *subjective significance* people attribute to these applications plays an important role in how AS applications affect everyday life. The substantial substitution of traditional online and offline alternatives by AS applications is a prerequisite if fears of AS-associated risks are to be justified. Assessing the significance that users assign to AS applications makes it possible to determine the accuracy of these theoretical estimations. Third, it is essential to investigate how aware people are of the fact that algorithms operate in the services they use and of the specific algorithmic modes of operation. *Awareness of AS* substantially affects the effectiveness and impact of algorithmic governance. A variety of risks is attributed to the use of AS applications (e.g., filter bubbles, diminishing diversity of content), which are often directly associated with the algorithmic modes of operation. Accordingly, without awareness, users cannot accurately assess potential benefits and risks [5]. The fourth factor of algorithmic governance is the *risks* people associate with the AS applications they use. Algorithmic governance per se is a neutral concept, but it can involve risks that lead to stronger governing effects of AS applications, especially when awareness is low. From a user perspective, applying *practices* that are opposed to companies' strategies is the most viable way to exert agency. Based on De Certeau (1984), algorithmic governance is understood in terms of strategies and tactics: platforms that apply AS postulate their own delimited territory from which they manage power relationships with an exteriority—in this case users. These platforms apply 'panoptic practices': they observe, measure, and control, and consequently turn users into measurable types. These panoptic practices allow the platforms to create user classifications based on a user habitus that reflects their social disposition. Through these panoptic practices, AS applications co-govern users' constructions of reality by mirroring their social dispositions in the form of scorings, recommendations, search results or advertisements. We consider user practices as tactics that are the counterpart of the strategies that companies or platforms apply. Accordingly, user practices are generally aimed at coping with risks that companies induce through their data collection and analysis strategies. Such practices are discussed as 'slow computing' by Fraser and Kitchin (2017). This term implies slowing down internet use, connectivity, and practices against *data grabbing infrastructures*. The practices can be seen as complementary to other measures like empowering users by governing algorithms with, for instance, consumer policies that improve the protection of user data (Larsson, 2018). The practices users apply to cope with the risks that they perceive associated with AS applications are thus the fifth factor of investigation when trying to assess the extent of algorithmic governance in everyday life.

THE MIXED-METHODS APPROACH

Suitable assessments of risks related to AS applications and corresponding policy measures require the empirical measurement of the governance that AS applications exert in users' everyday lives. To answer the call for taking algorithms' 'socio-technical assemblages' (Kitchin, 2017) into account and investigating how users engage with AS applications in their lives, existing top-down approaches should be complemented by a user-centred perspective (Bucher, 2017).

Therefore, we propose a user-centred, mixed-methods approach to measuring the significance of AS applications, which is comprised of three research phases. Based on a literature review, (I) semi-structured *qualitative interviews* are to be conducted for each of the four domains of everyday practice. As these practices (e.g., newsgathering, dating) are not limited to internet use, the significance of AS applications must be considered in relation to alternative online and offline activities. This enlarged and contextualised perspective promises to provide an understanding of individuals' life worlds and how AS applications are integrated within them. The qualitative interviews can provide in-depth information on individuals' perceptions, opinions and interpretations regarding AS applications in the four life domains.

These qualitative interviews should form the basis for the quantitative empirical part, which we propose to consist of a *representative online survey* (II) in combination with a *representative passive metering* (tracking) (III) of internet usage at the population level. The combination of self-reported survey measures and tracked internet use (passive metering) makes it possible to compare the tracked share of AS services used with the self-reports of internet use, which can be systematically biased (Scharkow, 2016) or subject to social desirability effects. Further, the non-transparent, "black-box" nature of algorithms raises questions about users' awareness of the mechanisms at play. When asking people about their experiences with algorithms, it must be kept in mind that their awareness of the existence of algorithms might be low and their statements could be biased accordingly. Therefore, a measurement of AS by means of tracking data additionally to the interview and survey data is inevitable 6. This could, for instance, be done by installing tracking software that records internet use on the survey respondents' mobile and desktop devices 7. It should, for instance, collect the websites they visit (URLs), the search terms they use and the time and duration of their visits.

All three methodological approaches lend themselves to the accomplishment of different goals and results, which are summarised in Table 2. Only in its entirety is this mixed-methods approach able to significantly contribute to closing existing research gaps with regard to the empirical understanding of algorithmic governance and the overall significance of AS applications in everyday life.

Table 2: Expected contributions of the three methods to the empirical assessment of algorithmic governance in everyday life

	Qualitative interviews with internet users	**Quantitative survey with internet users**	**Passive metering of individual internet use**
Usage of AS applications	Not primarily relevant, gather context data on circumstances of use	Determine frequency of use of offline alternatives	Determine frequency of use of online alternatives and AS applications
Subjective significance assigned to AS applications	Find reasons why AS applications are relevant, find out whether & how AS applications have changed behaviour	Quantify relevance of AS applications, online and offline alternatives for domains of everyday life	Not primarily relevant
User awareness of AS	Determine interviewees' understanding of AS applications, use results for appropriate measure for awareness in survey	Quantitatively determine knowledge about / awareness of algorithms at population level	Not primarily relevant
User awareness of related risks	Expand existing list of risks; understand context to explain, interpret and contextualise survey data	Determine perceived importance of risks associated with AS applications	Not primarily relevant
User practices to cope with risks	Find practices that users apply to cope with AS / associated risks	Quantitatively determine relevance of strategies by constructing measure for coping practices	

This mixed-methods approach allows for a re-assessment of opportunities and risks of AS applications in the different life domains that form the basis for evidence-based public policy and governance of AS applications, aiming at the democratic control of algorithmic power. The guideline that we propose is to be understood as an exemplary research design that has to be adapted to specific research questions 8.

CONCLUSIONS

In this paper we propose a guideline to both a theoretical understanding and an empirical measuring of algorithmic governance (= governance *by* algorithms) in everyday life. We argue that the assessment of algorithmic governance—a form of institutional steering by software—requires a nuanced *theoretical* understanding that differentiates between (a) different units of analysis, (b) intentional and unintentional governance effects, (c) public and private, human and nonhuman governing actors, (d) degrees of automation and of the remaining role of human actors in decision-making, as well as (e) the kinds of decisions that are taken by algorithms, their different contexts of applications and scopes of risks. Further, such an assessment needs *empirical evidence* to measure the actual significance of associated, theoretically derived risks of the governance *by* internet services that apply automated algorithmic selections in everyday life.

Our review of algorithmic-governance literature illustrates the lack of empirical studies from a user-centred perspective going beyond single platforms or services. Such limited empirical analyses in combination with purely theoretical considerations may lead to the derivation of exaggerated risks and unrealistic policy-relevant conclusions. So far, there is not a sufficient empirical basis to justify the detrimental risks and adventurous policy suggestions that are occasionally associated with AS applications. Rather, recent attempts to empirically investigate these phenomena have tended to reduce the significance of risks like manipulation, bias, or discrimination.

We propose a mixed-method, user-centred approach to make the significance of algorithmic governance in everyday life measurable and to provide a basis for more realistic, empirically grounded governance choices. We identified five variables—usage of AS, subjective significance of these services, awareness of AS, awareness of associated risks, and user practices—as relevant dimensions of inquiry to measure the significance of algorithmic governance in everyday life from a user-centred perspective. The mixed-methods approach consists of qualitative interviews, a representative online-survey and representative user tracking to empirically grasp the significance of algorithmic governance in four domains of everyday life—social and political orientation, recreation, commercial transactions, and socialising. This representative sample of affected life domains is derived from a representative, country-wide survey on internet usage.

Altogether, in the emerging field of critical algorithm studies, where empirical results are limited, contradictory or lacking, the guideline presented here permits a nuanced theoretical understanding of algorithmic governance and a more holistic and accurate measurement of the impact of governance by algorithms in everyday life. This combination of theoretical and evidence-based insights can form a profound basis for policy choices in the governance of algorithms.

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FOOTNOTES

1. This notion is related to Rammert's (2008) concept of "distributed agency between humans, machines, and programs".

2. e.g., simple alphabetical sorting.

3. e.g., personalised recommender systems in e-commerce using reinforcement learning.

4. Consideration of individuals' entire media repertoires, comprising online and offline sources, is vital because, for instance, the effects of using AS services like Facebook for news purposes vary with the person's use of other news channels or other (offline) sources.

5. Awareness is not to be misunderstood as knowledge of specific algorithmic modes of operation here. Our model suggests that, for instance, without being aware that Google search results are personalised, individuals can not grasp the concept of filter bubbles. They are therefore unable to understand this risk and maybe adapt their behaviour accordingly.

6. Tracking data can also be subject to different biases (e.g., self-selection biases), which must be considered when applying these novel methods (see e.g., Jürgens, Stark, & Magin, 2019).

7. When tracking individuals' internet use, it is vital to be very mindful of potential effects on participants' privacy. Specific study designs have to be approved by the responsible ethics committee and defining measures to protect individuals' privacy are crucial.

8. This guideline – combining the proposed theoretical model and mixed-methods research design – has already been applied by the authors in Switzerland. Results from qualitative internet user interviews and a representative online-survey combined with internet use tracking on a mobile and desktop device for a representative sample of the Swiss population are forthcoming.

Article VIII

Same, Same, but Different! Qualitative Evidence on How Algorithmic Selection Applications Govern Different Life Domains

Noemi Festic

Abstract

The term algorithmic governance describes institutional steering effects of algorithmic-selection applications that increasingly pervade all domains of everyday life. Empirical evidence on algorithmic governance is lacking and mostly limited to information services. This article compares the significance of algorithmic governance – measured by use, subjective significance, awareness, risk awareness, and coping practices – for four pivotal life domains (information, recreation, commercial transactions, and socializing). Drawing on qualitative, semi-structured interviews with Internet users, this article reveals important nuances in how differently users engage with algorithmic-selection applications across life domains and functional types like search or recommendation. While awareness of algorithmic selection and related risks is comparatively higher for information services, the findings reveal a significant lack of knowledge for algorithmic selection in other life domains and for specific algorithmic modes of operation. This article provides input for an evidence-based development of suitable regulation of algorithmic-selection applications, taking everyday practices of their users into account.

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Same, same, but different! Qualitative evidence on how algorithmic selection applications govern different life domains

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Abstract

The term algorithmic governance describes institutional steering effects of algorithmic-selection applications that increasingly pervade all domains of everyday life. Empirical evidence on algorithmic governance is lacking and mostly limited to information services. This article compares the significance of algorithmic governance – measured by use, subjective significance, awareness, risk awareness, and coping practices – for four pivotal life domains (information, recreation, commercial transactions, and socializing). Drawing on qualitative, semi-structured interviews with Internet users, this article reveals important nuances in how differently users engage with algorithmic-selection applications across life domains and functional types like search or recommendation. While awareness of algorithmic selection and related risks is comparatively higher for information services, the findings reveal a significant lack of knowledge for algorithmic selection in other life domains and for specific algorithmic modes of operation. This article provides input for an evidence-based development of suitable regulation of algorithmic-selection applications, taking everyday practices of their users into account.

Keywords: algorithmic governance, algorithmic selection, everyday life, qualitative interviews, reality construction.

1. Introduction

Digital technologies have undoubtedly fundamentally transformed modern societies, with Internet applications gaining ever-increasing relevance for virtually anything. In particular, there is no denying that the algorithmic age has dawned: Online applications that build on algorithmic selection (AS) – the automated assignment of relevance to selected pieces of information (Just & Latzer 2017) – have pervaded all life domains and become deeply embedded in everyday practices like information seeking, shopping, or interacting with others.

Algorithms are constantly evolving and generally opaque in nature (Kitchin 2017). As a society, we therefore do not know how algorithms exercise their power over us (Diakopoulos 2015). This article conceptualizes these effect mechanisms of automated AS applications as a form of institutional governance by software (Just & Latzer 2017).

The public and academic debate on AS, associated risks, and appropriate regulation has mainly been dominated by theoretical considerations. Empirical research has been limited to studies on single platforms, types of AS or life domains. For instance, interviews with developers of recommender systems – a specific type of AS – revealed practices that aim at user retention. Seaver (2018), therefore, refers to recommender systems as traps. However, there is little knowledge about whether users actually get caught or whether they manage to avoid these traps.

Algorithms are a key feature of many applications people use on the Internet. In order to accurately assess what risks (e.g., biases, threats to privacy, distorted information; see Just & Latzer 2017) accompany them and whether and how they should be governed, we need to know how people deal with them and acquire a holistic picture of their significance for everyday life. In a similar vein, Bucher (2017, p. 33) argues for the inclusion of user-centered approaches in the field of critical algorithm studies: "If we want to understand the social power of

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algorithms, it is important to understand how users encounter and make sense of algorithms, and how these experiences, in turn, not only shape the expectations users have towards computational systems, but also help shape the algorithms themselves". Therefore, this article takes a bottom-up, user-centered approach, which allows to take algorithms' "socio-technical assemblages" (Kitchin 2017) into account.

One primary motivation for studying the social power of algorithms is the search for appropriate regulation of these services. So far, research has either taken too broad a perspective ("How should algorithms be governed?") – implying that algorithms are a homogenous category – or too narrowly focused on governance suggestions for single platforms, neglecting their social contexts. Much like nation-level, macro indicators such as cultural values have been shown to influence commitment toward governance of cybersecurity (Kharlamov & Pogrebna 2019), individual factors matter when it comes to the adoption of AS applications: An empirically informed development of appropriate governance measures requires investigating how Internet users incorporate and are affected by AS applications in their everyday lives in the long run. Such a perspective complements other empirical approaches (e.g., reverse engineering code, interviewing programmers).

This study seeks to answer how significant algorithmic governance is for different domains of everyday life (social and political orientation, recreation, commercial transactions, and socializing) and compares the significance of algorithmic governance in these domains along five variables: amount and frequency of use of AS applications, subjective significance assigned to AS applications, user awareness of AS, user awareness of related risks, and user practices to cope with these perceived risks (Latzer & Festic 2019). We draw on qualitative interviews conducted with Swiss Internet users in 2018.

This article first defines AS and explains the need for studying AS applications within their socio-technical contexts. Then, we present the relevant dimensions that measure how important AS applications have become in everyday life and elaborate on how they have pervaded different life domains. After presenting the methodological design and the findings of the qualitative interviews, we conclude by discussing the results and deriving policy implications.

2. Algorithmic selection in everyday life

When assessing the extent to which AS applications have pervaded Internet users' everyday lives, the appropriate unit of analysis requires clarification (Latzer & Festic 2019). Studies that focus on algorithms per se usually seek to reveal the hidden modes of operation that algorithms employ. The need to analyze algorithms within their social ecology (Beer 2017) is often ignored although accounting for user adoption of AS applications, their perceptions and behavior is a prerequisite for appropriately assessing potential risks of their usage and their (social) implications. Therefore, this study focuses on online applications that apply AS and views algorithms as generative processes embedded in complex ecosystems (Beer 2017; Willson 2017). As such, they are subject to societal and individual adoption processes and are essentially shaped by their use(r)s as well as intertwined with and co-dependent on other technologies. This is particularly important since studies on algorithms in isolation are not suitable to empirically inform the governance of these services. Rather, the adoption of these applications must be taken into consideration to the extent that appropriate governance measures must account for the contexts in which these applications are used.

Algorithms automatically assign relevance to selected pieces of information (Just & Latzer 2017). As Diakopoulos (2015) explained, they make "atomic decisions" like prioritization, classification, association, or filtering – embedded in widespread Internet platforms that have become relevant for all life domains. Thereby, AS applications are constantly shaping how people acquire information, consume cultural content, or purchase goods. A categorization of AS applications according to their central societal functions (e.g., search, filtering, recommendation, forecasting, scoring) illustrates how they have come to comprehensively pervade central domains of everyday life (Latzer *et al.* 2016; see Table 1) and thereby have become a constitutive part of individuals' (mediated) reality construction (Berger & Luckmann 1967; Couldry & Hepp 2016; Just & Latzer, 2017).

Following the tenets of neo-institutionalism, AS can be understood as a set of norms and rules that govern behavior by both enabling and limiting activities and room for action (Napoli 2014). Ultimately, AS applications affect how people behave in their daily lives (Just & Latzer 2017). This influence of automated AS on Internet users' everyday practices can be conceptualized as a form of institutional steering or governance by technology

Table 1 Functional typology of algorithmic selection applications (adapted from Latzer *et al.* 2016)

Types	Examples
Search	General search engines (e.g., Google search, Bing, Baidu)
	Special search engines (e.g., findmypast.com, Shutterstock, Social Mention)
	Meta search engines (e.g., Dogpile, Info.com)
	Semantic search engines (e.g., Yummly)
	Question and answer services (e.g., Ask.com)
Aggregation	News aggregators (e.g., Google News, nachrichten.de)
Observation/surveillance	Surveillance (e.g., Raytheon's RIOT)
	Employee monitoring (e.g., Spector, Spytec)
	General monitoring software (e.g., Webwatcher)
Prognosis/forecast	Predictive policing (e.g., PredPol)
	Predicting developments: success, diffusion etc. (e.g., Sickweather, scoreAhit)
Filtering	Spam filter (e.g., Norton)
	Child protection filter (e.g., Net Nanny)
Recommendation	Recommender systems (e.g., Spotify, Netflix)
Scoring	Reputation systems(e.g., eBay)
	News scoring (e.g., reddit)
	Credit scoring (e.g., Kreditech)
	Social scoring (e.g., PeerIndex, Kred)
Content production	Algorithmic journalism (e.g., Quill, Quakebot)
Allocation	Computational advertising (e.g., Google AdSense, Yahoo!)
	Algorithmic trading (e.g., Quantopian)

(Just & Latzer 2017). This notion of algorithmic governance is related to Yeung's (2018, p. 3) understanding of "algorithmic regulation" and Eyert *et al.*'s (2020) extension of the framework, but goes beyond it by including not only intentional but also unintentional effects (Just & Latzer 2017; Latzer & Festic 2019). On an aggregate, societal level, AS applications, thus, influence social order (Just & Latzer 2017).

Taking into account that algorithms are never neutral, but include biases and carry social meaning (Gillespie 2014), a list of social benefits and risks that are induced by these applications has been proposed. The risks are derived from cost–benefit calculations and normative considerations concerning the use of AS applications and include, among others, manipulation, diminishing variety, threats to privacy, loss of control, surveillance, fear of repercussions, and deception (Latzer *et al.* 2016). These risks are primarily induced by the ever-increasing personalization online – the constant monitoring of users' online activities and tailoring of contents based on these data – which is usually contingent on nontransparent categorizations and mechanisms that make it next to impossible for users to comprehend. Online applications that AS have also come under public scrutiny for committing privacy violations, which goes along with fears of surveillance. More often than not, AS acts as the enabling technology for such potentially harmful practices.

2.1. Introducing the dimensions of the significance of algorithmic governance for everyday life

For an empirically informed governance of these applications, an assessment of the significance of the institutional governance they exert is necessary. In accordance with the measurement model for algorithmic governance in everyday life (Latzer & Festic 2019), this article relies on five variables that empirically address how significantly AS applications (co-)govern life domains: First, it must be addressed whether AS applications are used and to what extent they have become an essential part of everyday practices in various life domains. Since the relevance of risks that are associated with AS is often derived from their mere existence, we investigate what subjective significance individuals assign to AS applications relative to online and offline alternatives and whether they have substituted them.

Another dimension of comparison is how aware users are of the algorithms that are embedded in the Internet services they use. Some knowledge of these modes of operation is necessary to obtain informed citizenship, be able to build an opinion on these services, and use them competently. Additionally, this article seeks to compare how severe the interviewees perceive (social) risks associated with AS applications to be in the different life domains and how aware they are of their existence. Empirically assessing Internet users'risk awareness complements top-down assessments of relevant risks.

Lastly, it is important to look at which practices users apply to cope with these risks they perceive. Following de Certeau and Rendall (1984), Internet platforms apply "panoptic practices": By observing, measuring, and controlling user data, they transform their users into measurable types (Latzer & Festic 2019), and profile users relying on user habitus, which is an indicator for their social disposition by classical Bourdieusian theory. These strategies that Internet companies or platforms apply – otherwise captured by the notion of "data grabbing infrastructures" (Fraser & Kitchin 2017) – co-govern users' reality constructions by reflecting their social dispositions in search results, personalized recommendations, or tailored advertisements (Just & Latzer 2017). Despite these power structures, users are able to exert agency and counteract the platforms' strategies with practices that aim at coping with the risks that arise through the data collection, analysis, and sharing strategies by platforms.

2.2. Demonstrating the significance of AS applications for different life domains

This article follows a practice-related approach to everyday life (Latzer & Festic 2019; Pink 2012). Four domains of everyday life that jointly cover the pivotal areas of everyday practice were identified. This specific classification was derived from a representative CATI survey of Internet use in Switzerland. Applying a confirmatory factor analysis, four distinct Internet use factors were found that combine the most widespread Internet activities (Büchi *et al.* 2016):

1. Social and political orientation: Not only have social networking sites like Facebook or Twitter gained importance as news sites (Newman *et al.* 2018), but news aggregators like Google News and other sorting and ranking mechanisms on websites increasingly overtake the gatekeeping function journalists previously fulfilled (Anderson 2013).
2. Recreation: For everyday recreation, we analytically distinguish between entertainment (i) and health and fitness (ii). For entertainment, recommendations on services like YouTube, Netflix, or Spotify have become increasingly important. AS applications have pervaded the health and fitness domain of everyday life particularly in two ways: AS-based calculation of performance or health indicators based on vital data has spread, and people use the Internet for gaining health information.
3. Commercial transactions: Besides significant restructurings of the financial system (Pasquale 2015), recent years have seen fundamental changes in individual purchasing and selling habits due to recommender systems and the presence of online shops. E-commerce services increasingly personalize their platforms through recommendations or the allocation of tailored advertisements, thereby affecting consumer decisions and behavior.
4. Socializing: AS is a key feature of social networking sites and interaction services that fundamentally shape everyday communicative actions. The emergence of dating apps like Tinder has transformed how people get to know each other.

Although this article analytically distinguishes these four life domains to compare the significance of algorithmic governance for them, they are heavily interrelated and cannot always be clearly separated. Also, AS applications often serve different purposes and combine different types of AS (Just & Latzer 2017), e.g., Facebook as a source for interaction and news.

2.3. Existing empirical research on the significance of algorithmic governance

Thus far, the (subjective) *significance* of AS applications for different life domains has mostly been taken for granted and remains empirically largely unaddressed. For social and political opinion formation, it has been shown that social networking sites like Facebook have overtaken traditional media as news sources (Newman *et al.* 2018). The notion of the "algorithmic skin" addresses how the use of self-tracking devices as a way to surveil vital aspects of one's life leads to bodies that are measured, transparent, and connected to other systems (Williamson 2015). Self-tracking devices have been regarded as tools for empowering the individual toward medical professionals (Lomborg & Frandsen 2016).

Empirically studying algorithmic *awareness* is complicated by the fact that neither users of AS applications nor researchers have the capacity to access the black-box and reliably reveal an algorithm's inner workings (Hamilton *et al.* 2014). Therefore, studies on user awareness of algorithms have been mostly limited to small samples and single platforms. For instance, Eslami *et al.*'s (2015) qualitative study showed that a majority of the participants were unaware of the existence of the Facebook news feed curation algorithm and reacted surprised and angry when it was brought to their attention (Eslami *et al.* 2015). Other studies – although also limited in scope – contradict these findings, indicating higher awareness of the functionality of news feeds (Rader & Gray 2015). Generally, there is no consensus on how aware individuals are of algorithmic functionalities of the services they use and we are lacking validated scales for measuring such algorithmic skills in population-wide surveys.

For *risk awareness*, it has been shown that Facebook does not seem to meet its users expectations when it comes to the curation of news feeds, which has real-life consequences for social contacts (Rader 2017). A domain-overarching risk is the unequal treatment of different parts of the population, exposing vulnerable groups to more risks associated with AS (Eubanks 2018). Dubois and Blank (2018) find for a nationally representative sample of adult Internet users in the UK that only a small part of the population is likely to have such non-diverse media diets that they get trapped in echo chambers. On Facebook, social cues and characteristics of the recommender and characteristics of the media source matter for reading intention, indicating that the information seeking behavior users have established in the offline world transcends and is applicable to Facebook (Kaiser *et al.* 2018). For self-tracking applications in the health and fitness domain, applying Communication Privacy Management theory has revealed that the benefits from using a fitness tracker outweigh the privacy-related cons. Low privacy concerns were found due to the low sensitivity of the health and fitness data that trackers had about participants (Zimmer *et al.* 2018). Potential access to this private information by cybercriminals and possible repercussions for privacy and security (Lupton 2016), negative, demotivating effects of disappointing or upsetting results (Dennison *et al.* 2013), or the uncertainty about the accuracy of tracked data and output results(Sullivan & Lachman 2017) have been mentioned in this context. Bucher (2012) argued that Facebook users are exposed to a constant "threat of invisibility" – a fear of disappearing among the many voices on social media. Social visibility constitutes a necessary prerequisite for meaningful inter-person reciprocity (Berger & Luckmann 1967) and human interactions. It is strongly affected by platform logics that depend on AS and utilize data on past interactions to make decisions on the visibility of posts and people. Close attention has also been paid to the selection of potential partners on dating platforms (Hitsch *et al.* 2010). Due to the dominance of such applications in daily social interactions, there have been concerns about a social distortion of reality. These remain theoretically derived risks that have not been empirically confirmed. Although risk awareness is among the better-studied concepts related to the use of AS applications, empirical evidence on how aware internet users are of risks that can be associated with using AS applications is still insufficient, especially since many studies do not specifically focus on the algorithmic aspects of these applications.

When it comes to *practices*, Bucher (2017) describes how people deliberately endeavor to mislead the Facebook algorithm to protect their privacy online by trying to behave in an unpredictable manner, liking contradictory content, or generally employing data obfuscation practices. The application of privacy protection practices has a longer research tradition and developed even before the risk was amplified by the emergence of algorithms. Van der Nagel (2018) presents two specific examples of user tactics that users engage in to regain control over their connections with peers, online services, content, or advertisers from algorithms. Existing studies on such practices are generally limited to one specific AS application and usually ignore nondigital practices.

Among all life domains under investigation, by far the most attention has been paid to social and political orientation – not least since the potential negative consequences are presumably the greatest. Thus far, there is – to the best of the author's knowledge – no study that compares aspects of the significance of algorithmic governance for different life domains. This article seeks to contribute to filling this research gap and answer the call for more empirical and comparative research on algorithmic governance "in its diversity" (Eyert *et al.* 2020).

3. Research design and method

Given the sparse body of empirical research on the significance of algorithmic governance for everyday life that goes beyond single platforms or life domains, qualitative methods are most suitable for developing an initial, in-depth understanding of these mechanisms. The qualitative interviews reported in this article were the first phase in a mixed-methods study. The subsequent quantitative part consisted of a representative online survey – designed based on the results of the qualitative interviews – in combination with a representative passive metering (tracking) of Internet usage at the population level. Additionally to providing the basis for the design of a quantitative survey, these qualitative interviews revealed important, domain-specific findings.

As much as algorithms are a function of the social, economic, and political circumstances in which they are programmed and employed (Geiger 2014), how they are used and shaped by their users is equally as relevant (Gillespie 2014). Therefore, this article takes a bottom-up perspective and relies on qualitative interviews with Internet users to contribute to a better understanding of the "what" of the governance of algorithms (Levi-Faur 2011; Eyert *et al.* 2020).

As mentioned, AS applications were our main unit of analysis. Therefore, the research team spoke to the interviewees about their use of services like Facebook, Google News, Tinder, FitBit, Amazon, etc. Given the explorative nature of this study, the interviews were open to any kind of online behavior that was relevant to the interviewees' everyday lives and included basic, rather passive (e.g., information seeking through search engines) as well as more active (e.g., creating online content) ways of using the Internet. Since the goal of this study was to unpack how Internet users engage with these services in their everyday lives, the interviewers did generally not mention the word "algorithm" in the interviews at all. If the interviewees themselves mentioned the term in connection with the AS applications, the research team was advised to follow up. Toward the end of the interview, we revealed to the participants that AS was the common denominator of the discussed services and asked them whether they had heard of the term and knew its meaning.

3.1. Recruitment and sample

Since the primary aim of the study was to talk to a variety of Swiss Internet users, we spread a leaflet with basic information on the study, contact details, and a link to an online survey as widely as possible. The recruitment questionnaire included questions on amount of Internet use, Internet skills, and Internet use for different purposes as well as questions on gender, age, and education. We made a conscious decision in order to reach maximum variation within the sample regarding age, gender, education, and amount of Internet use and contacted a subsample of individuals that had completed the recruitment survey. We provided further information about our project, stating that we were conducting research on media use in everyday life. We consciously did not mention that AS applications were our core concern to avoid biasing or priming the respondents before their interviews. Of 75 people contacted, 58 consented to participating in an interview. The sample characteristics for both the entire sample and the subsamples for each life domain are provided in Table 2.

3.2. Data collection

Prior to the interviews, we informed the participants about the study's funding, provided a statement of informed consent, and informed the participants of their rights to withdraw their answers. We conducted the interviews between May and July 2018. The average duration was one hour. A team of three researchers conducted the interviews. We closely collaborated during the recruitment phase, the development of the interview guides and the actual interview process to ensure maximum inter-interviewer reliability.

The methodological design pursued two main goals: Each interview specifically focused on one life domain to gather in-depth domain-specific findings (i). However, we also asked all interviewees how the aspects they addressed compared to other domains of their lives to reveal differences and similarities between life domains when it comes to the significance of algorithmic governance (ii).We conducted all interviews face-to-face in the same room, relying on a similarly structured interview guide. The interview guides for each life domain contained identical questions on all five dimensions of comparison as well as a few specific questions for each life domain. For investigating the subjective significance assigned to AS applications, we applied a sorting technique (Hasebrink & Hepp 2017): the interviewees were asked to name and rank online AS, online non-AS, and offline functional equivalents according to their relevance for different life domains.

The interviews were conducted in German, which is the mother tongue of all interviewees and interviewers. The accounts presented in the results section were translated into English as literally as possible.

Table 2 Interview sample characteristics

	Total sample		Life domains			
			Information	Recreation	Commercial Transactions	Socializing
	Number (N = 58)	Percentage of sample	Number (N = 15)	Number (N = 14)	Number (N = 14)	Number (N = 15)
Sex						
Female	31	53	7	9	7	8
Male	27	47	8	5	7	7
Age group						
18–25	11	19	2	4	3	2
26–35	16	28	6	1	5	4
36–45	10	17	2	3	2	3
46–55	7	12	3	0	0	4
56+	14	25	2	6	4	2
Education level						
Low	13	22	4	3	4	2
Medium	22	38	5	5	5	7
High	23	40	6	6	5	6

Note: The education categories correspond to the following highest degrees: Low education: primary or secondary school; medium education: vocational training; high education: college degree.

3.3. Data analysis

Each interview was audiotaped and transcribed, and the text files were shared among the team of three researchers to enable iterative coding. Our five variables that measure the significance of AS applications for everyday life – usage, awareness of AS, awareness of related risks, subjectively assigned significance, and user coping practices – served as the primary guidance for the coding procedure. Since the interviews aimed at revealing hitherto unknown aspects, particularly with regard to the comparison between the life domains, and due to the explorative nature of the study, we applied a thematic coding approach (Gibbs 2008). Based on the tradition of social phenomenology, we added codes both inductively from the data and deductively from previous theoretical considerations (Fereday & Muir-Cochrane 2006). Each team member primarily coded the interviews they had conducted for one life domain. During the coding procedure, the research team met regularly to re-evaluate and extend the codebook. Using the qualitative data analysis software MAXQDA, excerpts from the interviews were assigned to the codes. Although there were codes that were specific to certain life domains, the research team aimed at keeping the codebook applicable for all life domains to enable comparisons.

4. Empirical findings from user interviews

This section summarizes how the significance of algorithmic governance compared between the four life domains along the five dimensions of comparison. For confidentiality reasons, pseudonyms are used in lieu of the interviewees' actual names.

4.1. Usage of AS applications

Unsurprisingly, the interviewees reported using AS applications in all life domains. The main finding with regard to the usage of AS applications that holds for each life domain was that the amount and frequency of use of AS applications does not necessarily correspond to the subjective significance assigned to them: The interviewees did not tend to ascribe the highest subjective significance to the services they reported to be using most extensively.

Conceptualizing the usage of AS applications within the space and time of everyday life was fruitful for understanding the context-dependent implications of different types of uses. However, it proved difficult to separate the different AS types. The interviewees were more inclined to speak about their experiences with specific platforms rather than functional AS types.

4.2. Subjective significance assigned to AS applications

The respondents assigned relevance to AS applications in all four life domains. Table 3 provides an overview of selected online AS, online non-AS, and offline alternatives mentioned in the interviews. Although the categorization is not always clear, it is noteworthy that examples for online, non-AS applications were very rare for all life domains.

For the formation of their social and political opinion, the participants mentioned using an array of AS applications (mainly search, recommendation, or aggregation). For searches, they mentioned a low number of alternatives to Google. The significance of search engines was amplified by the finding that many users utilize them as a substitute for their browser's URL bar to access websites. Recommender systems were also ascribed a high relevance for information purposes, especially when the interviewees had a particular interest in a niche topic or were bored. The significance of recommender systems on websites of media outlets seemed low. The very few interviewees who reported using news aggregators assigned high subjective significance to them.

Without knowing the focus of the interviews, each interviewee mentioned at least one AS service in their list of relevant entertainment sources. In the sample, the relevance of AS services appeared to be higher for younger respondents who particularly reported that Netflix, Spotify, and YouTube have completely substituted traditional, offline alternatives.

In the health and fitness domain, two main activities were mentioned where AS services play a role: First, the respondents reported continuously tracking a variety of data (step count, sleep, weight, calorie intake, etc.) on themselves with the help of wearable devices or applications that rely on AS. Second, the Internet – AS services

Table 3 Algorithmic selection (AS) applications, online non-AS and offline alternatives in life domains

Life domains	Online AS alternatives	Online non-AS alternatives	Offline alternatives
Social and political orientation	Search engines (e.g., Google), news aggregators (e.g., Google News), video platforms (e.g., YouTube), online encyclopedias (e.g., Wikipedia), social media, news websites, online TV	Newsletters	Print media, traditional TV, offline conversations, text messages, official material
Entertainment (recreation)	Search engines, video platforms, streaming services (e.g., Netflix), music streaming services (e.g., Spotify), social media, online TV	Online games	Print media, traditional TV, offline conversations, text messages, CDs/DVDs, cultural events
Health and fitness (recreation)	Search engines, social media, fitness SNS (e.g., Strava), online encyclopedias, video platforms, online shops, wearable trackers		Offline conversations, text messages, health professionals, own intuition, competitions/races, offline measurements (e.g., scale)
Commercial transactions	Search engines, video platforms, social media product reviews (e.g., blogs), price comparison sites, online shops, online TV, online advertisements		Product reviews in traditional media, traditional TV, offline conversations, in-store browsing
Socializing	Social media, dating platforms (e.g., Tinder), online communities	Video/voice online calls, voice messages	Offline conversations, text messages, letters, cultural events

Note: This table contains a selection of the alternatives mentioned in the interviews to provide illustrations for the findings. The examples for the different services are only mentioned the first time the service occurs in the table. Whether an online service applies AS is not always clear and depends on the specific usage situation.

in particular – were an important source of health and fitness information due to the availability of topical information, although trustworthiness of information was an issue of concern.

The interviews on commercial transactions suggest that the relevance of and attitudes toward AS are related to their perceived usefulness and expected gratifications. The respondents generally ascribed online shops that apply different types of AS a high significance, although they still viewed offline sources like recommendations from friends as more influential for their buying decisions.

The significance of AS for socializing seemed low. The most relevant criterion for the use of online platforms was their social relevance. Several interviewees reported their discontent with Facebook's news feed, complaining about too many irrelevant posts. For getting to know new people, AS applications were not perceived to be very important, whereas social media were an important way to keep in touch with people.

Across all domains, the significance of AS applications was qualified by the high subjective relevance that the interviewees assigned to offline functional equivalents: Every single interview participant across all domains mentioned an offline alternative as most important. For instance, although YouTube and Netflix recommendations were mainly perceived as good, the respondents agreed that recommendations from friends or family are more valuable since they know about their tastes, have similar backgrounds, and are more likely to recommend content that will appeal to them. The same was found for information seeking, although personalized recommendations and advertisements based on AS essentially seek to mimic real-life recommendations by gathering extensive amounts of data on users, getting to know them as well as possible and tailoring online contents to their interests. Equally, the most important way to communicate for all interviewees was face-to-face interactions and the respondents perceived offline shopping as most influential on their buying decisions. Also, one's own wellbeing and intuition was unequivocally ascribed the highest relevance for health information by all respondents, relativizing the significance of tracking devices and online health information. For instance, Finn (m, 40) expressed the opinion that with very few exceptions, tracking devices cannot measure anything common sense could not and warned against using the tracking results without thinking: "My tracker might tell me to go on a run someday because I have not moved enough that day. However, the tracker might not know that it is hot outside or that I was physically active earlier that day without wearing my tracking device. Under these circumstances, it would make no sense to go on a run, although my tracker tells me to. Only my intuition and common sense can tell me that."

Regarding subjective significance, a particularity of the health and fitness domain was health professionals serving as ultima ratio for individuals' health decisions. The respondents reported turning to trustworthy professionals despite using self-tracking devices and searching for health information online, mainly because their health was perceived to be an important and sensible topic. For seeking other types of information, there is no such instance that people turn to in order to verify, cross-check, and contextualize the information they find online.

Another argument that emphasized the importance of using AS applications as units of analysis was the same AS types being perceived very differently across life domains. While recommendations on Spotify orNetflix were perceived as useful and significant for everyday entertainment, the same systems in online shops were mostly associated with vile commercial intentions, regarded as an instrument of persuasion, and perceived as irrelevant for everyday purchasing decisions. However, potential price reductions through such recommendations were mentioned as beneficial and made the attitude more positive. For YouTube – where the information and entertainment domains of everyday life evidently become blurred – the same favorable opinions toward personalized recommendations were found. Roger's (m, 30) account illustrates this finding: "With Netflix, for example, I really love that I receive recommendations based on my past behavior and consumption. The mix that Spotify curates based on the music I listen to is also really good. But when, let's say, Amazon constantly tells me 'you need that too!', that actually rather annoys me. I often feel like they just want to sell more and more."

Personalized advertisements – which rely on allocation – were perceived as irrelevant for all life domains by the interviewees, mainly because they received advertisements for products they had already bought. Such personalized advertisements were perceived as annoying or even obtrusive and manipulative.

Another domain-overarching finding was that the respondents tended to report heavy usage of AS applications and assigned significance to them, but often used the applications in a way that – consciously or unconsciously – largely avoided their algorithmic functionality. This was especially true for recommendation services.

For instance, the respondents repeatedly reported ignoring recommended content on Netflix, using the search bar to access specific series that they knew they wanted to watch instead. The relevance of AS services often stemmed from practical characteristics like Spotify's genre-specific playlists or the large amount of content available on Netflix for a comparatively cheap price.

4.3. User awareness of AS

The interviews revealed that the participants – except for few highly educated, technology-affine individuals – had very little knowledge of AS and its underlying modes of operation. This was reflected by the finding that the respondents appeared to not know the correct terms to describe their experiences with AS. The awareness of the automated nature of AS was particularly low: The respondents tended to refer to AS applications as "they, them", indicating that they perceived the applications as human-like actors. For instance, Clara (f, 56) believed to have confused whoever is analyzing her online profile because she has looked for a variety of health information on a number of different illnesses. She believes that "the people at Google" think she is a medical student based on her past search behavior.

While specific knowledge was generally low and the respondents were only able to offer vague explanations for the phenomena they experience, all respondents had some idea of what AS was and narrated various folk theories. For instance, one respondent compared allocation algorithms in personalized advertisements to bonus programs of a grocery store where data are collected to tailor offers to him. The interviewees showed general understanding that search results are dynamic, can vary between different people and are influenced by their own and other people's online activities. This was particularly brought to the respondents' attention when using a different computer and being confronted with unusual search results. When asked about how the ranking of search results is generated, Beata's (f, 57) account illustrates the most widespread idea: "If you want to be at the front, you [companies] have to pay more I think. I have heard of that." The (profit-maximizing) interests of Google or YouTube themselves were rarely mentioned and the respondents did not seem to be very aware of them. Moreover, the interviewees were largely unaware of potential political motives for the application of AS.

Besides the news media, their main source of such information were the consequences of AS they perceived during their everyday Internet use. The incident fostering participants' awareness of AS most was the occurrence of personalized advertisements for a product on one site they had searched for on another platform. However, the respondents seemed far less aware of more subtle forms of AS like less obviously personalized content.

The awareness of AS differed across functional types of AS: For all life domains, the respondents had mostly heard of AS in the context of the Google search and reported having thought about how recommendations or allocation (e.g., personalized advertisements) applications work. Regarding recommendations, the respondents held the belief that they were recommended content that was similar to content they had already consumed. However, the participants were unaware that variables like their demographic characteristics or their location can be input data for such algorithms.

Even for one AS type, the awareness varied across different platforms. For instance, the respondents seemed to be much more aware of recommendations on Netflix than on YouTube.

Rather than understanding how AS works, the respondents tended to report being aware of not knowing much about these processes. Reto (m, 64), for instance, reported being uncertain whether AS works separately for each device (e.g., through cookies) or whether the mechanism works device-overarchingly, which he would find worrying.

Hugo (m, 64) reported that he does not trust Google and he thinks that data are collected about him, which he is unaware of. He thinks that he would be astonished if he received a list of data he has already disclosed to Google. He believes that almost all his clicks are recorded when he uses Google and that there is a massive data set lying around somewhere because they would be unable to personalize advertisements otherwise. This uneasy feeling and a sense of knowing to not know anything but living with it regardless was a reoccurring theme and often lead to a diffuse fear and skepticism toward these services. Mirjam (f, 18) reported a creepy feeling in this context: "I don't really know. Sometimes, my friends and I feel like it is magic. You look for something on an application and you receive an advertisement for that exact thing somewhere else. That makes me think 'oh my

God, they know everything, help me' […] I think that these services are somehow connected. It is all Google somehow anyway."

Despite being aware of their own low knowledge of AS, the interviewees generally felt resistant to these applications and their effects, denying that they influenced their behavior.

Comparing life domains, the awareness of AS was clearly the highest for applications that serve information purposes; search and recommendation applications in particular. This indicates that users are aware that the media contents they consume are selected by nonhuman actors to some extent. The specific workings and types of evaluative criteria remained largely unclear. The users appeared to be more aware of recommender systems within the Facebook ecosystem than when it came to suggested articles on online media sites. The awareness that AS is applied in tracking devices they use for health purposes was very low. Except for one interviewee who is very active in the "quantified self" movement, none of the respondents mentioned AS in the context of health applications. For searching health information online, however, the awareness that AS plays a role was higher. Particularly in this domain, the respondents repeatedly voiced the idea that their Google searches were analyzed either by Google or the government to find out how certain illnesses are spreading.

For commercial transactions, personalized online advertising rendered cross-platform data collection intelligible for the users and was the main generator of algorithmic awareness, too. For socializing, some interviewees reported that they sometimes wonder why they receive certain posts or ads. These experiences stimulate reflections on how the news feed is curated and translate into different degrees of awareness.

4.4. User awareness of associated risks

The participants generally tended to talk about risks in relation to the Internet in general and were not able to distinguish between general Internet-related risks and risks that are specific to AS applications. Nevertheless, most risks that the participants mentioned were illustrated with examples from AS applications and can only occur when AS is applied. However, the participants did not seem to be aware of that.

The most frequently mentioned risk was threats to privacy. Privacy concerns were particularly pronounced when breaches could result in financial losses. A consistent finding across life domains was that respondents only started protecting their privacy online after they had suffered from a negative experience. Additionally, media reports on privacy breaches made respondents more aware of these risks.

While threats to privacy were mentioned in all interviews, there were differences: Content (mostly pictures) that the respondents had uploaded to the Internet was perceived as worthy of protection. Related were fears of personal or professional repercussions, being cyberbullied, publicly denounced, or having one's identity stolen. Meta-data, login information, email addresses, and demographic data were not perceived to be at danger. When using services like Netflix or Spotify, privacy concerns were much lower because of the perception that the companies do not have any relevant information on users. When we asked Linda (f, 18) about her privacy concerns regarding entertainment services, she said: "When I created my Instagram account, I thought about that more. With Netflix and YouTube, actually not at all. That has never crossed my mind. I have heard that when you post a picture on Instagram, it will always remain online for anyone to see. That is why I do not post content that I do not want certain people to see." While she has taken measures to protect her privacy on Instagram (e.g., private profile) and wants to keep control over who sees her content, it would not bother her if someone knew what she watches on Netflix. Mirjam (f, 18) agreed that data on her search or viewing history is not relevant enough to be at danger. These accounts revealed that the interviewees a) are unaware of the (meta-)data they are sharing with services like Netflix, b) do not think about potential privacy infringements beyond services that are often mentioned in this context and c) do not realize that data are shared across platforms but rather think of their privacy platform-specifically. Accordingly, the worst possible outcome they could perceive was that data on videos they had watched would be exposed.

Similarly, the results on health and fitness revealed that privacy concerns were moderate. There was one case – again when financial consequences could occur – where privacy concerns were exceptionally pronounced: When they were asked about their willingness to share vital data with their health insurer, every respondent expressed concerns about rising healthcare costs. Similarly, to the entertainment domain, participants reported doing a cost–benefit calculus when it comes to disclosing their tracking data. Andre (m, 25) reported a particular account where sharing his home address enabled him to take part in a competition on a particular segment.

The following account also illustrates how people seem to distinguish between commercial and political uses of their data: Tina (f, 43) mentioned that data collection for advertising or bonus program purposes is okay, but use for political reasons worries her. The interviewees perceived their privacy threatened by illegal misuses of their data, but not so much by regular strategies of online platforms.

Although diminishing variety through personalized content has been theoretically identified as a potential risk, it was rarely mentioned in the interviews. Content or supplier diversity did not appear to be a highly rated value for entertainment consumption.

Diminishing variety was not perceived as a worrisome risk in the domain of commercial transactions, but rather as influential on the subjective benefit of a service. The participants mentioned being annoyed when receiving recommendations for a product they had already bought. Dominic (m, 41) tries to avoid promoted search results and describes a shift from content-driven to advertisement-driven indexing. He suggests that the latter prioritizes results with regard to ad revenues and is a constraint to his freedom of information.

Diminishing variety was a bigger concern for social and political orientation, but varied within the sample. Sabine (f, 48) was worried about certain pieces of information only reaching certain societal groups, denying everyone else an informed opinion formation. Other users connected the loss of diversity with platform business models: They realized that a longer duration of media exposure leads to higher advertisement revenues for particular platforms.

Another risk mentioned was manipulation. In the commercial transactions domain, manipulation concerned the consumer and their behavior. Personalized recommendations and advertisements were associated with commercial intentions. The interviewees reported feeling at risk to be seduced to unnecessarily spend money. The risk

Table 4 User practices to deal with risks associated with algorithmic selection applications

Type of practice	Examples
Physical/cognitive	Conscious/mindful use
	Ignoring advertisements
	Proxy use
	Ignoring recommendations
	Using offline information to verify online information/measurements
	Reducing amount of Internet use
	Disclosing as little information as necessary
General digital	Deleting cookies/browser history
	Browsing in incognito/private mode
	Using ad-blockers
	Using privacy-friendly software
	Using different email accounts
	Manual filtering
	Not saving passwords
	Setting bookmarks
	Visiting websites one knows and trusts
Platform-specific digital	Providing false information about oneself
	Using fake profiles
	Adjusting search terms
	Adjusting privacy settings
	Conscious use of (hash)tags
	Using news feed settings
	Unsubscribing from channels/services
	Avoiding scrolling; navigating directly to profiles

[Correction added on 31 July 2020, after first online publication: In Table 4, the layout of text in the 'Examples' column has been corrected.]

of manipulation was only mentioned once in the entertainment-focused interviews: One respondent suspected that Spotify has contracts with well-known musicians and prioritizes their music in their recommendations, actively shaping their users' music consumption. Manipulation or deception was not perceived as risks associated with using AS applications for information, health, or socializing purposes.

The interviewees reported losing control over their data and a feeling of constant surveillance for the Internet in general. There were no notable differences between life domains.

The interviews led to an expansion of the existing list of risks: The respondents mentioned feeling at risk of overusing the Internet and linked this sentiment directly to tailored content. This overabundance of personalized information could lead to a sense of information overload. This risk was particularly voiced in the entertainment domain: The respondents viewed autoplay settings and personalized recommendations on Netflix or YouTube as responsible for their perceived overconsumption of content. Although this risk was most pronounced for entertainment services, the interviewees also mentioned it in connection with search engines: "Although the search engine gives me a list of results that they think is relevant for me, I still have to check myself whether it is trustworthy. That makes it more difficult to find information online" (Ella, f, 27). The overabundance of information was also mentioned in connection with self-tracking devices and online shopping, but not with socializing services.

An overarching theme for the risks mentioned was a self-empowering narrative where the respondents perceived other people to be more at risk than themselves. The users were confident that their own behavior cannot be influenced byAS.

4.5. User practices to cope with perceived risks

The respondents mentioned an array of practices that they apply more or less frequently to counteract companies' strategies. However, the practices were generally not targeted at specific risks. Table 4 provides an overview of the three types of practices that were mentioned in the interviews: First, there were physical or cognitive practices that do not require any digital actions. Second, we found general digital practices that were mostly executed at the level of a browser. Third, the interviewees mentioned applying platform-specific digital practices that have to be specifically executed for each platform.

The interviewees reported applying most practices when it comes to information consumption and did so most frequently in this life domain. They were inclined to apply practices where they felt that a lot was at stake, especially in light of diffuse fears of privacy violations.

The following account exemplarily indicates that a context-independent interpretation of the application of such practices can be misleading: Linda (f, 18) reported often giving videos on YouTube a thumbs-up. Rather than doing that to express her opinion or feed the algorithm, she used this practice to be able to find the videos again easily. This needs to be taken into consideration when deriving risks from the mere existence of these applications or even empirical data on their high frequency of usage and subjectively assigned relevance.

5. Discussion

This article comparatively investigated the significance of algorithmic governance for four domains of everyday life, drawing on data from qualitative, semistructured interviews with Swiss Internet users.

5.1. Summary of the main results

Although the interviewees *used* and assigned *significance* to AS applications in all life domains, they unanimously perceived offline contacts or their own intuition as more relevant.

For *awareness*, we found that particularly experiences with "algorithmic moods" (Bucher 2017) are in a circular interdependency with awareness of AS and increase it. Due to the strong public discourse on the social relevance of algorithms, the respondents tended to evoke the impression of knowing something about it. Since news coverage is the strongest for AS in the domain of social and political orientation, the awareness of AS in such services was much higher than for entertainment, health, socializing, or commercial applications. The knowledge on specific modes of operation was very vague, often even factually wrong, and mostly based on folk theories. The interviewees' own perceptions of not knowing much about AS further indicated a generally low awareness and feeling of resignation.

Regarding *risks*, the interviewees in the sample were most aware and concerned about having their privacy online threatened. Our methodological approach provides indications for the relevance of risks that are associated with AS. For instance, while the diminishing variety of content online has been theoretically derived as a potential risk, our results reveal that the interviewees used a set of different sources in their media repertoires, reported to be aware of this risk and to apply practices to counteract it. However, it might be more important to also make users aware that this risk is not – as often portrayed in the media – solely relevant for social and political orientation, but also every other life domain where AS is applied (e.g., entertainment platforms, dating sites).

We further identified a set of user *practices* that the respondents reported applying to cope with the risks they perceive, which were also most pronounced for the information domain.

5.2. Interpretation of the main results

The findings complement research on and potentially qualify the relevance of theoretically derived risks of AS applications from a user perspective.

Within critical algorithm studies, much research has been conducted regarding social implications of specific algorithms or AS applications. However, when we proclaim an algorithmic age where algorithms change our perceptions of the world and social order at large, this does not stem from single algorithms but from a system of various applications that people use for diverse everyday activities. These applications have in common that an algorithmic logic is embedded within them, which is potentially subject to biases and bears risks. Applying a practice-related approach to everyday life allowed comparing the significance of algorithmic governance between life domains.

Our results further emphasize the importance of distinguishing between different platforms, their purposes and contexts of uses and the need to take into consideration what users do with and to algorithms. Rather than studying these platforms in isolation, we need to integrate research across disciplines to achieve an encompassing picture of the significance of algorithmic governance and derive conclusions for the governance of algorithms (Danaher *et al.* 2017).

The functional typology of AS from the standpoint of their societal functions has not proven helpful for categorizing services from a user-perspective. In accordance with the finding on generally low awareness of specific algorithmic modes of operation, the respondents seem to rather perceive AS applications as similar that they use in one life domain. The differences in perception of one type of AS in different domains point to the difficulties of a governance approach based on a functional typology of AS, partially due to the strong context-dependence.

5.3. Limitations

There are a few limitations to consider for this article. We measured the significance of AS for everyday life through individuals' self-reports, which is an adequate methodological design for investigating how users deal with AS applications and how they perceive them. Research on the perception of media effects has long shown the existence of a third-person effect (Davison 1983): People tend to report that media effects are stronger for others, especially for antisocial messages (Eveland & McLeod 1999). Applied to AS services, Tsay-Vogel (2016) has shown that Facebook users tend to report that Facebook use has stronger effects on other people than on themselves and pointed to differences regarding age and gender. Since the interviews were a face-to-face situation, social desirability effects cannot be ruled out. For instance, it might be the case that the respondents were inclined to not admit that AS services were more relevant to them than e.g., friends or family in certain life domains.

In addition, qualitative data do not allow for the inference of the results beyond the sample of this study. Therefore, to assess the significance of algorithmic governance, there is a need for quantitative, population-wide empirical assessments. However, qualitative studies like the one at hand are a vital first step for developing such instruments in a field where encompassing empirical results are lacking.

5.4. Policy implications

While our empirical findings provide important conclusions for the governance of algorithms by explaining how AS applications govern Internet users' everyday lives, they are not sufficient for deriving specific governance measures. Rather, they complement results from other studies, provide important input for other methods (surveys, experiments), and improve existing conclusions for the process of developing governance measures.

To begin with, the results of this article reveal that when developing governance measures from theoretically derived risks, some questions must be addressed: Are these services relevant for people's everyday lives? How do they use these services? Are they exposed to potentially associated risks? Do they apply counteracting practices?

The low awareness of AS combined with perceptions of individual, personal data being irrelevant prompts the need for educational measures. In general, the results of the interviews revealed that the participants tended to be most aware of AS applications in the information services they use. They also perceived risks in connection to services that were relevant to their opinion formation most severely and tended to apply most practices there. For the other life domains – apart from big players like Google and Facebook that are also heavily covered in the news media – we found a lot less awareness, risk awareness, and practices. For instance, awareness of algorithmic modes of operation and associated risks on Netflix and YouTube was very low. While especially Google and Facebook are already in the public eye for their use of algorithms, services like Netflix or YouTube might merit closer inspection, too. In general, the public understanding of algorithms seems to be largely shaped by the prominent media discourse on filter bubbles, micro targeting etc. More subtle – but ever so relevant – implications of AS applications seem to be far less widespread. This raises questions regarding the responsibility of news media coverage for a beneficial use of AS applications.

This article not only sought to compare algorithmic governance for different life domains, but also types of AS applications. One key takeaway is that users' (risk) awareness and assigned significance of AS applications varies across services relevant for different life domains. While, for instance, recommendations might be beneficial for Internet users' daily entertainment, they may bear more risks when employed in the context of an information service. This needs to be considered when developing governance solutions.

As mentioned, the perceived significance of AS applications for different life domains was low. The question on how strongly people rely on algorithms has been addressed in other research traditions. Initially, people were believed to be skeptical of algorithmic decisions, not overtly relying on them (Promberger & Baron 2006). More recently, under the notion of "algorithm appreciation", experiments have shown that people tend to adhere to advice more strongly when it comes from algorithms than other people (Logg *et al.* 2019). While the self-perceptions reported in this article cannot resolve these contradictions, they can be interpreted in two ways in light of this literature: The low subjective significance of AS could either reflect Internet users' resilience against these potentially harmful effects or it could be an expression of a social desirability effect and the users could actually underestimate the effects of AS on their lives. A definite conclusion is not possible based on the data in this study and future research should address this.

The field of critical algorithm studies needs more systematic studies regarding the feasibility, suitability, and performance of potential alternative modes of governance additionally to state interventions (Latzer *et al.* 2019). When assessing the appropriate level of state intervention for the governance of algorithms, Internet users should not be underestimated as they do show some (however strongly varying) levels of risk awareness and protective behavior. Their adoption of services must be taken into account. For instance, it is an unrealistic assumption that users blindly trust recommendations or even always look at them at all. At the same time, the results on low awareness and low use of protective practices reveal that exclusively making individual Internet users responsible for their own use of AS applications is not promising. Self-help measures must be accompanied by other forms of regulation to ensure a use of AS applications that is beneficial to individuals and society. The finding that a lot of individuals feel resigned and helpless when dealing with AS applications further emphasizes the need and desire for better governance measures.

In general, the lines between Internet governance and the governance of algorithms become increasingly blurred. Since AS has become so ubiquitous online, postulating a need for an encompassing regulation of algorithms from a techno-centric view seems too narrow-minded and would entail practically any online service. This amplifies the need for the development of specific regulatory measures that are empirically grounded. Further, the social context of an AS application's adoption needs to be taken into consideration when developing governance measures. This conclusion is supported by the diverse findings presented in this article.

5.5. Concluding remarks

To conclude, algorithms have undoubtedly gained relevance for all aspects of everyday life. As such, they fulfill different purposes, embedded in a plethora of online applications. The way users engage with them highly varies across life domains. The endeavor to develop governance mechanisms for all them together in a "one-size-fits-all" manner – largely neglecting how and in what contexts users actually deal with them – oversimplifies and trivializes these differences.

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Article IX

The Relevance Internet Users Assign to Algorithmic-Selection Applications in Everyday Life

Michael Reiss, Noemi Festic, Michael Latzer & Tanja Rüedy

Abstract
The rapidly growing academic and public attention to algorithmic-selection applications such as search engines and social media is indicative of their alleged great social relevance and impact on daily life in digital societies. To substantiate these claims, this paper investigates the hitherto little explored subjective relevance that Internet users assign to algorithmic-selection applications in everyday life. A representative online survey of Internet users comparatively reveals the relevance that users ascribe to algorithmic-selection applications and to their online and offline alternatives in five selected life domains: political and social orientation, entertainment, commercial transactions, socializing and health. The results show that people assign a relatively low relevance to algorithmic-selection applications compared to offline alternatives across the five life domains. The findings vary greatly by age and education. Altogether, such outcomes complement and qualify assessments of the social impact of algorithms that are primarily and often solely based on usage data and theoretical considerations.

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The relevance internet users assign to algorithmic-selection applications in everyday life

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Abstract
The rapidly growing academic and public attention to algorithmic-selection applications such as search engines and social media is indicative of their alleged great social relevance and impact on daily life in digital societies. To substantiate these claims, this paper investigates the hitherto little explored subjective relevance that Internet users assign to algorithmic-selection applications in everyday life. A representative online survey of Internet users comparatively reveals the relevance that users ascribe to algorithmic-selection applications and to their online and offline alternatives in five selected life domains: political and social orientation, entertainment, commercial transactions, socializing and health. The results show that people assign a relatively low relevance to algorithmic-selection applications compared to offline alternatives across the five life domains. The findings vary greatly by age and education. Altogether, such outcomes complement and qualify assessments of the social impact of algorithms that are primarily and often solely based on usage data and theoretical considerations.

Keywords
algorithmic governance, algorithmic selection, algorithms, subjective relevance, everyday life, survey data, social media

1 Introduction

Algorithmic selection is the automated assignment of relevance to certain selected pieces of information (Latzer, Hollnbuchner, Just, & Saurwein, 2016). On social media, for instance, algorithmic selection is responsible to filter users' news feeds, to allocate advertisements, and to recommend specific content to users. The great attention toward algorithmic selection in public and academic debates reflects widespread assumptions that it has an extensive influence on daily life in digital societies (Beer, 2017; Gillespie, 2014; Latzer & Just, 2020; Willson, 2017).

Such appraisals of the relevance of algorithmic selection, combined with assumptions on the associated risks including political and economic manipulation, discrimination, data breaches, and a biased perception of the world (Latzer et al., 2016), form the rationale for the need and kind of governance of algorithmic selection. Appropriate governance choice, however, calls for an accurate and up-to-date understanding of the social relevance of algorithmic selection in order to, among other things, assess the scope and magnitude of potential risks associated with it. This paper aims to contribute to the systematic assessment of the social relevance of algorithmic selection in order to provide for a profound basis for governance measures. For this purpose, it suggests including the Internet users' assigned relevance of algorithmic-selection applications in such assessments.

Investigations about algorithmic selection all share the commonality that algorithms are a complex concept and difficult to grasp in empirical social science research (Kitchin, 2017). In practice, algorithmic selection is embedded in and applied by a wide and fast-growing range of online applications such as social media, search engines, news websites, or online shops. These applications are the place

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where users experience and are potentially influenced by algorithmic selection. Hence, the social relevance of algorithmic selection mainly unfolds via such applications and along the lines of users' usual but manifold and deliberate daily online practices (Bucher, 2017; Willson, 2017).

Previous studies have predominantly deduced the relevance of algorithmic selection and algorithmic-selection applications either from purely theoretical reasoning or from non-generalizable empirical investigations (Abril, 2016; Baek & Kim, 2016; Beer, 2017; Park, 2019, Yang & Men, 2020). These empirical accounts approximate the social relevance of algorithmic selection from a user perspective by measuring the amount and frequency of the use of algorithmic-selection applications and the effects of or attitudes toward them.

In order to question and substantiate these existing assessments and to gain a more holistic understanding of the relevance of algorithmic selection for Internet users' everyday life, this paper argues for an additional empirical indicator: the relevance that people *subjectively assign* to algorithmic-selection applications.

This approach takes into account that algorithmic selection is experienced by users often unknowingly in everyday situations: Although search engines fundamentally build on algorithmic selection, users may not be aware of it, for example. However, the social relevance of algorithmic selection, its benefits, and risks are provided with or without users' awareness. Asking users about concrete applications (e.g., Google Search) and not about the software technology that lies behind them is therefore imperative when aiming to assess the relevance of technologies like algorithmic selection in daily life that users might not even be aware of. The measurement of users' assigned relevance of algorithmic-selection applications is hence a valuable, but hitherto missing piece in current efforts to assess the actual relevance of algorithmic selection in digital societies.

This paper uses the term algorithmic selection and not algorithm in order to highlight that the focus is on the socio-technical context algorithms are embedded in, and not merely on algorithms as technical artefacts (Latzer & Festic, 2019). Consequently, this article chooses algorithmic-selection applications as its unit of analysis, as the tangible and accessible manifestation of algorithmic selection. Measuring the subjective relevance makes it possible to weight and better interpret existing findings on the overall social relevance of algorithmic selection that are solely based on the amount and frequency of use (Latzer & Festic, 2019).

Drawing on a combination of qualitative interviews and a nation-wide, representative online survey of Swiss Internet users, this study examines five domains of everyday life: *political and social orientation*, *entertainment*, *commercial transactions*, *socializing*, and *health*. Furthermore, in order to establish a benchmark for the assessment of algorithmic-selection applications, the relevance of alternatives, i.e., non-algorithmic online and offline daily services and activities, such as reading news, watching television, and talking to friends, is investigated as well.

The main contributions of this article to the literature on the social relevance of algorithmic selection are its subjective user perspective, the comprehensive, empirical assessment of the assigned relevance of algorithmic-selection applications relative to online and offline alternatives, and comparisons between different life domains and socio-demographic groups. These representative results complement the current debate, promote more nuanced assessments, and may form the basis for empirically better-informed policy-making regarding the governance of algorithmic selection and algorithmic-selection applications. Such up-to-date, empirical results are especially essential in the light of ongoing discussions about regulatory interventions regarding social media, for example in the context of manipulation and biased political information (Bayer et al., 2019; European Commission, 2018).

The paper continues by providing a literature review on existing research regarding the social relevance of algorithmic selection in five life domains. Subsequently, an overview of current measurements on the social relevance of algorithmic selection discusses suitable methodological approaches. Finally, the guiding research questions are derived, and the empirical research design is presented. The final sections summarize the results, discuss implications, and draw conclusions.

2 The relevance of algorithmic selection – existing evidence for five life domains

According to recent research, algorithmic selection is increasingly prevalent in peoples' everyday lives. As a result, algorithmic selection increasingly governs what Internet users see and, consequently, how people perceive the world (Just & Latzer, 2017). The distinction between the following five life domains observed in this paper: political and social orientation, entertainment, commercial transactions, socializing, and health helps to investigate ramifications of algorithmic selection in a more nuanced way:

The life domain *social and political orientation* has so far received the most attention from research on the social relevance of algorithmic selection. The widest academic focus lies on the usage time of online services for political topics (Baek & Kim, 2016; Gil de Zúñiga, Ardèvol-Abreu, & Casero-Ripollés, 2021; Karakaya & Glazier, 2019; Lee, Lee, So, Leung, & Chan, 2017; Park, 2019; Vraga & Tully, 2021; Westerwick, Johnson, & Knobloch-Westerwick, 2017; Yang & Men, 2020). The results indicate increased social media use for information seeking (Newman, Fletcher, Schulz, Andı, & Nielsen, 2020; Shearer, 2018) and the consideration of online services as alternative daily news sources (Althaus & Tewksbury, 2000; Bialik & Matsa, 2017; Schmidt, Merten, Hasebrink, Petrich, & Rolfs, 2019). Facebook's news feed algorithm's logic can also directly influence news production and lead to increasingly similar content across different media outlets (Caplan & Boyd, 2018).

Mainly through the emergence of online applications like Spotify, YouTube, or Netflix, which automatically recommend content to individual users, algorithmic selection has also become key for everyday *entertainment*. However, more traditional recommendations have repeatedly been shown to influence everyday music consumption more heavily (Hamilton, 2019), although there are different usage types for which applications based on algorithmic selection are not equally relevant (Lepa & Hoklas, 2015).

Algorithmic selection increasingly accompanies people's daily *commercial transactions*, including recommender systems and the allocation of personalized advertisements. While the advertising industry heavily relies on algorithmic allocation of user-specific content (eMarketer, 2020), various findings from a user perspective show that users mainly perceive algorithmically allocated advertisements as useless, inaccurate, or even offensive (De Keyzer, Dens, & De Pelsmacker, 2015; Kim & Huh, 2017; Smit, Van Noort, & Voorveld, 2014). This rather negative attitude likely reflects concerns caused by the collection of user data (Phelan, Lampe, & Resnick, 2016). Furthermore, with regard to product recommendations, scientific findings show that even though algorithmic recommender systems may be considered helpful (Chen, 2012), they lead to less conversion than recommendations from real people, such as other Internet users (Lin, 2014).

With regard to *socializing*, algorithmic selection increasingly governs the interaction between Internet users (Bucher, 2012, 2017; Celik & Dokuz, 2018). For instance, by rating and scoring user profiles, algorithmic selection is responsible deciding who is considered a potential friend on social network sites or a match on dating services. In terms of dating services, recent studies show that these services are especially of interest for people belonging to societal minorities, such as the LGBT community (Sumter & Vandenbosch, 2019; Wang, 2020). On the one hand, these applications likely facilitate the social interaction not only within but also across various societal groups. On the other hand, scholars have raised concerns that an increased governance of rating and scoring algorithms likely fuels existing discrimination and strengthens biases (Courtois & Timmermans, 2018; Wang, 2020). However, to better assess who is most likely to be exposed to these risks, more research that takes account of different societal groups is needed.

People have increasingly been seeking *health* information online for a long time (Rains, 2007). More recently, self-tracking devices that gather vital data can be empowering for patients when dealing with medical professionals (Lomborg & Frandsen, 2016). They are positively related to the overall health status and can be a superior alternative to traditional paper-and-pencil tracking (Abril, 2016). Their adoption depends on various characteristics of the devices (Adapa, Nah, Hall, Siau, & Smith, 2018) as well as user and context variables (Canhoto & Arp, 2017). Using self-tracking devices to monitor vital aspects about oneself can result in measurable, transparent, and connected bodies. This consequence has been called "algorithmic skin" (Williamson, 2015).

As this literature review shows, comprehensive research with respect to algorithmic selection is lacking, especially when aiming to compare the relevance of algorithmic-selection applications to alternatives, such as print media or human interactions apart from the digital sphere. Furthermore, to better assess risk exposure, there are no comparative findings on the social relevance of algorithmic selection that take different societal groups into account. Beyond this, as the following chapter shows, there is a methodological research gap regarding the relevance that people subjectively assign to algorithmic-selection applications.

3 Approaches to measuring the social relevance of algorithmic selection: An overview

The assessment of the social relevance of algorithmic selection and risks arising from its applications as well as related initiatives to regulate such services have predominantly been based on purely theoretical reasoning and their mere existence (Pariser, 2011; Seaver, 2019). However, there is an increasing number of empirical approaches illuminating this topic using different methodological designs to expand the understanding about algorithmic selection and its societal relevance (Kitchin, 2017), each with their own advantages and disadvantages. Subsequently, an overview of the methodological approaches to measuring the social relevance of algorithmic selection is given. From this review, we derive the need for including measures on the subjective significance assigned to algorithmic-selection applications and proceed to contribute to filling this gap.

Existing empirical research on the social relevance of algorithmic selection can be divided into two broad perspectives: a bottom-up user, or a top-down supplier perspective. Of the two, the former is by far the more popular and frequent approach. The user perspective is mainly acquired by collecting self-reported data in order to approximate individuals' Internet behavior (de Vreese & Neijens, 2016), predominantly relying on surveys of the amount and frequency of usage of online services. Repertoire studies also fall into this category and they increasingly take online sources including social media into consideration, enabling a partial assessment of the social relevance of algorithmic-selection applications. To avoid potentially biased self-reported data, a rather novel strand of research – which, like the previously mentioned approaches, also utilizes the amount and frequency of usage of algorithmic-selection applications as a proxy for their relevance – gathers respective data by *tracking online behavior* (Kilger & Romer, 2013; Mattlin & Gagen, 2013). Studies based on tracking data are still quite rare and often limited to social media behavior (Deng et al., 2019; Junco, 2013).

Self-reported data and tracking data are also combined and compared in order to investigate usage time as a proxy for the social relevance of algorithmic-selection applications (Thorson, Cotter, Medeiros, & Pak, 2021). Results reveal that self-reported data are often inaccurate because people are likely to overestimate the time they spend online (Araujo, Wonneberger, Neijens, & de Vreese, 2017; Deng et al., 2019; Guess, Munger, Nagler, & Tucker, 2019; Junco, 2013; Scharkow, 2016). This suggests that even though self-reported usage time is widely employed, it does not permit precise but rather distorted assessments of the relevance of algorithmic-selection applications. But tracking data can also be subject to specific biases, e.g., self-selection (Jürgens, Stark, & Magin, 2019). Another limitation is its methodological restriction to the online sphere, hence being insufficient to appraise the social relevance of algorithmic-selection applications compared to offline alternatives.

A limited number of qualitative studies consider a broader range of settings where people rely on algorithmic selection in daily situations (Bucher, 2017; Festic, 2020) and allow a more in-depth understanding of their social relevance. Qualitative studies also rely on self-reporting from a user perspective. In contrast to quantitative survey data, they provide a more in-depth understanding, for example, of the embeddedness of algorithmic-selection applications in Internet users' daily practices but lack generalizability across services and life domains.

In addition to studies on the usage of algorithmic-selection applications, *attitudes* toward them are examined to derive their social relevance from users' reliance on them, mainly measured through the credibility ascribed to algorithmically produced content. These studies can produce contradictory findings. On the one hand, research indicates that people may be rather skeptical toward applications that build on algorithmic selection (Logg, Minson, & Moore, 2019; Promberger & Baron, 2006), and on the other hand, Internet users are more likely to adhere to advice proposed by algorithms as opposed to human sources (Logg et al., 2019).

The social relevance of algorithmic selection is also assessed by directly investigating the effects that the use of algorithmic-selection applications has on individuals' attitudes and behaviors, instead of indirectly inferring them from theoretical reasoning or mere usage data. Effect studies usually apply experimental settings.

Lastly, there are endeavors to measure the social relevance of algorithmic selection taking the *top-down, supplier-side perspective* by simulating algorithms (Möller, Trilling, Helberger, & van Es, 2018), reverse-engineering algorithmic program code (Diakopoulos, 2015), or interviewing programmers (Rosenberg, 2008) in order to understand exactly how algorithms seek to and may actually influence Internet users' everyday lives. Table 1 provides an overview of the existing methodological approaches presented in this chapter.

Table 1: Existing methodological approaches to measuring the social relevance of algorithmic selection

Who?	What?	How?	
User perspective (bottom- up)	Usage (amount/ frequency/ repertoires)	Quantitative	Surveys
			Tracking
		Qualitative	Interviews
	Effects	Experiments	
		Multivariate analysis of survey data	
	Attitudes	Surveys	
Supplier perspective (top-down)	Code	Reverse engineering	
	Output	Simulations	
	Input	Interviews programmers	

We argue that one crucial missing piece in this field of research is to ask the users how relevant they regard algorithmic-selection applications to be for their lives. There have been limited endeavors to fill this gap for single issues such as gathering information on the 2016 US presidential campaign (Gottfried, Barthel, Shearer, & Mitchell, 2016), but comprehensive empirical assessments are lacking.

The methodological approach used in this article fills this gap: We take a user perspective and aim at empirically approximating the social relevance of algorithmic selection by measuring the subjective relevance Internet users assign to algorithmic-selection applications. This approach will be introduced in greater detail subsequently.

4 Introducing assigned relevance as a measurement of the social relevance of algorithmic selection

To measure the social relevance of algorithmic selection, empirical approaches have already addressed a few important questions but also come with limitations, as outlined above. We propose exploring subjectively assigned relevance as a complementary measurement in quantitative surveys in order to provide more comprehensive, nuanced empirical assessments of the social relevance of algorithmic selection in people's daily lives.

Algorithmic selection is associated with a variety of social risks to which Internet users are often understood to be highly vulnerable and helplessly exposed. Such a view widely neglects Internet users' agency by underestimating their capacity to manage their Internet use and its consequences. It has been shown, for example, that people are well aware and make sense of the algorithms they encounter online (Bucher, 2017), apply various practices to deal with them (van der Nagel, 2018), and thereby significantly shape algorithms in turn. Hence, it seems vital to investigate individuals' perceptions of the relevance of algorithmic selection.

Previous studies have shown that perceptions of relevance and preferences are likely to differ from usage time and should therefore be considered an additional element in assessing the social relevance of algorithmic selection (Festic, 2020; Swart, Peters, & Broersma, 2017). For example, people may use social media very extensively but still rate information from a printed newspaper as more relevant and more influential for their social and political orientation, even though they spend much less time on it. The primary purposes for which people use social media are not necessarily information seeking but rather being entertained, passing time, or maintaining social relations (Quan-Haase & Young, 2010; Whiting & Williams, 2013). Consequently, empirical data on the relevance subjectively assigned to algorithmic-selection applications considering users' perceptions and preferences is required in order to interpret and weight data on the usage of these services. By functioning as an additional, weighting dimension, the subjective relevance complements existing findings, allows for a more differentiated interpretation of them, and contributes to a more nuanced assessment of the social relevance of algorithmic-selection applications. When people are asked to assess the relevance of a service or activity it is intentionally left to them to intuitively decide how they conceptualize relevance in the given context; for example, why they assess online games as very relevant for their daily entertainment. Although people might have varying concepts of relevance or reasons for their evaluation, this openness assures that the relevance is assessed exactly as each individual finds it most appropriate. This leads to the intended unbiased *subjective* relevance assessment. The reasons behind a certain subjective relevance assessment can be manifold but are not the focus of this study.

Another argument for the measurement of subjectively assigned relevance is that people's perceptions of the relevance of algorithmic-selection applications are likely to influence how concerned they are about potential risks. Regardless of whether these concerns are justified or not, they are likely to affect users' protective behavior (e.g., deleting cookies), which in turn affects their exposure to risks of algorithmic-selection applications (e.g., biases by search engines or manipulations by targeted ads).

To conclude, investigating what people regard as relevant contributes another component to the empirical assessment and understanding of the social relevance of algorithmic selection.

Following the tenets of media repertoire research (Hasebrink & Domeyer, 2012), the social relevance of algorithmic selection can only be accurately assessed when taking individuals' media repertoires into account as comprehensively as possible. For example, to measure the relevance of algorithmic-selection applications for people's everyday entertainment, it is imperative (1) to assess all the services and activities that individuals use for entertainment purposes in their everyday life and (2) to compare the relevance of algorithmic-selection applications with the relevance of their alternatives. Scholars agree that Internet users' news repertoire should be considered cross-media, since in a digitized environment recipients can choose between a growing number of media outlets (Dimmick, Chen, & Li, 2004; Picone, Courtois, & Paulussen, 2015; Schmidt et al., 2019; Swart et al., 2017). Accordingly, the following research question is at the core of this article (RQ1): What subjective relevance do Internet users assign to algorithmic-selection applications relative to online and offline alternatives?

A large amount of research theoretically discusses the social relevance of algorithmic selection in the context of everyday life (Bucher, 2017; Willson, 2017). Because of the great public interest in effects of algorithmic selection on news consumption, there has been a strong focus on this life domain. But algorithmic-selection applications are also important to several other domains of everyday life. More comparative research is needed to assess their social relevance across these domains because any governance of algorithmic selection ideally requires considering the manifold contexts in which algorithmic-selection applications operate and hence the varying social relevance thereof. This leads to the second research question (RQ2): How does the subjective relevance assigned to algorithmic-selection applications differ across five selected life domains (political and social orientation, entertainment, commercial transactions, socializing, and health)?

Lastly, it is likely that the subjective relevance of algorithmic-selection applications is not equally distributed within a society. Previous findings show, for example, that younger Internet users rely on certain algorithmic-selection applications more heavily than older Internet users, including social media (Shearer & Matsa, 2018; Gottfried et al., 2016; Shearer, 2018), online dating (Smith, 2016; Sumter & Vandenbosch, 2019), and mobile fitness tracking (Abril, 2016). However, so far, there are no findings to evaluate whether social groups with higher levels of usage time also assign higher levels of relevance to those algorithmic-selection applications. Hence, to better grasp whether certain social groups are more exposed to risks associated with algorithmic selection, information on subjective relevance is needed as an additional dimension to better interpret existing findings on frequency and amount of use. This is why the third research question addresses these differences (RQ3): How are socio-demographic variables (gender, age, education, income, and region) and personal characteristics (political interest, Internet use) associated with the subjective relevance that individuals assign to algorithmic-selection applications?

In order to answer these research questions, this article relies on a combination of qualitative interviews and quantitative survey data.

5 Measuring subjectively assigned relevance

This study consists of a mix of a qualitative (1) and a quantitative (2) phase, which are both described in-depth below.

5.1 Data collection

(1) Between June and August 2018, qualitative interviews were conducted with Swiss Internet users on the relevance of algorithmic-selection applications, the awareness of risks associated with algorithmic selection, and related questions (Festic, 2020). The interviewees were recruited through leaflets that were spread as widely as possible (train stations, fitness centers, youth clubs, retirement homes, restaurants, etc.) and received a gift card as a remuneration for their participation. The face-to-face interviews were conducted in German by a team of three researchers and lasted one hour on average. To ensure

a congruent planning, data collection, and interpretation, all team members collaborated closely during all phases of the interviewing process.

(2) The quantitative survey data were collected between November 2018 and January 2019. Participants were recruited from an existing Internet panel by an independent market research company and received a small pecuniary incentive for their participation. The samples for the online survey and the qualitative interviews did not overlap. All participants in the quantitative survey gave informed consent about their participation and the research design was approved by the university's ethics review board. The survey lasted 30 minutes on average and covered topics such as attitudes towards algorithmic selection, risk assessments, awareness of algorithmic selection, and the subjective relevance assigned to algorithmic-selection applications and online and offline alternatives.

As stated above, both the interviews and the survey relied on five life domains. The classification of life domains was adopted from Büchi, Just, & Latzer's (2016) analysis of the most widespread Internet activities in Switzerland.

5.2 Sample characteristics

Both the qualitative and the quantitative empirical parts of the study relied on a sample of Swiss Internet users. In Switzerland, 92 % of the population used the Internet in 2019. Hence, Switzerland continually ranks among the highest-diffusion countries worldwide, similar to other Western countries (Latzer, Büchi, & Festic, 2020).

(1) The sample for the qualitative interviews consisted of 58 Swiss Internet users and was composed applying a conscious choice and with the goal of reaching maximum variation within the sample regarding age, gender, education, and amount of Internet use (Festic, 2020).

(2) The sample for the quantitative survey comprised 1202 participants and is representative of the Swiss online population over the age of 16 with respect to age, gender, language region, household size, and employment status. Table 2 describes the sample characteristics in detail.

5.3 Measures

(1) In the qualitative interviews, we asked the interviewees to name algorithmic-selection applications, online non-algorithmic selection, and offline services and activities that are relevant for the life domains under investigation. Applying a sorting technique (Hasebrink & Hepp, 2017), the interviewees named and ranked the activities and services they mentioned. For example, being on social media (algorithmic-selection application), calling on Skype (non-algorithmic selection online service), or meeting friends (offline activity) are among the relevant services and activities for the life domain of socializing. Interviewees sometimes had varying conceptualizations of how they define relevance but all could easily solve the task and give reasons for their choices.

Table 2: Sample characteristics

	Mean (SD)	Percentage (N)
Age	43.5 (15.91)	
Female		49 % (590)
Secondary education		66 % (797)
Higher education		25 % (301)
Income (CHF per month, median category)	6001–8000	
Political interest (5-point likert scale, 5 = high interest)	3.33 (1.35)	
Internet use (hours per day)	3.52 (2.82)	
German-speaking		72 % (865)
French-speaking		24 % (288)
Italian-speaking		4 % (49)

(2) The aggregated list was used as a basis for the development of the questionnaire for the subsequent quantitative online survey. The survey participants were asked to assess the relevance of the list of given services and activities for five life domains on a 5-point Likert scale with 1 = "not at all relevant" and 5 = "very relevant". For each of the five life domains, participants had to assess ten to fourteen services and activities, comprising algorithmic-selection applications, as well as non-algorithmic selection online and offline services and activities. In order not to restrict the subjectivity of participants, the survey questions on the relevance assessment were intentionally left open and non-leading to reflect and allow for varying concepts of relevance participants might have. Non-users of "social media" and "YouTube etc." did not have to state their relevance for the respective service and were hence assigned the lowest relevance score "not at all relevant".

It is important to note that for both the qualitative interviews and the quantitative survey, the participants were asked to rate the relevance they assigned to a list of different services and activities for different life domains. They were not given any information about whether the services and activities under investigation were based on algorithmic selection or not. Rather, the team of researchers classified the services and activities according to Latzer et al.'s (2016) definition of algorithmic selection. This approach appears appropriate given the black-box nature of algorithms and the oftentimes low awareness of algorithmic selection among Internet users. Furthermore, where possible, participants were not asked for specific services or activities but for the broader category of similar services or activities (e.g., "music streaming services such as Spotify, Soundcloud, iTunes").

5.4 Analysis

(1) The qualitative interviews were audiotaped and transcribed verbatim. Using the qualitative data analysis software MAXQDA, we composed a list of mentioned services and activities for all life domains which served as an input for the development of the questionnaire. This approach appeared fruitful since the subjectively assigned relevance to algorithmic-selection applications has not been empirically addressed hitherto and sufficient literature for the development of the survey questions and items was lacking.

(2) The dependent variable of interest in the quantitative data is the relevance participants assigned to various services and activities. To answer the first and second research question, the distribution of the ascription of relevance and means for all services and activities grouped by life domains are presented. This provides a comprehensive overview of the relevance assigned to algorithmic-selection applications and to their online and offline alternatives. Moreover, similarities, differences, and general patterns regarding the assignment of relevance to algorithmic-selection applications in five life domains are identified. The third research question is approached by exploring the influence of socio-demographic characteristics on the individual assignment of relevance. Standardized linear regression models for selected activities and services show its association with age, gender, education, income, political interest, Internet use, and language region.

6 Results

Figures 1 and 2 present the distribution of the subjectively assigned relevance (lower x-axis) to respective activities and services in five life domains as well as the mean relevance attribution (vertical bars, higher x-axis) by life domain. The activities and services are sorted in descending order regarding the mean relevance assignment. Algorithmic-selection applications are in bold while online alternatives are in italics.

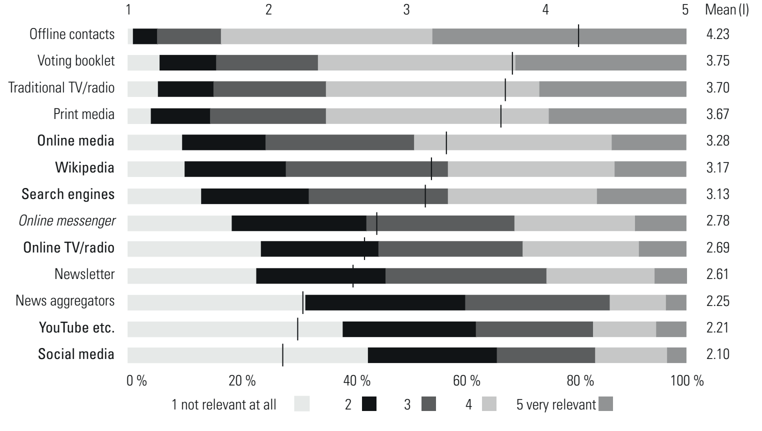
Results for the *political and social orientation* life domain can be interpreted as follows. Participants assigned the relevance that 13 activities and services had for their individual orientation on political and societal issues. "Offline contacts" such as talking to family and friends were not only most frequently assigned the highest relevance score (45%) but also had the highest mean relevance. With the "voting booklet" (a printed information brochure that is mailed to every Swiss household prior to each vote), "traditional TV/radio", and "print media" ranking second to fourth, offline alternatives were assigned the highest relevance. "Social media", an algorithmic-selection application, was ascribed the lowest relevance of all activities, both when looking at the frequency of the highest relevance score (3%) and measured by the mean (2.10). Ranking fifth (3.28), "online news media" was attributed the highest relevance of all algorithmic-selection applications for *political and social orientation*, closely followed by "Wikipedia" and "search engines".

The results for the other four life domains are presented in figure 2 in analogue form. In the *commercial transactions* life domain, "online reviews" and "online shops" were amongst the most relevant services and activities. They seem to have substituted traditional alternatives substantially and were more relevant than other algorithmic-selection applications such as "personalized ads". In the *health* domain, algorithmic-selection applications ("health websites", "Wikipedia", "search engines") were reported as relevant, though still less relevant than "offline contacts" or "blood pressure etc.". The results further suggest that people rather rely on non-algorithmic activities to keep in touch and to meet new people (*socializing*).

Uniformly across all domains, offline alternatives ranked comparatively high whereas algorithmic-selection applications, in particular "social media", were assigned a low relevance. This was especially the case in the *entertainment* and *socializing* domains.

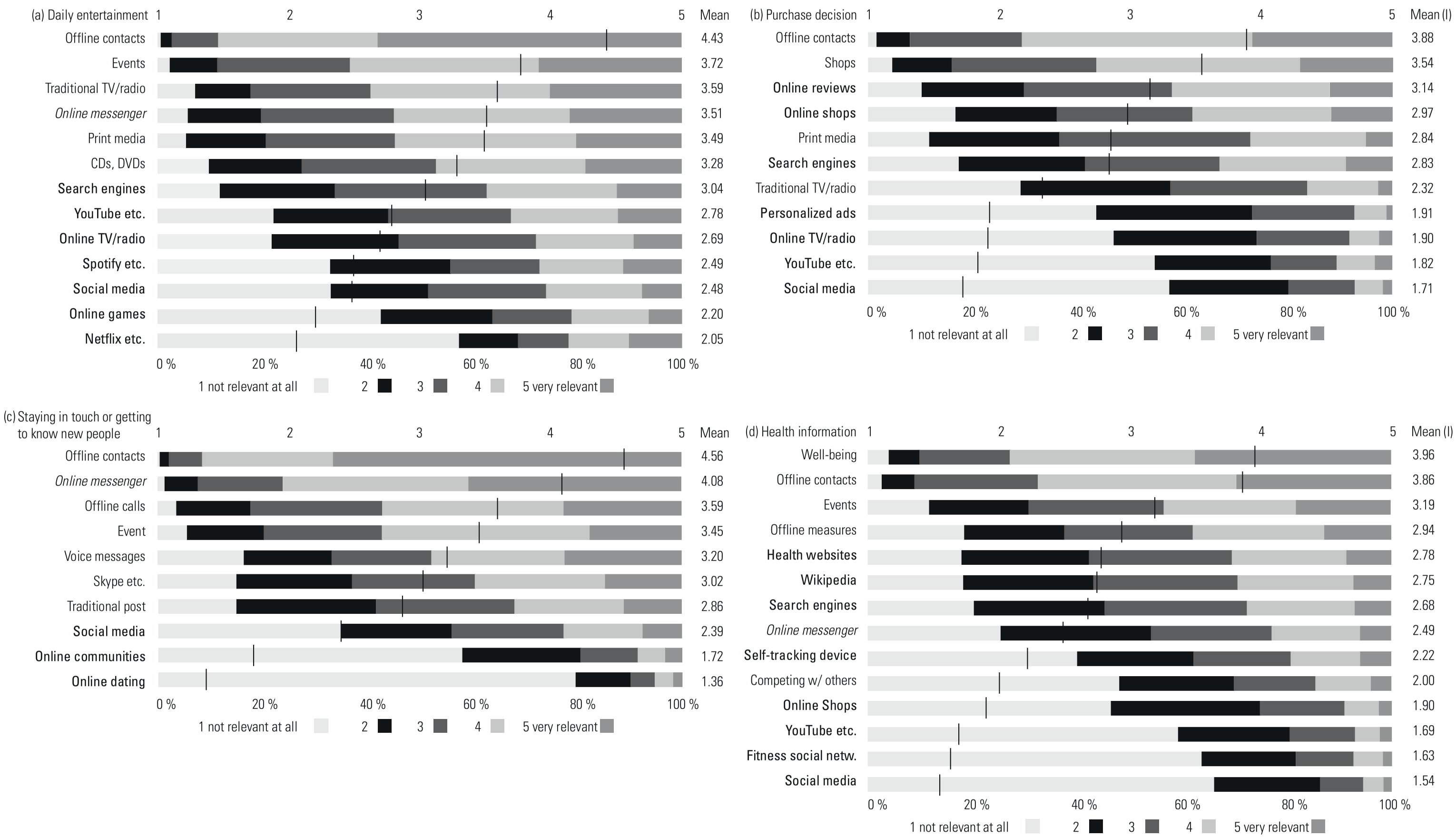
Table 3 on the page after next summarizes the results of five standardized linear regression models on the relevance of "social media" for the five life domains, controlling for the participants' socio-demographics. Coherently across all five life domains, increasing age was associated with a lower assignment of relevance for "social media". Except for the socializing domain, the same applied for having higher education, whereas increased Internet use was associated with higher assignments of relevance to "social media" for all life domains. For all domains, the effects of education were the greatest, followed by age. No uniform pattern was found for gender, income, political interest, and different regions.

Figure 1: Subjectively assigned relevance for political and social orientation



Note: The question was formulated as follows: *Please assess the relevance of the following services and activities for your orientation on political and societal issues.* N = 1,202. Algorithmic-selection applications are in bold, other online services in italics.

Figure 2: Subjectively assigned relevance for entertainment (a), commercial transactions (b), socializing (c), and health (d)



Note: The questions were formulated as follows: *Please assess the relevance of the following services and activities (a) for your daily entertainment, (b) for your purchase decisions, (c) for staying in touch or getting to know new people, (d) for health information.* N = 1,202. Algorithmic-selection applications are in bold, other online services in italics.

Table 3: Assigned relevance to social media in five life domains

	Pol./soc. orientation		Entertainment		Commercial trans.		Socializing		Health	
Age	–.216	(.034)***	–.294	(.033)***	–.234	(.034)***	–.254	(.033)***	–.124	(.035)***
Female	.038	(.032)	.071	(.031)*	.030	(.034)	.052	(.032)	.013	(.034)
Sec. education	–.272	(.153)	–.262	(.148)	–.492	(.186)**	–.188	(.148)	–.388	(.189)*
High. education	–.508	(.159)**	–.435	(.155)**	–.614	(.194)**	–.291	(.156)	–.497	(.194)*
Income	–.042	(.032)	–.013	(.032)	–.021	(.034)	.002	(.032)	–.074	(.034)*
Political interest	–.065	(.035)	–.056	(.034)	–.106	(.036)**	–.044	(.034)	–.057	(.036)
Internet use	.104	(.034)**	.113	(.03)***	.104	(.034)**	.115	(.033)***	.098	(.040)*
French-speaking	.134	(.076)	.122	(.074)	.033	(.080)	.221	(.075)**	.166	(.080*)
Italian-speaking	–.049	(.151)	–.055	(.129)	–.100	(.113)	–.134	(.124)	.023	(.162)
R^2	.122		.163		.140		.129		.075	
Adj. R^2	.114		.156		.133		.121		.067	
Num. obs.	1043		1044		1045		1044		1041	
RMSE	.926		.910		.933		.924		.969	

***p<.001, **p<.01, *p<.05; standard errors in parenthesis. Absolute effect sizes of significant coefficients are highlighted for >.15 (light grey), >.3 (grey) and >.45 (dark grey).

Table 4 presents standardized linear regression models on the association of the assignment of relevance regarding selected services and activities with sociodemographic variables. These models represent typical patterns and noteworthy cases. An overview of all activities and services can be found in the online supplement to this study.

Altogether, a few patterns emerged across the five life domains for their associations with different socio-demographic variables. Age was positively associated with the relevance assigned to “print media”, and, with only a few exceptions, age and the relevance assigned to algorithmic-selection applications were negatively associated.

Across all life domains, being female was associated with a greater relevance assigned to offline activities and a lower one to algorithmic-selection applications. However, there were noteworthy exceptions with contrary relationships: “social media” for entertainment (see table 3), “traditional TV/radio” for commercial transactions, and “health websites” and “competing with others” in the life domain health.

Higher education was negatively associated with some algorithmic-selection applications such as “social media” and “YouTube etc.” for the life domains political and social orientation, entertainment, commercial transactions, and health. Overall and for most services and activities, education had the greatest effect.

In contrast, a greater amount of Internet use was never negatively associated with the relevance assigned to any algorithmic-selection application. Often, there was a positive effect of a greater amount of Internet use on the assignment of the relevance of algorithmic-selection applications. The level of Internet use had no significant effect on most offline activities and services.

7 Discussion

This paper argues for the inclusion of the perspective of subjectively assigned relevance in order to adequately assess the relevance of algorithmic selection in Internet users’ daily lives. Qualitative interviews and a representative survey were conducted in Switzerland to assess the relevance that people assign to various algorithmic-selection applications and to their online and offline alternatives in five life domains. The findings substantiate current claims regarding the social implications of algorithmic-selection applications and can contribute to an empirically better-informed basis for policy-making regarding the governance of algorithmic selection. Evaluating the usage time of a specific algorithmic-selection application

Table 4: Assigned relevance for selected services and activities in five life domains

	Political and social orientation						Entertainment					
	Search engines		Print media		Voting booklet		**Netflix etc.**		**YouTube etc.**		Events	
Age	.017	(.036).	.203	(.031)***	–.108	(.033)**	–.311	(.034)***	–.226	(.034)***	.018	(.035)
Female	.015	(.034)	.091	(.031)**	.077	(.033)	–.039	(.031)	–.153	(.031)***	.121	(.032)***
Sec. education	–.063	(.123)	–.120	(.155)	.117	(.134)	–.385	(.146)**	–.350	(.142)*	.315	(.151)*
High. education	–.222	(.135)	.057	(.124)	.128	(.146)	–.423	(.154)**	–.348	(.149)*	.531	(.160)***
Income	.007	(.033)	.074	(.032)*	.030	(.033)	.029	(.033)	–.066	(.030)*	–.046	(.032)
Political interest	–.122	(.036)***	.218	(.034)***	.221	(.036)***	–.058	(.034)	–.048	(.034)	.123	(.035)***
Internet use	.074	(.036)*	–.066	(.035)	–.021	(.039)	.141	(.035)***	.148	(.033)***	–.041	(.032)
French-speaking	–.079	(.078)	–.119	(.069)	.041	(.075)	–.006	(.073)	.043	(.074)	–.044	(.075)
Italian-speaking	–.115	(.126)	.404	(.130)**	.436	(.130)***	–.049	(.112)	–.034	(.123)	–.074	(.140)
R^2	.028		.137		.052		.175		.140		.045	
Adj. R^2	.019		.129		.044		.168		.132		.036	
Num. obs.	1041		1043		1040		1011		1045		1044	
RMSE	.985		.917		.964		.898		.921		.958	

	Commercial transactions				Socializing				Health			
	Online shops		Personaliz. ads		Online dating		*Onl. messenger*		Wearables		Well-being	
Age	–.181	(.33)***	–.101	(.036)**	–.127	(.036)***	–.155	(.032)***	–.068	(.035)	–.052	(.033)
Female	–.098	(.032)**	–.088	(.034)**	–.117	(.031)***	.180	(.030)***	.004	(.034)	.107	(.032)***
Sec. education	–.101	(.129)	–.330	(.172)	–.304	(.186)	.251	(.130)	.047	(.143)	.083	(.137)
High. education	–.105	(.141)	–.430	(.181)*	–.420	(.191)*	.361	(.137)**	.052	(.155)	.215	(.148)
Income	.021	(.031)	.012	(.034)	–.087	(.035)*	–.002	(.031)	–.002	(.034)	–.021	(.031)
Political interest	–.036	(.034)	–.434	(.034)	.018	(.034)	.076	(.032)*	–.050	(.035)	.117	(.035)***
Internet use	.148	(.032)**	.069	(.033)*	.114	(.038)**	.087	(.032)**	.060	(.035)	–.044	(.033)
French-speaking	–.323	(.077)***	.011	(.078)	.128	(.080)	–.139	(.080)	–.139	(.073)	–.709	(.086)***
Italian-speaking	–.228	(.144)	.120	(.155)	–.007	(.106)	–.353	(.142)*	–.031	(.140)	–.227	(.123)
R^2	.101		.039		.077		.079		.017		.119	
Adj. R^2	.094		.031		.069		.071		.008		.111	
Num. obs.	1043		1039		1017		1044		1034		1043	
RMSE	.945		.987		.947		.925		.980		.932	

***p<.001, **p<.01, *p<.05; standard errors in parenthesis; algorithmic-selection applications are in bold, other online services in italics. Absolute effect sizes of significant coefficients are highlighted for >.15 (light grey), >.3 (grey) and >.45 (dark grey).

is not sufficient for the assessment of its relevance and effects in daily life. In line with a comprehensive, mixed-methods measurement model of algorithmic governance (Latzer & Festic, 2019), this paper suggests using subjectively assigned relevance as a weighting for the interpretation of other findings such as data on the amount and frequency of social media use.

Major findings according to the paper's research questions include, first, that Internet users perceive algorithmic-selection applications as less relevant in particular compared to offline but also to online alternatives. This empirically supports claims from qualitative news repertoire studies that – although increasingly used – algorithmic-selection applications are unlikely to replace established sources such as traditional journalistic content for news consumption (Schmidt et al., 2019).

Second, algorithmic-selection applications, in particular social media, are found to be of relatively low assigned relevance for all life domains investigated. Offline activities are consistently ranked highest. Search engines are ranked as the most relevant algorithmic-selection applications across all life domains. This is in line with studies (Pew Research Center, 2016; Purcell, 2011) that document the wide embeddedness of search engines in daily lives.

Third, younger and more frequent Internet users assign greater relevance to various algorithmic-selection applications across life domains. This underlines earlier findings that younger people integrate algorithmic-selection applications such as fitness trackers, music streaming, or social media more heavily in their everyday lives (Abril, 2016; Anderson, 2016; Shearer & Matsa, 2018; Gottfried et al., 2016; Shearer, 2018; Smith, 2016). Further, people with higher educational levels are more likely to assign a lower relevance to algorithmic-selection applications than lower-educated Internet users. This result may qualify findings by the Pew Research Center (2019), that the proportion of social media users is greater for those with higher education (79 %) than for the less well educated (64 %). Subjectively assigned relevance proves beneficial as an additional dimension to weight previous findings on usage time.

Altogether, results on assigned relevance allow for a better interpretation of usage data. The relevance for people does not necessarily rise with the amount of use. Services may be highly influential, even if people report a low usage time – and vice versa. These discrepancies seem to apply in particular for social media like Facebook. Its assigned relevance is consistently very low across all life domains, including political and social orientation, where it ranks lowest. This qualifies and calls for rethink of concerns about the prevalence of risks in societies, if they are solely raised on the basis of intensive social media use.

Findings that algorithmic-selection applications are assigned a comparatively low relevance can be interpreted in two ways (Festic, 2020). On the one hand, the social relevance of algorithmic selection may generally be overestimated and – despite their high user counts and long usage times – these applications may not be so relevant after all when comparing their relevance to more traditional online and offline alternatives. On the other hand, since this article relies on self-reported assignments of relevance, it is conceivable that people may be misjudging the relevance of certain services and activities, algorithmic-selection applications in particular.

There could be two reasons for this: (1) there is the notion that (media) effects are often undetectable for individuals. Third-person effects may occur (Davison, 1983), people may tend to overestimate media effects on others and underestimate them on themselves (Tsay-Vogel, 2016). (2) Effects may be denied, because individuals do not want to accept the influence of algorithmic selection or because of social desirability (Holtgraves, 2004). Moreover, there may be different reasons why people under- or overestimate the relevance assigned to algorithmic-selection applications. Altogether, further research is needed to determine the likelihood of such effects on self-reported data in the respective cases.

There are a few limitations to consider when interpreting the results of this article. The selection of activities is derived from qualitative interviews conducted prior to this study and the life domains that we refer to in this study draw on a selection suggested by Büchi et al. (2016). Although meticulously aiming for saturation for these selections, neither the lists of offline and online activities nor the chosen life domains are necessarily exhaustive and simplify everyday realities. Furthermore, to allow interaction by participants, data was gathered on the subjective relevance for the specific services but not directly the actual algorithmic aspects of it. Hence, one could rate "YouTube etc." or "social media" as very relevant without being affected by its algorithmic aspects. Additionally, the degree to which the algorithmic aspects interfere with the main usage purpose of a service varies greatly.

Moreover, spillover effects between different activities and services are likely but difficult to grasp. An influencer who became famous via social media might subsequently be present on traditional TV, in print, or be the topic of offline conversations. Further investigations may resolve these relations, for example, by explicitly asking for such instances. Taking all limitations into account, it is likely that people underestimate the actual relevance of algorithmic-selection applications, "YouTube etc." and "social media" especially, for their lives.

Finally, cultural differences between countries should be taken into consideration. Our representative results on the relevance assigned by the Swiss population should not be applied uncritically to qualify empirical usage data from countries with a quite different cultural imprint.

8 Conclusion

An adequate and up-to-date understanding of the social relevance of algorithmic selection is a prerequisite when aiming to regulate algorithmic selection. Applications that are based on algorithmic selection have been under public scrutiny for bearing a plethora of risks. For example, algorithmically curated social media feeds are claimed to be responsible for manipulation and the distribution of biased information. From a public-policy perspective, this raises questions about the need for regulatory measures. Choosing an appropriate governance of algorithmic-selection applications can be supported by accurate knowledge about their social relevance. This includes, for example, information on how strongly Internet users actually rely on social media for their daily social and political orientation, what other sources they consult and how much they know about the process of algorithmic selection. Only such a thorough empirical investigation can form an appropriate basis for assessing the magnitude of risks that might be induced by algorithmic selection and consequentially the adequate governance measures. This paper adds to the debate on the relevance of algorithmic selection in two ways.

First, it introduces subjectively assigned relevance as an additional approach to weight findings on the overall social relevance of algorithmic selection that rely on measures of the frequency and amount of use of algorithmic-selection applications. The combination of these measures can lead to a more realistic assessment of the matter at hand, allowing more appropriate policy decisions.

Second, by taking a user perspective and analyzing subjectively assigned relevance on a nation-wide, representative level for five different life domains, the paper directly adds to a more comprehensive and nuanced empirical understanding of the social relevance of algorithmic selection, provides novel empirical insights for the ongoing debate and informs policy-makers aiming for adequate governance decisions.

According to the findings, young as well as heavy Internet users assigned a high relevance to algorithmic-selection applications. As a result, members of these groups are more likely to be exposed to risks associated with algorithmic selection. To mitigate these risks, policymakers should focus on these high-risk groups when attempting to raise awareness regarding potentially negative consequences of algorithmic selection.

In addition to existing self-reported data on the amount and frequency of use and this paper's approach to subjectively assigned relevance, further research could include tracking data, for example, to reduce problems with inaccurate and biased self-reporting. This would facilitate an improved assessment of the social relevance of algorithmic-selection applications.

With slight variations across life domains and socio-demographic groups, this article suggests that Internet users generally perceive algorithmic-selection applications as not overwhelmingly relevant for their everyday lives. Within this group of services, search engines are assigned a relatively high and social media a very low relevance. Although potential risks should not be trivialized, these findings render the image of an Internet user who is at the mercy of algorithms and strategies of platform companies slightly less likely. Differences identified in the relevance assigned to algorithmic-selection applications in societies should be appropriately considered in the assessment and governance of chances and risks they pose for them.

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Supplementary material

Supplementary material for this article is available online in the format provided by the authors (unedited). https://www.hope.uzh.ch/scoms/article/view/j.scoms.2021.01.005

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Article X

Algorithmic Self-Tracking for Health: User Perspectives on Risk Awareness and Coping Strategies

Noemi Festic, Michael Latzer & Svetlana Smirnova

Abstract
Self-tracking with wearable devices and mobile applications is a popular practice that relies on automated data collection and algorithm-driven analytics. Initially designed as a tool for personal use, a variety of public and corporate actors such as commercial organizations and insurance companies now make use of self-tracking data. Associated social risks such as privacy violations or measurement inaccuracies have been theoretically derived, although empirical evidence remains sparse. This article conceptualizes self-tracking as algorithmic-selection applications and empirically examines users' risk awareness related to self-tracking applications as well as coping strategies as an option to deal with these risks. It draws on representative survey data collected in Switzerland. The results reveal that Swiss self-trackers' awareness of risks related to the applications they use is generally low and only a small number of those who self-track apply coping strategies. We further find only a weak association between risk awareness and the application of coping strategies. This points to a cost-benefit calculation when deciding how to respond to perceived risks, a behavior explained as a privacy calculus in extant literature. The widespread willingness to pass on personal data to insurance companies despite associated risks provides further evidence for this interpretation. The conclusions—made even more pertinent by the potential of wearables' track-and-trace systems and state-level health provision—raise questions about technical safeguarding, data and health literacies, and governance mechanisms that might be necessary considering the further popularization of self-tracking for health.

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Article

Algorithmic Self-Tracking for Health: User Perspectives on Risk Awareness and Coping Strategies

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Abstract
Self-tracking with wearable devices and mobile applications is a popular practice that relies on automated data collection and algorithm-driven analytics. Initially designed as a tool for personal use, a variety of public and corporate actors such as commercial organizations and insurance companies now make use of self-tracking data. Associated social risks such as privacy violations or measurement inaccuracies have been theoretically derived, although empirical evidence remains sparse. This article conceptualizes self-tracking as algorithmic-selection applications and empirically examines users' risk awareness related to self-tracking applications as well as coping strategies as an option to deal with these risks. It draws on representative survey data collected in Switzerland. The results reveal that Swiss self-trackers' awareness of risks related to the applications they use is generally low and only a small number of those who self-track apply coping strategies. We further find only a weak association between risk awareness and the application of coping strategies. This points to a cost-benefit calculation when deciding how to respond to perceived risks, a behavior explained as a privacy calculus in extant literature. The widespread willingness to pass on personal data to insurance companies despite associated risks provides further evidence for this interpretation. The conclusions—made even more pertinent by the potential of wearables' track-and-trace systems and state-level health provision—raise questions about technical safeguarding, data and health literacies, and governance mechanisms that might be necessary considering the further popularization of self-tracking for health.

Keywords
algorithmic selection; coping strategies; mHealth; risk awareness; self-tracking apps; self-quantification; societal risks; user perception; wearables

Issue
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1. Introduction

Algorithms are shaping many domains of our datafied lives, from the curation of news content to recommendations for what to buy. Self-tracking for health is no exception: this digital variant of self-surveillance is performed with the help of wearable devices (e.g., sports bracelets, smart jewelry) and mobile applications. It typically involves continuous data collection, storage, and analysis, which results in algorithmically-derived health recommendations, quasi-human motivational communication, and competitive benchmarking against peers. While self-trackers measure various aspects of their lives, the central focus of this article is on health, fitness, and wellness tracking, which revolves around measuring and analyzing aspects of physical and mental well-being (e.g., sleep, diet, stress) and athletic performance.

In the last decade, self-tracking has grown exponentially in popularity and reach. In 2020, close to half a billion wearables were in use worldwide. The market of related mobile applications is highly concentrated: From more than 300,000 healthcare apps available, 36 account for more than half of all downloads (estimates by IMS Institute for Healthcare Informatics, 2015). Similarly, the market for wearables is split between five dominant players—Apple, Xiaomi, Fitbit, Samsung, and Huawei—accounting for nearly two-thirds of devices sold (Statista, 2020).

Self-tracking applications have in common that they rely on *algorithmic selection*, defined as a special kind of selection that builds on the automated assignment of relevance to certain pieces of information (Latzer et al., 2016). Risks that can be associated with the employment of algorithmic selection in widespread online services are receiving much public and academic attention. Personalized algorithmic selection shapes the practice of self-trackers in multiple and unknown ways. The self-tracking industry has developed a persuasive narrative that values self-optimization, personalization, prediction, and self-management of health. Not least owing to the opacity of these applications and the sensitive, health-related data they use, self-tracking applications have come under public scrutiny. A glance at the historical evolution of the adoption of self-tracking applications reveals that the need for a debate on their risks and benefits has amplified: While such applications were initially designed for personal use only and data was maybe shared with peers on social networks for comparison and motivation, the stakes for users have dramatically increased. A rapidly growing number of public and corporate actors are promoting the use of these services, using the data and linking financial benefits to achieving certain objectives, thereby exacerbating the potential for a variety of social risks: Self-tracking applications have not only been shown to be of dubious scientific quality (Mercurio et al., 2020), but the industry is also poorly regulated, especially when it comes to handling personal data. The European General Data Protection Regulation (GDPR) has, for instance, been assessed as ineffective in adequately accounting for the fast-paced evolution of self-tracking practices (Marelli et al., 2020). Consequently, different governance options such as self-help protection behaviors by users are likely to play an important role in coping with the risks associated with algorithmic-selection applications for health self-tracking (Ireland, 2020). Coping strategies allow users to exert agency against the "panoptic practices" that companies apply (De Certeau, 1984): By monitoring, measuring, and controlling internet user data, they transform their users into measurable types and classify them based on their habitus that mirrors different aspects of their social disposition. Thereby, these internet platforms and services co-construct users' realities by "mirroring their social dispositions in the form of scorings, recommendations, search results or advertisements" (Latzer & Festic, 2019, p. 10). In the context of self-tracking applications, this specifically involves health-related recommendations or scorings, which have an influence on the users' perceptions of themselves and the world. This article defines coping strategies as internet users' counterparts to the companies' data collection and analysis strategies that induce certain risks for users. This understanding is related to Kitchin and Fraser's (2020) notion of "slow computing," which captures a way for users to regain autonomy over their digital lives in the face of ever-accelerating and increasingly encompassing data grabbing infrastructures on the internet. In the context of self-tracking applications, one exemplary risk, induced by their algorithmic nature, is the inaccurate measurements and resulting fitness recommendations that are scientifically unfounded and inapt for the respective user (Depper & Howe, 2017). Double-checking measurements with the aid of different tools is one possible coping strategy for users to regain autonomy (Kitchin & Fraser, 2020) and mitigate risks.

Extant research has not sufficiently studied self-tracking for health in the wider context of the social power of algorithms—although personalized algorithmic selection lies at the core of these applications and provides a helpful framework to investigate associated risks. The call for more representative empirical research from a user perspective (see Albrecht, 2016) has so far not been sufficiently answered. Against the conceptual backdrop of algorithmic selection, this article first contributes to filling these gaps by empirically investigating how aware self-trackers are of the risks associated with health applications and how they cope with them. Second, this article contributes to the understanding of the coping behavior observed. While we know little about risk awareness and coping strategies by individual users in the realm of self-tracking for health, scholarship on online privacy lends a helpful concept to consider: the privacy calculus, which describes cost-benefit calculations that internet users perform when negotiating their online behavior in response to perceived risks to their privacy (see Baruh et al., 2017). As we described above, social risks associated with self-tracking applications for health have been linked to the growing interest of corporate actors in this data. Using the example of sharing personal self-tracking data with insurance companies as a case study, this article empirically explores self-trackers' behaviors in response to risks and in light of benefits attached to sharing personal data. In combination with the first aim introduced above, this article contributes to our (empirical) understanding of the relationship between risk awareness and coping strategies, which could help to shed light on how self-trackers evaluate risks and deal with them.

To fulfil these tasks, this article draws on representative survey data from Switzerland, a highly digitized country where 95% of the population use the internet and self-tracking applications for health are gaining popularity: while 29% of internet users reported using them in 2017, this share has risen to 41% in 2021 (Latzer et al., 2021).

This article begins by conceptualizing self-tracking applications for health as algorithmic-selection applications. We then present a review of the existing literature on associated risks and coping strategies and introduce the concept of the privacy calculus. After the methodological approach is explained, the results section outlines our empirical insights. Lastly, the findings are interpreted and we conclude by identifying further research directions.

2. Theoretical Background and Review of Relevant Literature

2.1. Self-Tracking as an Algorithmic-Selection Application

While research on self-tracking applications and their implications is emerging, engagement with literature on algorithms often remains superficial. Bol et al. (2019, p. 2) are some of the few who explicitly address the personalized nature of self-tracking applications by referring to "customization," which captures users' "ability to *self*-tailor…mobile health app content and features." While this user-driven self-tailoring as an affordance of self-tracking applications is included in our understanding of algorithmic selection as introduced below, it goes beyond user-initiated personalization and also includes the automated selection of contents that is outside of what users are aware of and can influence.

In general, algorithmic selection describes the process that transforms *input* with the help of automated computational procedures (*throughput*) into *output* (Cormen et al., 2009; Latzer et al., 2016). Figure 1 illustrates how this model aids to understand the functionality of self-tracking applications for health.

The starting point for this algorithmic-selection process embedded in widely used self-tracking applications for health is a user request (e.g., for a training plan) paired with available user characteristics such as personal demographic factors (e.g., gender, age), user behaviors (e.g., levels of physical activity, diet), and personal goals. These user requests and characteristics combined with a basic data set are used as input by these applications to derive output that ranges from graphs of daily step counts and motivational reminders to be physically active, to an alarm being triggered automatically during a specific stage of sleep to ease waking or a prompt to meditate in response to rising stress levels. The inner functioning of algorithmic-selection applications (throughput) remains largely obscure to users, can form the basis for different biases, and relies on computational operations (Latzer et al., 2016). This process of algorithmic selection functions as follows in the context of a specific type of self-tracking for health: Based on data about fitness levels, past running experience, and age (input), a health application and its designated algorithms (throughput) can identify the ideal training strategy and make personalized recommendations to prepare someone for a marathon (output).

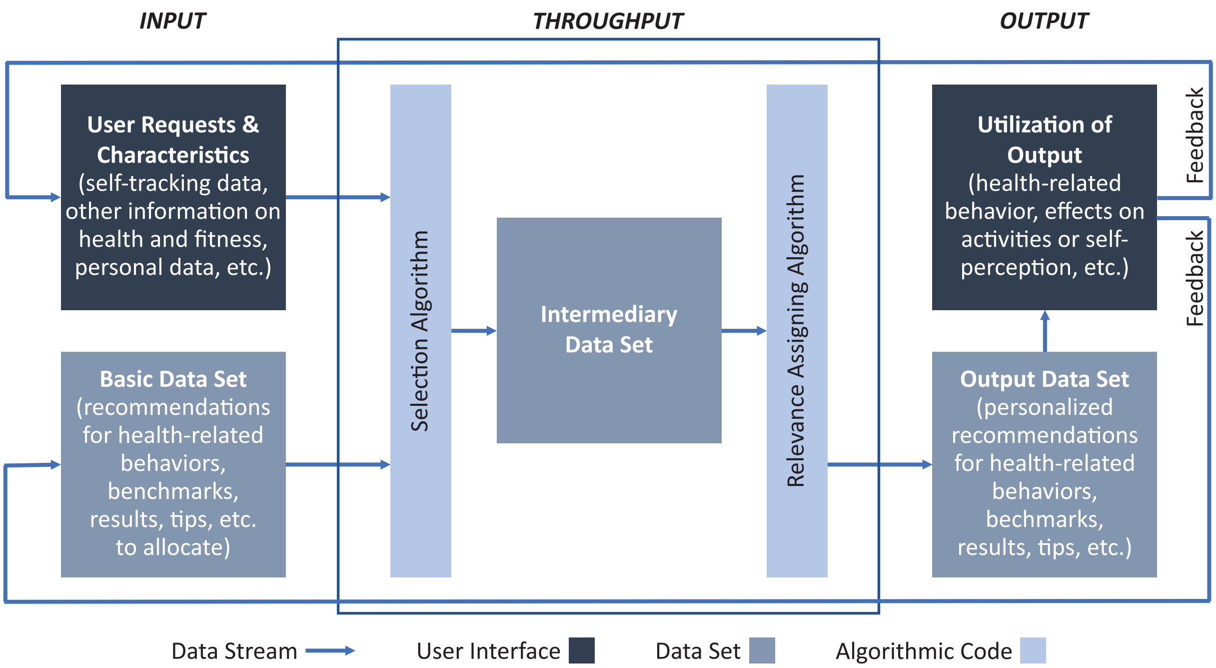

Figure 1. Input–throughput–output model of algorithmic selection applied to self-tracking applications for health and fitness. Source: Adapted from Latzer et al. (2016).

This conceptual understanding of self-tracking applications for health will guide and structure the following considerations on related risks and coping strategies.

2.2. Algorithmic Self-Tracking: Risks and Coping Strategies From a User Perspective

The central arguments of critical scholarship regarding users' risk awareness and coping strategies can be summarized as follows.

While there has been much discussion identifying the *risks* of the spread of algorithmic-selection applications in all domains of life, empirical evidence is only just emerging. Most of the critique directed at algorithmic-selection applications for self-tracking is derived from theoretical reasoning and does not rely on empirical data from a user perspective (for a critique of visualization and analytics, see Fawcett, 2015; and Hepworth, 2017; for a critique of Western-centered, ableist assumptions embedded in tracking systems, see Elias & Gill, 2018; Elman, 2018; Mills & Hilberg, 2020). Risks such as the spread of misinformation (Albrecht, 2016) or use-errors and resulting wrong treatments (Israelski & Muto, 2012) have also only been theoretically derived so far. In their SWOT (strengths, weaknesses, opportunities, and threats) analysis, Li and Hopfgartner (2016) recognize over-tracking and erosion of privacy as weaknesses and negative societal consequences in terms of privacy as a threat of self-tracking applications.

Lack of transparency, particularly in relation to medical evidence, is of special concern given the health-focused nature of the practice. There is robust empirical evidence revealing that expert involvement and adherence to medical evidence is low for various health applications (Chen et al., 2015; Subhi et al., 2015) and longitudinal comparisons reveal that smartphone health apps are not improving in terms of safety or quality (Mercurio et al., 2020). Empirical evaluations of self-tracking applications for weight loss (Mercer et al., 2016) concluded that goals were not adequately backed up by science, sponsorships were not disclosed, sources of information were not cited, and major behavior change techniques were missing.

Qualitative, user-centered research has revealed a variety of self-trackers' concerns, especially considering the output of self-tracking devices: accuracy of data and analysis, inability to edit erroneous entries, weak analytics, and unusable feedback. To exemplify, the accuracy of measurements, the universality of benchmarks (e.g., 10,000 steps or eight hours' sleep at night) and embedded heteronormative assumptions have been sources of concern (Barassi, 2017; Depper & Howe, 2017; Matthews et al., 2017).

Furthermore, privacy remains a significant issue that has been explored in relation to the practice. The risks related to privacy include data trading and access by third parties, lack of legal protection merited by the sensitive nature of data, extensive collection of data irrelevant to the functioning of the application, and users' inability to foresee the extent of data collected on them (Cyr et al., 2014; Daly, 2015; Katuska, 2019). In regard to privacy-related risks, earlier studies showed that self-trackers underestimated the amount of data they shared with companies and lacked knowledge of the conditions of data storage, sharing, and retention, as well as privacy policies, and what they could do to minimize unwanted privacy invasions (Goodyear et al., 2019; Lupton & Michael, 2017; Spiller et al., 2017; Vitak et al., 2018). Recent studies have also suggested that while self-trackers might know about their data being used and believe that harm may come from that (e.g., ovulation data used by an employer for human resources planning), they also think that such scenarios are unlikely to affect them personally (Alqhatani & Lipford, 2019; Gabriele & Chiasson, 2020), which is why they might not engage in mitigation strategies.

As one of the few studies with large-scale survey data in the field, Grzymek and Puntschuh (2019) found across all EU member states that people have little awareness of the potential of algorithms to assist in diagnosing diseases and there was significant concern about medical decisions made by algorithms.

In the realm of coping strategies, existing scholarship suggests that self-trackers use a range of techniques to deal with concerns related to their self-tracking. For example, ethnographic studies have explored how intermediation and reflection are employed by users to cope with problems of inaccuracy, data incompletion, and device breakage (Pink & Fors, 2017a, 2017b; Pink et al., 2017). Alternatively, multiple qualitative studies have illustrated how self-trackers engage in reframing their data, paying selective attention to some data points, or resisting the use of devices as designed (Gorm & Shklovski, 2019; Mopas & Huybregts, 2020; Sjöklint et al., 2015). Other than general research on privacy protection behavior, there is, to the best of our knowledge, no quantitative empirical evidence on how users cope with potential risks in the context of self-tracking applications.

Overall, there is a lack of representative, nation-level data that addresses how aware self-trackers are of various risks and how they cope with them. The discussion of related risks has so far lacked conceptual clarity and not sufficiently taken into account the algorithmic nature of self-tracking applications. When assessing the current state of research with the input-throughput-output model of algorithmic selection in mind, it becomes apparent that most research on risks and coping strategies is limited to the output dimension. We derive the following two research questions from the extant literature for this article:

> RQ1: How aware are Swiss self-trackers of the risks associated with the applications they use and how do they cope with them?

RQ2: How is risk awareness related to the employment of coping strategies among Swiss internet users?

Since the process of personalized algorithmic selection, which underlies the commonly used self-tracking applications, relies heavily on personal data, this topic is intertwined with critical scholarship on online privacy, which has been concerned with questions about how worried internet users are about their data online and how they attempt to protect it. From an (empirical) communication science perspective, privacy-related risks are among those studied most extensively in terms of internet users' awareness and their behavioral and cognitive reactions to it. While early research in the field revealed a seemingly paradoxical relationship between privacy concerns and behavior (e.g., Barnes, 2006; Norberg et al., 2007), more recent studies have replaced this image of ignorant internet users who do not protect their personal data online despite being concerned about their privacy with one where they constantly perform cost-benefit calculations: People engage in online behaviors if the benefit of disclosing personal data or not engaging in protective behaviors, respectively, outweighs the cost (Baruh et al., 2017). Bol et al. (2018) provided experimental empirical evidence for such a "cost-benefit trade-off" in the context of health websites, indicating that both privacy risk perception and perceived benefits were associated with the participants' willingness to self-disclose personal data. When it comes to protection behavior, extant research has shown that—based, for instance, on protection motivation theory—low levels in protective behaviors may be explained by a low perceived self-efficacy despite of high perceived severity of related threats (Boerman et al., 2018). For a convenience sample, Kordzadeh et al. (2016) found empirical proof of a privacy calculus effect on self-disclosure in virtual health communities. Dienlin and Metzger (2016) expanded the privacy calculus framework to include not only self-disclosure, but also self-withdrawal (e.g., deleting posts)—accounting for internet users' co-existing desires for disclosing and withholding information predicted by communication privacy management theory (see Petronio, 2012)—and found empirical evidence for this extended model for a representative sample of adult Facebook users in the US.

Applying this calculus logic to the research interest at hand provides indications for engaging in self-tracking and not applying coping strategies despite being aware of potential risks because the benefits outweigh the cost. A specific, real-world example for these cost-benefit calculations is provided by the rising interest of insurance companies in self-tracking data, offering financial benefits in exchange for personal tracking data. Sharing highly sensitive data on one's health with a third party through an opaque algorithmic-selection application despite a multitude of risks that can arise from this behavior in the short and long run can arguably only be explained if the perceived benefits of this behavior (i.e., a financial compensation) exceed the perceived cost (i.e., any harms from the risks). We use insurance settings as a case study to explore if user behavior is consistent with a calculus logic in the context of self-tracking applications by answering the following question:

RQ3: To what extent are Swiss self-trackers willing to share their data with insurance companies for financial benefit?

An extensive body of research has repeatedly shown that traditional societal fault lines are replicated in the digital space: Male, younger, more affluent members of a society tend to reap more benefits from their internet use and are able to deal with associated risks better (see van Dijk, 2020). Therefore, this article analyzes risk awareness and coping strategies in the realm of self-tracking for health against this backdrop of sociodemographic differences, too.

3. Method

3.1. Data Collection

The empirical section of this article relies on a representative survey of Swiss internet users conducted between October 2018 and February 2019. The survey covered the significance of algorithmic selection for everyday life (Latzer et al., 2020) and included questions on the frequency and purpose of tracking device use, attitudes, risk awareness, and coping strategies, as well as on the willingness to share personal data with insurance companies for financial benefit.

The survey was conducted as part of a larger project in which we also collected internet use tracking data: All participants, who were actively recruited from an existing mobile tracking panel by the LINK Institute, received installation instructions for a passive metering software for their desktop or laptop device (provided by Wakoopa) at the beginning of the field phase. We collected tracking data on private mobile and desktop or laptop devices. The following variables were collected: URL of visited webpages or name of visited app, duration and time of the visit, device, and operating system. On completion of the tracking, the participants received an invitation to complete the online survey questionnaire. While the research questions of this article will be empirically answered with the survey data, the sample description below includes relevant results from the tracking data on the use of self-tracking applications to provide context for the interpretation of the survey results.

3.2. Sample

The original survey sample consisted of $N_{\text{participants}}$ = 1,715. As part of the aforementioned questionnaire, the participants were asked to evaluate the relevance they assign to various online and offline services and activities (e.g., self-tracking applications, offline contacts, search engines) for obtaining information on their personal health. They rated how relevant they believed each of these sources to be for their health information on a scale from 1 = *not at all relevant* to 5 = *very relevant*. For this study, we used a subsample of those participants who assigned some relevance (>1) to an application or device that automatically monitors their fitness or health (*N* = 716).

The tracking sample consisted of $N_{\text{tracked events}}$ = 13,486,101. We compiled a list of 675 websites and applications which allow their users to automatically track their fitness and health or connect to a wearable device (e.g., a watch) by systematically searching the Apple App Store, Google PlayStore, and Microsoft Store, and by conducting an extensive Google search. By searching the tracking data for occurrences of these app and website names and extracting these cases from the data set, we filtered all uses of self-tracking applications for health from the tracking data set to get descriptive results on the use of these applications in the sample.

Before addressing the guiding research questions, descriptive statistics on self-trackers in Switzerland are presented. Based on the survey data, one in 10 users of tracking applications (11%) reported using such services several times a day and a quarter (25%) reported using them daily. The majority used them either at least weekly (32%) or less than monthly (29%). There were no major differences in the frequency of use of these applications with regard to gender, age, or education. The most common purposes that the respondents reported using their devices for (multiple responses were possible) were fitness and sports (79%), sleep (28%), nutrition (16%), and documenting symptoms associated with a disease (11%).

Of all tracked events, .5% (*N* = 65,753) were uses of self-tracking applications. We identified 24 unique services used. Table 1 reveals the 10 most used self-tracking applications in descending order (as a share of all tracked use events of self-tracking applications for health). As becomes apparent from the most widespread services, Swiss internet users who engage in self-tracking through mobile applications almost exclusively track their physical activity (e.g., steps, training) and potentially related vital data (e.g., heart rate).

These descriptive characteristics of the self-tracking population are important to be kept in mind when interpreting the subsequent empirical answers to this article's guiding research questions.

Table 1. Most used self-tracking applications in Switzerland (based on tracking data).

Name	% of self-tracking events
Fitbit	93.14% (*N* = 61,243)
Google Fit	3.14% (*N* = 2,062)
TomTom Sports	<.01% (*N* = 562)
Mi Fit	<.01% (*N* = 550)
Beurer HealthManager	<.01% (*N* = 357)
VeryFitPro	<.01% (*N* = 283)
Huawei Health	<.01% (*N* = 197)
Sports Tracker	<.01% (*N* = 136)
Visana-App	<.01% (*N* = 81)
FunDo Pro	<.01% (*N* = 57)

3.3. Survey Measures

Based on existing literature introduced in Section 2.2, risk awareness was measured for four key risks: The respondents answered on a five-point Likert scale (1 = *do not agree at all*, 5 = *totally agree*) how strongly they agreed that they used their tracking device too much (overuse), were uncertain about the accuracy of their device's measurements (measurement inaccuracy), did not know how their device calculated the results it provides (lack of transparency), and were concerned about what happens with their data (loss of control over data).

To measure coping strategies, the respondents answered how often (1 = *never*, 2 = *rarely*, 3 = *sometimes*, 4 = *frequently*) they checked the accuracy of the measurements by comparing them to other results (checking measurements), how often they did not blindly trust their tracking device's results but actively thought about their meaning (reflecting on results) and how often they consciously refrained from using their tracking device (conscious non-use). Some of these risk awareness and coping strategy items can be clearly situated at one level in the input-throughput-output model of algorithmic selection (e.g., lack of transparency at the throughput level; checking measurements at the output level), others transcend this categorization and concern multiple levels. The goal of this empirical approach was to cover all levels in the measurement of both risk awareness and coping strategies.

The respondents indicated their willingness to share personal data with their insurance company by stating their agreement on a five-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) to the following statement: "I would be willing to give my insurance access to my data if I received financial advantages for doing so." While potential risks (i.e., the cost) of using self-tracking applications were not explicitly part of the question, they were made salient to the respondents through multiple questions on risk awareness placed prior in the questionnaire.

The respondents were further asked to report their gender (female, male) as well as their age in years, which was recoded into four groups (16–29, 30–49, 50–69, 70–85) for certain analyses below. They also reported their completed levels of educational attainment, which were recoded into three levels: individuals whose highest completed education level was compulsory schooling were assigned the value *low* and those with tertiary qualifications were assigned the value *high*.

3.4. Data Analysis

Data analysis for RQ1 and RQ3 relied on descriptive statistics. To test the relationship between risk awareness and coping strategies (RQ2), we estimated a path model with the lavaan package in *R* (Rosseel, 2012). For the path model, we used all items separately with the raw scales introduced in Section 3.3. This allowed a detailed analysis of the relationship between different risks and coping strategies. A positive relationship between a risk awareness and a coping strategy item in the model can therefore be interpreted as follows: "stronger agreement with a risk is associated with applying coping strategies more frequently." We freely estimated the covariances between the items for risk awareness and coping strategies, respectively (the script for the analysis and further results are available in the Supplementary Material).

4. Results

The following sections detail our empirical results for the three research questions based on the survey data.

To answer RQ1, we address how widespread the awareness of risks associated with self-tracking applications and the employment of coping strategies is. Figure 2 shows the distribution of responses to the survey questions about risk awareness (*N* = 716).

Overall, awareness of the surveyed risks was low: About four out of ten (39%) to seven out of ten (69%) self-tracking users were not concerned about the risks associated with their self-tracking practice. For overuse and lack of transparency, "do not agree at all" was the modal category: About half of the internet users did not agree at all that they use their tracking device too much (48%) and disagreed or fully disagreed that they do not know how their application calculates health results (54%). Loss of control over data and measurement inaccuracy were different in that the responses were roughly equally distributed: 27% and 30%, respectively, agreed (4) or fully agreed (5) with the statements. Users of self-tracking applications felt more at risk of losing control over their data or being presented with inaccurate measurements than they feared overusing their device or not knowing how their results are calculated.

The application of coping strategies, which can counteract these risks, was distributed as shown in Figure 3 (*N* = 716).

Figure 3 shows that the practice of cross-checking tracking measurements was uncommon: almost half of users (46%) never do this and only a quarter (24%) engage in the practice at least sometimes. One third (33% and 34%, respectively) of self-trackers never consciously decide to not use their tracking device or engage in this practice at least sometimes. Reflecting on one's

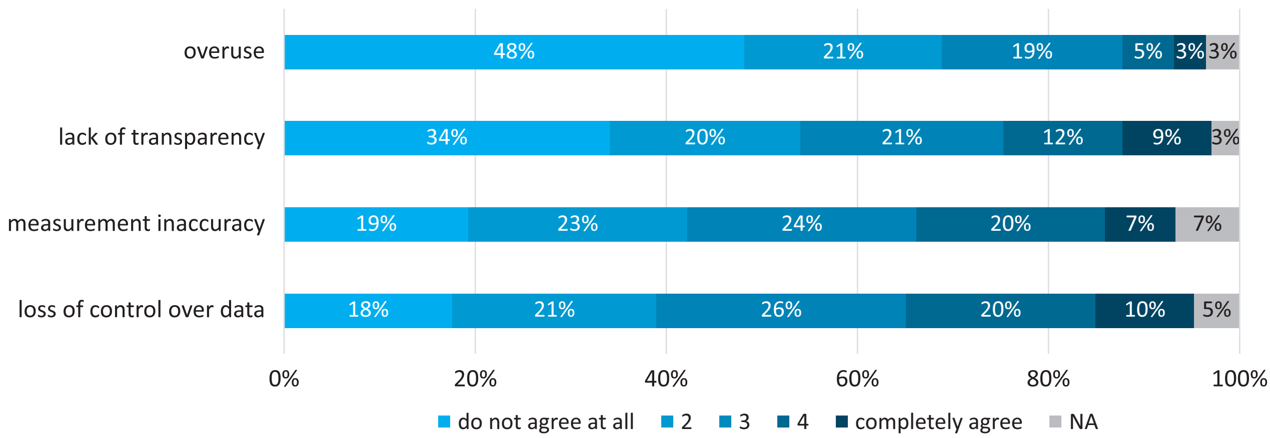

Figure 2. Distribution of indicators of risk awareness.

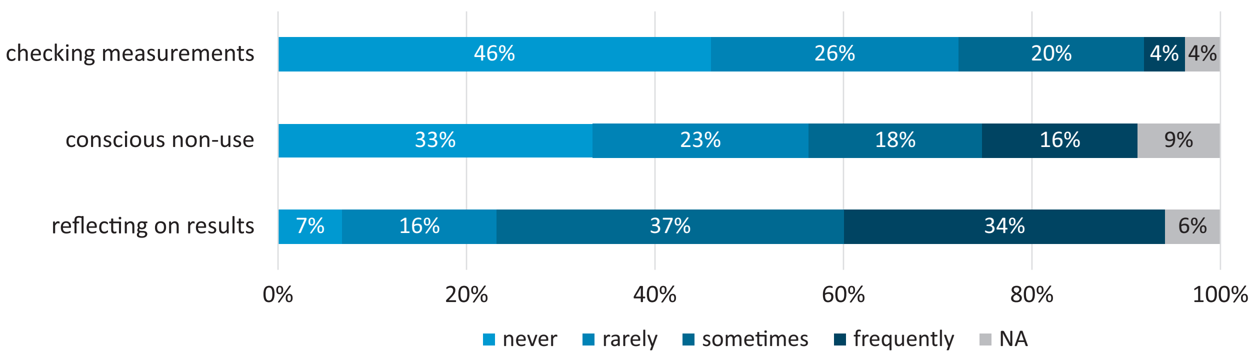

Figure 3. Distribution of indicators of coping strategies.

results was the most widespread coping strategy: only 7% never do this, while 71% of users engage in this practice at least sometimes.

To answer RQ2, we assessed the relationship between risk awareness and coping strategies. The awareness of specific risks and the frequency with which self-tracking users employed coping strategies was only weakly correlated both for the single items and for the two respective mean score indices (for further results see the Supplementary Material).

Figure 4 depicts a path model for the relationship between risk awareness and coping strategies. While gender and education were not significantly related to the two variables of interest, age was added as a control variable.

The model fit the data well: $\chi^2(3, N = 716) = 3{,}433$ ($p = .330$), $\chi^2/\text{df} = 1{,}144$, CFI = .999, TLI = .991, RMSEA = .014, SRMR = .012. Overall, the awareness of risks related to self-tracking devices explained only very small proportions of the variance in coping strategies. While there were some indications for a positive association between risk awareness and coping strategies—i.e., awareness of the risk to overuse self-tracking was positively associated with double-checking measurements and awareness of the risk of losing control over one's data was positively associated with consciously not using self-trackers—these effects were weak. Age was only significantly (and negatively) associated with the awareness of the risk of measurement inaccuracy.

While the application of coping strategies as a protection behavior does not appear to be meaningfully explained by risk awareness, this article also investigates whether Swiss self-trackers are willing to self-disclose their self-tracking data to insurance companies despite having been made aware of associated risks. RQ3 can be empirically answered as follows: 43% of tracking-device users in Switzerland agreed (4) or completely agreed (5) that they would generally be willing to share their data with their insurance company if they received financial advantages for doing so. This willingness was relatively uniformly distributed across all societal groups (see Figure 5). There was a weak tendency for older people and females to be less willing to share their data. Female self-trackers aged 70 and over reported the lowest willingness to share their data with an insurance company. There were no differences regarding education.

The following section discusses our empirical findings and details how they contribute to answering our research questions.

5. Discussion

Overall, our results reveal that awareness of risks associated with algorithmic self-tracking applications is relatively low and coping strategies are not regularly used. In the realm of risks, the results highlight that users perceive some risks—inaccuracy of measurements and losing control over their data—as more pertinent than others. However, even for those risks, less than a third of Swiss self-trackers reported awareness (RQ1). It is not necessarily the case that those who are more aware of risks engage in coping strategies more often (RQ2). This seemingly paradoxical result could be explained by a "calculus'' logic: Although Swiss self-trackers are somewhat aware of the risks they face, they still engage in the practice and do not apply many coping strategies because they rate the benefits higher than potential risks. Their willingness to share their self-tracked data with insurance companies (when there are direct financial benefits attached) further reiterates the plausibility of this explanation (RQ3). This result extends the extant literature on the privacy calculus (see e.g., Masur, 2019), from which this calculus logic was derived, to other types of risks associated with a specific type of everyday internet use that is dominated by algorithmic selection: self-tracking for health. In accordance with Dienlin

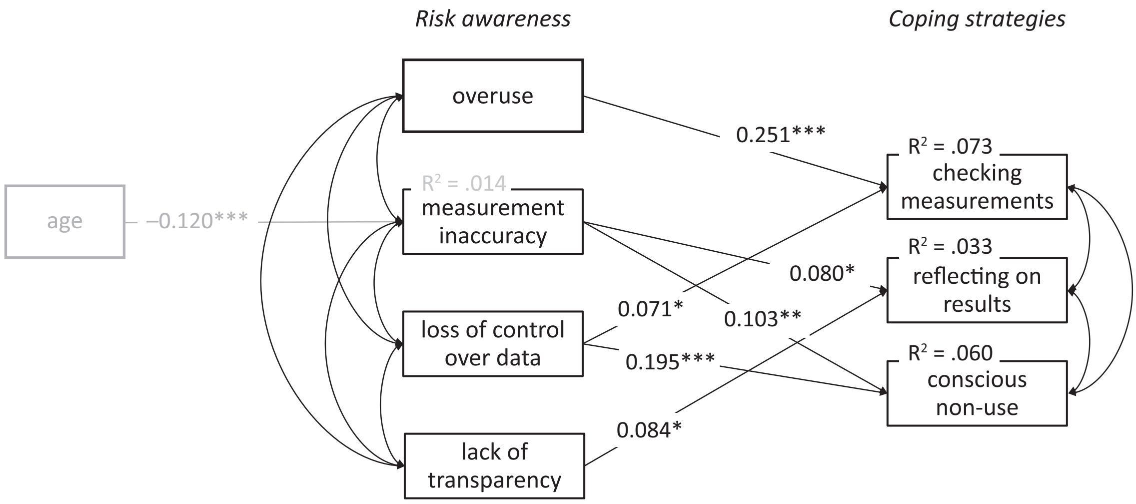

Figure 4. Path model: Risk awareness and coping strategies. Notes: Standardized estimates are shown; only significant paths are shown; ***$p < .001$, **$p < .05$, *$p < .1$

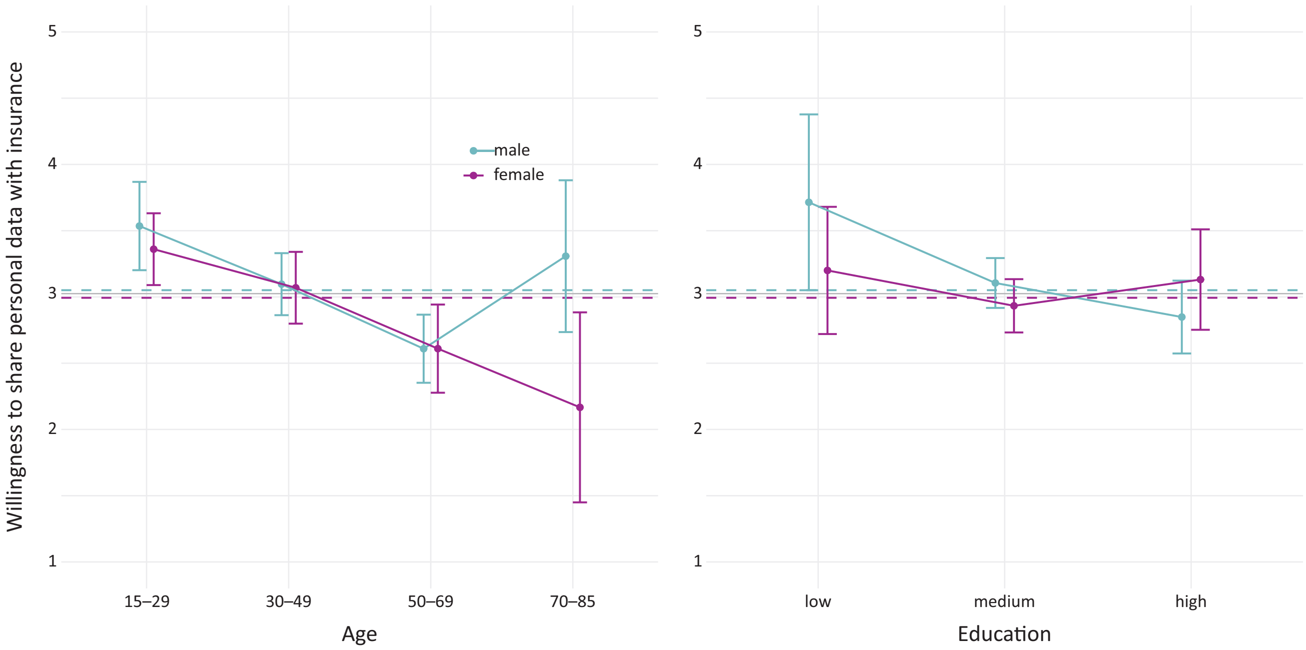

Figure 5. Willingness to share personal data with insurance company: Mean scores by gender, age, and education. Notes: Vertical bars represent 95% confidence intervals; horizontal lines represent overall (solid) and group means (dashed); Y-axis indicates means on a continuous scale (1 = *do not agree at all* to 5 = *completely agree*); *N* = 692.

and Metzger's (2016) empirical results, this effect was also likely present for coping strategies that reflect self-withdrawal behavior (i.e., conscious non-use).

From a public-policy perspective, these are important results to keep in mind when assessing the need for regulatory interventions to mitigate the possibility of certain risks occurring: While users may be familiar with some aspects of algorithmic selection and associated risks, this understanding does not deter them from engaging in the practice of self-tracking in their everyday lives. Alternative interpretations of this weak relationship could include skepticism about the efficacy of coping strategies (Boerman et al., 2018) or mediating effects of personality traits, internet skills, or more general concerns about being online. Our path model for the relationship between risk awareness and coping strategies (see Figure 4) also showed that coping strategies that are arguably effective in light of certain risks (e.g., conscious non-use as a coping strategy in response to awareness about the risk of overuse) were empirically not those most strongly associated with the respective risks. This provides further indications for the aforementioned interpretations and substantiates the need for further research on this relationship.

There are limitations to acknowledge when considering the results and implications of this study. Both survey and tracking data can be subject to biases such as effects of social desirability in surveys or the self-selection of people with certain personal characteristics into tracking samples. Another limitation concerns the list of risks included in this article. We examined a limited number of risks that we perceived as key, but future research should also consider emerging risks that have been associated with self-tracking, such as distorted self-perceptions (Strübing, 2021).

We found that existing research conceives self-tracking applications as a homogenous group. However, such applications and devices vary in the services they offer, the volume, type, and sensitivity of data they collect, the algorithms they employ, and the outputs they provide. Accordingly, the social risks we addressed in this article carry a different weight depending on the context of the self-tracking practice: While the potential risks of incorrect recommendations or data leaks for a chronically ill person relying on a self-tracking device for reminders of their medicine intake may be detrimental for their life chances, the effects of the same events in the context of a healthy person using a step counter are much less significant. This could be an additional, different explanation for the weak association between risk awareness and the application of coping strategies we found in our representative data set, which was almost exclusively composed of individuals who track arguably non-sensitive data (e.g., step counts) and where the potential for harm is therefore comparatively low. With this in mind, our data offer some specific indications that those who are chronically ill or require medical assistance are a group that future research should specifically focus on: Those in the sample who reported engaging in self-tracking to monitor symptoms in connection with a disease were more concerned about losing control over their data (38%, vs. 30% in the entire sample) and less willing to share their data with an insurance company for financial benefit (36%, vs. 43% in the entire sample)—arguably because the potential harms are much more detrimental for them, even if their occurrence is unlikely. Future research should account for this diversity in self-tracking applications when investigating their uses, implications, and the need for governance interventions. In any circumstance, throwing all self-tracking applications into one basket and proposing generalized, one-size-fits-all explanations or solutions is unpromising for a realistic assessment of their harms and benefits. The identified tensions raise further research, normative, and regulation questions. For instance, it remains an open question if users would be more concerned about the implications of their self-tracking practice if their life chances were more transparently linked to its outcomes (e.g., by tracked data having an impact on premiums).

Examining users' understanding of algorithmic selection embedded in self-tracking applications and associated risks is becoming more pressing as the practice permeates deeper into formal medical settings and drives up the costs of opting out (Lupton, 2015). Today, dominant corporate quantification players are expanding their reach into organizational settings: For example, Fitbit, has developed a dedicated product that is marketed to employers, and a health insurance provider has integrated the use of Apple watches into their wellness plans (United Healthcare, 2021). Organizations (e.g., Target, Barclays, BP, Emory University) and nation-states alike (e.g., Singapore, the UK National Health Service) have initiated the integration of self-quantification into their health delivery operations. Results from more fine-grained studies will be particularly relevant in light of the fast-paced evolution of the adoption of self-tracking applications: from being mere tools for measuring health-related indicators for personal use only, they have more recently attracted the interest of powerful, profit-maximizing institutions that are looking to capitalize on individuals' self-tracking practices and are increasingly pervading private domains such as sleep, mental health, and family planning.

In terms of governance conclusions, we can derive from our results that self-help by individual internet users in the form of coping strategies alone is not a promising path forward when it comes to mitigating the risks associated with algorithmic self-tracking applications that apply panoptic practices. Is there a need for self-, co-, or state regulation and if so, how might the transnational nature of dataflows hinder such efforts? Should the functioning of algorithmic selection (throughput) be made more transparent? While there are attempts such as the mHealth App Trustworthiness checklist (van Haasteren et al., 2019) to systematically assess and improve the quality of self-tracking applications, these studies should take into account that algorithms are at the core of these applications and consider scholarship in the field of critical algorithm studies to advance these endeavors.

6. Conclusion

This article makes two central contributions: On the conceptual level, we have elaborated on the functionality of self-tracking as algorithmic-selection applications and discussed related risks and coping strategies. On the empirical level, we have provided hitherto missing representative evidence of the relationship between risk awareness and coping strategies. Based on tracking data, we also found evidence of a highly concentrated usage of self-tracking applications in Switzerland.

The findings highlight that users recognize some risks associated with algorithmic selection for shaping their practice; however, this awareness is sparse and mostly limited to the applications' input and output levels. The findings also suggest that users employ a limited range of coping strategies to mitigate these risks. Based on these conclusions, we argue that limited awareness of algorithmic functioning and the associated risks does not deter users from adopting self-tracking practices in their everyday lives. In that vein, this article also provides empirical indication for a cost-benefit calculus derived from the weak relationship between risk awareness and coping strategies as well as from the high willingness to share personal data with insurance companies. The blind spots in risk awareness and the toothless nature of coping strategies, however, call for further consideration as the practice continues to permeate medical, corporate, educational, legal, and nation-state settings. Our results substantiate the need for a more differentiated analysis of self-tracking applications, taking into account different types of applications, user groups, and data with different degrees of sensitivity.

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Conflict of Interests

The authors declare no conflict of interests.

Supplementary Material

Supplementary material for this article is available at https://osf.io/ekjx9/?view_only=a513ba966d204966ac388079dfe84d62

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