

The Role of Digital Communication Needs and Norms for Dataveillance-Related Self-Inhibition

Emerging Media
2026, Vol. 4(3) 518–545
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DOI: 10.1177/27523543261471831
journals.sagepub.com/home/emm



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Abstract

Perceived salience of dataveillance—the collection and analysis of digital traces by corporate and state actors—can increase expectations of negative consequences from digital communication, leading to online self-inhibition. This process, known as the chilling effects of dataveillance, can limit participation in today's digital society, where being online is a need and norm. The uses and gratifications (U&G) approach and social norms theories suggest that users are motivated to engage in digital communication based on felt needs and perceived norms, which would reduce their susceptibility to chilling effects. This study investigates whether such need- and norm-based motives for free digital communication mitigate chilling effects. Using a representative survey sample from the Swiss-German internet population ($N = 898$), we conducted mediation and moderation analyses to test this assumption across three prevalent digital communication behaviors: searching for information, expressing opinions, and disclosing personal information. Results revealed that perceived salience of dataveillance and expected negative consequences from digital communication were overall associated with self-inhibition. In contrast, need- and norm-based motives did not mitigate these associations, suggesting that chilling effects of dataveillance do not depend on stronger motives driving free digital communication in this study. By introducing U&G and social norms approaches into chilling effects research, this study advances our limited understanding of chilling effects' boundary conditions. It offers representative, behavior-specific evidence aligning with the theoretical process of chilling effects, highlighting the potential gravity of being exposed to dataveillance in everyday life.

Keywords

dataveillance, chilling effects, motive, need, social norms

Received: March 9, 2026; revised: July 9, 2026; accepted: July 10, 2026

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Introduction

Let's imagine Anna and Max. Anna enjoys reading about politics and often feels the need to search online to better understand what she reads. Max, whose close friends are highly active on social media, often feels expected to comment on their posts. Yet both sometimes self-inhibit these activities because they hear about data scandals in the news.

These two examples illustrate the *chilling effects of dataveillance*. As a defining characteristic of today's digital society, dataveillance refers to continuous data surveillance practices (Clarke, 1988; Van Dijck, 2014) carried out by institutional actors such as corporations and states to achieve goals like financial gain and public security (Büchi et al., 2022; Christl et al., 2017). When dataveillance becomes *salient* in everyday life, this can increase people's sense of dataveillance, that is, their feeling of being dataveilled (Büchi et al., 2022). This may lead them to expect *negative yet uncertain consequences* from their legitimate digital communication and ultimately to *self-inhibit* their free digital communication. This chilling effects process may have unintended, socially undesirable consequences, including potentially missed opportunities for self-development, reduced civic and political online participation, and diminished well-being (Kappeler et al., 2023; Penney, 2017).

Although there is some empirical evidence to support chilling effects, effect sizes tend to be small, and studies on their determinants remain limited (e.g., Meier & Masur, 2026; Stoycheff, 2023; Strycharz & Segijn, 2024a, 2024b; Stubenvoll & Binder, 2024). Given the potential harms of chilling effects, and because limiting internet use is often unrealistic, we need to better understand which moderators might make these effects less likely to occur. Such a moderator may be individuals' stronger *motives* to engage in digital communication, which could reduce their susceptibility to chilling effects. We understand motives as sources of motivation guiding individual action (see Kleinginna & Kleinginna, 1981), here motivating free digital communication. While many motives can foster free digital communication, uses and gratifications (U&G), and social norms approaches suggest that internet users are particularly motivated to engage online based on their "felt needs" (Katz et al., 1973b, p. 166) and "perceived norms" (Chung & Rimal, 2016; Lapinski & Rimal, 2005, p. 129). Both motive types may encourage online participation to satisfy needs and build social capital, facilitating access to digital opportunities and enhancing beneficial internet use.

Accordingly, this study asks *whether need- and norm-based motives to engage in digital communication mitigate the chilling effects of dataveillance*. Put simply, we ask whether Anna's need to search for political information or Max's perceived expectation to comment on his friends' posts are strong enough to weaken their tendency to self-inhibit when perceiving dataveillance as salient and expecting negative consequences. We focus on both motives because individuals are not only driven by their own needs when engaging online but are also susceptible to social influence (Flanagin & Metzger, 2001; Valkenburg et al., 2016).

To address this aim, we conducted a cross-sectional survey among a representative sample of the Swiss-German internet population and performed mediation and moderation analyses. Switzerland offers a relevant case for studying chilling effects, as its very high internet use, political stability, strong civil rights, and data protection framework (FDPIC, n.d.; Freedom House, 2025) would encourage free digital communication. Yet, a majority of Swiss internet users report self-inhibiting online behaviors at least occasionally (Latzer et al., 2025), an outcome detrimental to the expression of individual rights promoted in liberal democracies.

This work contributes to chilling effects and user-centered dataveillance research. Theoretically, we integrate insights from U&G and social norms approaches into chilling effects research, an intersection largely unexplored. This integration offers a foundation for future work on how

motivational drivers of digital communication relate to individual responses to dataveillance. Empirically, we investigate the boundary conditions of chilling effects, that is, the “circumstances under which a given theory cannot be expected to hold” (Slater & Gleason, 2012, p. 225). In this study, if stronger need- and norm-based motives weaken the associations between the variables involved in the chilling effects process, this would suggest that such effects may be less likely to occur. While some chilling effects studies have considered normative aspects (Hermstrüwer & Dickert, 2017; Stoycheff, 2016), the role of need- and norm-based motives has received limited attention. Additionally, we examine how perceiving dataveillance as salient and expecting negative consequences from digital communication are associated with self-inhibition. In doing so, we provide representative evidence aligning with the theoretical process of chilling effects (Büchi et al., 2022), highlighting the potential gravity of dataveillance effects in everyday life. Finally, we demonstrate the importance of considering behavior-specific differences, as comparisons across behavior types tend to be rare in chilling effects research (e.g., Penney, 2017). We observe distinct response patterns across three highly prevalent behaviors—searching for information, expressing opinions, and disclosing personal information—providing a more nuanced understanding of chilling effects.

Chilling Effects of Dataveillance and Motives to Engage in Digital Communication

Chilling effects of dataveillance may prevent people from fulfilling their *felt needs* and adhering to *perceived norms* to engage in free digital communication. This study draws on the theoretical model of the chilling effects of dataveillance (Büchi et al., 2022) and insights from the U&G and social norms approaches (Chung & Rimal, 2016; Katz et al., 1973a) to determine whether need- and norm-based motives for digital communication mitigate these chilling effects.

Process of the Chilling Effects of Dataveillance

Dataveillance represents the “automated, continuous, and unspecific collection, retention, and analysis of digital traces” by corporate, state, and public actors (Büchi et al., 2022, p. 1). According to the theoretical process of chilling effects of dataveillance (Büchi et al., 2022, pp. 6, 7), this process begins when dataveillance becomes salient in everyday life through exogenous salience shocks, such as data scandals covered in the news, but also through everyday recurring salience shocks, or triggers, that increase the salience of dataveillance, such as personalized content, cookies, and diverse encounters with dataveillance practices. These everyday triggers then heighten individuals’ sense of dataveillance (Odermatt et al., 2025), that is, the feeling of being dataveilled through dataveillance practices. An increased sense of dataveillance is then expected to amplify expectations of negative consequences from digital communication behaviors due to dataveillance possibilities, especially for behaviors deemed sensitive. In turn, these expectations decrease favorable attitudes toward and intentions to engage in such behaviors, ultimately leading to the self-inhibition of these behaviors. As chilling effects depend on the “type of communication behavior” (Büchi et al., 2022, p. 2), their magnitude is expected to vary across different forms of legitimate, everyday behaviors leaving digital traces.

Empirical evidence tends to support the existence of chilling effects of dataveillance; however, studies on this topic in communication and media research remain overall limited and fragmented in democratic countries of the Global North. Descriptive cross-sectional survey research suggests that intentions to restrict online behaviors arise in response to corporate and state surveillance scenarios (Penney, 2017), while inferential survey research shows that individual- and system-level variables,

like privacy concerns and cross-country differences, are related to intentions to decrease media use in response to dataveillance practices in advertising (Strycharz & Segijn, 2024a). Quasi-experimental time series analyses have also shown that major salience shocks like the 2013 Snowden revelations and 2022 U.S. Supreme Court decision on abortion were followed by decreases in views for Wikipedia articles related to terrorism (Penney, 2016) and period-tracking apps (Penney et al., 2025). Furthermore, experimental research suggests that perceptions of online surveillance and data collection practices relate to intentions to self-restrict political online behaviors when one perceives an unfavorable climate of opinion (Stoycheff, 2016, p. 307) or feels fear or anger when using the internet (Stoycheff, 2023).

Yet investigations of the associations proposed in the chilling effects theoretical model (Büchi et al., 2022) remain rare (e.g., Meier & Masur, 2026). This study tests the associations between three variables central to this model: everyday salience shocks or triggers (operationalized as the perceived salience of dataveillance), expectations of negative consequences from digital communication, and self-inhibition. We first address the core chilling-effects hypothesis, indicating that:

H1: Higher perceived salience of dataveillance is positively associated with higher self-reported self-inhibited digital communication.

Beyond this direct association, we argue that perceived salience of dataveillance, via a heightened sense of dataveillance, is also associated with higher expectations of negative, yet highly uncertain, consequences in response to the perceived collection and analysis of one's digital traces. These expectations should, therefore, be associated with self-inhibition and mediate the relationship between perceived salience and self-inhibition. This reasoning closely aligns with the large body of literature on self-censorship, surveillance, and the spiral of silence, which generally posits that individuals withhold expression and other legitimate behaviors that may be watched by surveilling actors out of fears of legal and social sanctions (Hayes et al., 2005; Noelle-Neumann, 1974; Penney, 2025; Stoycheff, 2023). More specifically, the spiral of silence theory assumes that fear of social isolation makes people less likely to express themselves when perceiving an unfavorable climate of opinion (Noelle-Neumann, 1974). Because expressive acts like liking or posting can leave observable digital traces (Stoycheff, 2016), the theory helps explain why chilling effects may vary across online behaviors. Behaviors like expressing opinions or disclosing personal information may expose users more directly to potential negative consequences when their views or identities reflected in those digital traces are perceived to diverge from the majority. Accordingly, we hypothesize:

H2: Higher perceived salience of dataveillance is positively associated with higher expectations of negative consequences from digital communication.

H3: Higher expectations of negative consequences from digital communication are positively associated with higher self-reported self-inhibited digital communication.

H4: The relationship between perceived salience of dataveillance and self-reported self-inhibited digital communication is mediated by expectations of negative consequences from digital communication.

Motives to Engage in Digital Communication

While H1–H4 test associations derived from the theoretical model of the chilling effects of dataveillance (Büchi et al., 2022), the model remains less specific about moderators that might weaken these associations. We therefore examine the mitigating role of need- and norm-based motives

to engage in digital communication as theory-informed, exploratory extensions of the original model. Based on theory, we formulate exploratory rather than confirmatory predictions of negative moderation: stronger motives may negatively moderate chilling effects by raising the threshold at which self-inhibition occurs in response to higher perceived salience of dataveillance and expected negative consequences from digital communication. Accordingly, self-inhibition may be less likely to be triggered when individuals are motivated to fulfill digital communication needs and adhere to related perceived social norms. Examining these motives is theoretically relevant, as a wide range of theoretical approaches in the social sciences recognize the joint (Grady et al., 2022; Masur, 2019; Ryan & Deci, 2000) and distinct roles of internal needs and motivations (Katz et al., 1973a; Maslow, 1943) and external sources of social influence (Ajzen, 2020; Chung & Rimal, 2016; Fulk et al., 1990; Kelman, 1961) in shaping general and media use behaviors.

Prior research has also begun to identify factors negatively associated with chilling effects. For instance, factual knowledge of dataveillance practices can reduce self-reported chilling effects related to political topics (Stubenvoll & Binder, 2024). Experiencing beneficial online experiences is also negatively related to intended inhibited internet use (Meier & Bol, 2025). In the context of synced advertising, trust is less likely to relate to decreased or changed media use, though this varies depending on country differences, data collection practices, media use behaviors, and institutional actors trusted (Strycharz & Segijn, 2024b). However, our understanding of what makes chilling effects less likely to occur remains limited.

Need-Based Motive to Engage in Digital Communication. We first conceptualize *need-based motives* as moderators of chilling effects of dataveillance and define them as felt needs to engage in digital communication within the U&G tradition, which emphasizes that individuals actively engage in media use “to satisfy their needs” (Katz et al., 1973a, p. 510). The U&G theoretical approach centers on “(1) the social and psychological origins of (2) needs, which generate (3) expectations of (4) the mass media or other sources, which lead to (5) differential patterns of media exposure [...], resulting in (6) need gratifications and (7) other consequences, perhaps mostly unintended ones” (Katz et al., 1973a, p. 510). The approach assumes the active and goal-directed role of media users, who purposively choose and use media because they are “aware of their needs” and want to meet them (Katz et al., 1973a; Lin, 1999, p. 201; Rubin, 2008, p. 167). U&G primarily focuses on what individuals “do with the media,” and views media as functional alternatives in competition with other means for need fulfillment (Katz et al., 1973a; Lin, 1999; Quan-Haase & Young, 2010, p. 351). Although widely used in communication and media research, the U&G approach has been criticized for conceptual imprecision, as terms like *need*, *motive*, *motivation*, and *gratification* tend to be used interchangeably (Alhabash & Ma, 2017; Rubin, 2008; Ruggiero, 2000). Following Lin (1999), needs to use media can be conceived as self-actualization needs aiming to “enhance one’s self-development” (p. 201) and can comprise cognitive, affective, social, escape, and personal integrative needs (Katz et al., 1973b, pp. 166, 167). These needs then shape more specific motives, that is, “desires created by the types of needs that require further drive-reduction or fulfillment,” for instance, motives to use media for information or entertainment (Lin, 1999, p. 202).

Empirical U&G research has extensively examined which needs, motives, and gratifications (sought and obtained) are associated with different media use types (for an overview, see Rubin, 2008; Ruggiero, 2000). With the advent of the internet, survey-based studies have identified these dimensions in the context of internet use (e.g., Flanagin & Metzger, 2001; Papacharissi & Rubin, 2000) and online services, particularly on social media (Aikat et al., 2024; Quan-Haase & Young, 2010). U&G research has shown that users are motivated to use the internet and social media for various purposes, such as social interaction, self-expression, information seeking, entertainment,

and learning (Aikat et al., 2024; Alhabash & Ma, 2017; Stafford et al., 2004). For instance, in a 4-week experience sampling study, Wang et al. (2012) asked 28 U.S. students to report their social media and other media activities, and their level of needs and need gratification for each. They found that higher emotional, social, cognitive, and habitual needs led to increased social media use, compared to only emotional and social needs for other media.

While the U&G approach underlines their importance, needs are “not directly observable and typically are inferred from individuals’ stated or observed motives” (Rubin & Rubin, 1985, p. 41). This study thus directly asked to what extent participants feel the need to engage in different online behaviors. Because need-based motives reflect a stronger orientation toward free digital communication, higher motives may attenuate self-inhibition in response to higher perceived salience of data-veillance or expectations of negative consequences. Returning to our initial example, Anna’s strong need to search for political information may make her less likely to self-inhibit due to perceived salience of dataveillance in everyday life. We formulate these exploratory hypotheses:

H5: The relationship between perceived salience of dataveillance and self-reported self-inhibited digital communication is negatively moderated by the need-based motive to engage in digital communication.

H6: The relationship between expectations of negative consequences from digital communication and self-reported self-inhibited digital communication is negatively moderated by the need-based motive to engage in digital communication.

Norm-Based Motive to Engage in Digital Communication. Since being online is widely prevalent and expected in today’s digital society, we examine whether norm-based motives for digital communication may also moderate chilling effects. We define *norm-based motives* as perceived norms to engage in digital communication, which reflect individuals’ perceptions of a prevalent or expected behavior, and act as a source of behavioral motivation (Cialdini et al., 1990). Social norms represent “unwritten codes of conduct that are socially negotiated and understood through social interaction” (Chung & Rimal, 2016, p. 2). We focus here on the individuals’ perception of these codes (Lapinski & Rimal, 2005, p. 129). Perceived norms are often categorized as descriptive, injunctive, and subjective norms, referring respectively to the perceived prevalence, appropriateness, and expectation to engage in a given behavior; however, their conceptualization and operationalization tend to be inconsistent in the literature (Chung & Rimal, 2016; Masur et al., 2023, p. 6; Shulman et al., 2017). Perceptions of how others behave or what they expect can guide behavioral decisions and prevent social sanctions (Chung & Rimal, 2016, pp. 6, 7). Social science theories, such as the theory of planned behavior (Ajzen, 2020) and the theory of normative social behavior (Rimal & Yilma, 2022), emphasize the distinct influence of perceived norms on behavior. The U&G approach also acknowledges that social context can shape media users’ needs, use patterns, and need satisfaction (Blumler, 1979; Katz et al., 1973a). For instance, Lichtenstein and Rosenfeld (1984) empirically found that independent ratings of perceived media gratifications for other people correlated strongly with those for oneself, suggesting that these perceptions “have a strong, socially learned, normative influence” (p. 410).

The abundant body of (empirical) research across the social sciences demonstrates the importance of social norms for understanding people’s behaviors (Gelfand et al., 2024). In digital contexts, norms emerge, operate, and vary, and shape, for instance, interactions on social media (Heitmayer & Schimmelpfennig, 2024; Zillich & Müller, 2019). Empirical research from the neighboring field of self-disclosure has examined how people engage in free digital communication and manage their digital traces through a normative lens, often in social media use contexts. Studies

with experimental manipulations have shown that online self-disclosure cues can make people more likely to disclose or intend to disclose content or personal information (Dogruel et al., 2023; Masur et al., 2021; Spottswood & Hancock, 2017). Findings from cross-sectional studies with non-general-population samples also suggest that norms pertaining to self-disclosure can be positively associated with related self-reported, intended, or actual online behaviors (Cheung et al., 2015; Masur et al., 2023; Mesch & Beker, 2010).

These insights overall support our argument that internet users are also motivated to engage freely online in response to perceived norms. We thus asked participants to what extent engaging in different behaviors is normal or expected in their private or professional life. In our example, Max feels expected to comment on his friends' social media posts and may therefore be less likely to self-inhibit when he perceives dataveillance as salient or expects negative consequences. Following the same exploratory logic, we hypothesize:

H7: The relationship between perceived salience of dataveillance and self-reported self-inhibited digital communication is negatively moderated by the norm-based motive to engage in digital communication.

H8: The relationship between expectations of negative consequences from digital communication and self-reported self-inhibited digital communication is negatively moderated by the norm-based motive to engage in digital communication.

The model in Figure 1 illustrates the hypothesized associations between the variables involved in the chilling effects process (H1–H4) and its exploratory moderators (H5–H8).

Methods

To test our hypotheses, we used cross-sectional survey data from a representative sample of the Swiss-German internet population and conducted path analyses with mediation and moderation. This approach assesses the population prevalence of the model variables and the strength of their associations, contributing to the limited empirical testing of the theoretical model of the chilling effects (Büchi et al., 2022) and to the exploration of theory-informed moderators.

Data Collection and Participants

The study is part of the larger research project "The Chilling Effects of Dataveillance," funded by the Swiss National Science Foundation. Participants were recruited through the market research firm YouGov Schweiz (previously LINK), completed the online survey in fall 2023, and were financially compensated for their participation. The sample ($N = 898$)¹ is a quota sample representative of the German-speaking internet population in Switzerland and is composed of 50.7% women ($n = 455$). The average age is 47.2 years ($SD = 14.9$, min = 16, max = 79). Most participants had a medium (42.2%, $n = 378$) or high (53.2%, $n = 476$) level of education. Before completing the survey, participants took part in a preregistered 6-week longitudinal field experiment assessing whether an experimentally manipulated, heightened sense of dataveillance leads to online self-inhibition (Festic et al., 2023). To prevent priming, participants were informed at the beginning of the experiment that the study was on online news consumption and information search and were debriefed on the actual study's goal after completing the survey.

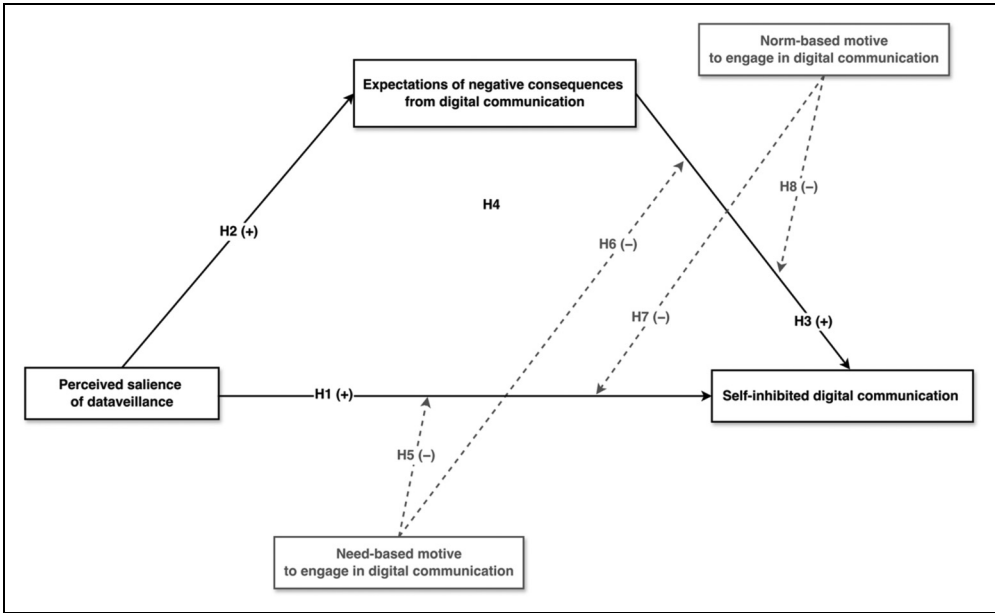


Figure 1. Model with hypotheses.

Measures

The following items were used in our analyses.

Perceived Salience of Dataveillance. As everyday life events can act as everyday salience shocks, or triggers, that increase the salience of dataveillance (Odermatt et al., 2025), participants were asked, on a scale of 1 (never) to 6 (several times a day), how often they encounter the topic of data collection and online surveillance on the internet (*salience_netuse*), think about data collection and surveillance on the internet (*salience_think*), talk to other people about this topic (*salience_talk*), and read or hear news about this topic (*salience_news*).

Expectations of Negative Consequences From Digital Communication. Participants evaluated, on a scale of 1 (do not agree at all) to 5 (fully agree), whether searching for information (*expect_search*), expressing their opinions (*expect_opinion*), and sharing information about themselves (*expect_disclose*) can have negative consequences for their own life. The “privacy risk beliefs” measure from Bol et al. (2018) informed the development of these items.

Need-Based Motive to Engage in Digital Communication. To explicitly measure needs, participants were asked to evaluate to what extent they feel the need to search for information (*need_search*), express their opinions (*need_opinion*), and share personal information (*need_disclose*) on the internet on a scale of 1 (does not apply at all) to 5 (fully applies).

Norm-Based Motive to Engage in Digital Communication. Participants rated, on a scale of 1 (not expected at all) to 5 (strongly expected), to what extent it is normal or expected in their private or professional life to be online to search for information (*norm_search*), express their own

opinions (*norm_opinion*), and share personal information (*norm_disclose*). The development of these items was informed by the work of Masur et al. (2023) on social norms on social media.

Self-Reported Self-Inhibited Digital Communication. Because individuals may self-inhibit for various reasons, we employed a scenario-based conditional formulation to situate self-inhibition specifically in the context of online surveillance and to reduce social desirability bias. This approach is consistent with the use of hypothetical and conditional wording in items from measures like the “willingness to self-censor scale” (Hayes et al., 2005) and the latent variable of “chilling effects-related behaviors” (Stubenvoll & Binder, 2024). Participants read examples of digital communication behaviors and were told that surveillance possibilities on the internet deter some people from engaging in them. They indicated, on a scale of 1 (never) to 5 (always), how often this situation applies to them when they want to find out more about a sensitive topic on the internet (*chilling_search*), express their interest, feelings, or opinions (*chilling_opinion*), or share information about themselves (*chilling_disclose*).

Privacy Concerns. Participants were asked to rate, on a scale of 1 (do not agree at all) to 5 (fully agree), how concerned they are that their data will be misused by others (*privacyconcern_abuse*), will not be securely stored and processed online (*privacyconcern_safe*), will be made available to others without their knowledge (*privacyconcern_share*), and will be seen by people they do not know (*privacyconcern_foreign*). Privacy concerns were treated as a covariate because past research has shown that privacy concerns are associated with chilling effects and self-censorship (Kim & Zo, 2025; Strycharz & Segijn, 2024a).

Sociodemographic Characteristics. As past research showed sociodemographic differences in intended inhibition (Meier & Bol, 2025; Penney, 2017), the following measures were included as covariates: *gender* (male, female), *age* (numeric value), and *education level* (low, medium, high). *Gender* was dummy-coded with male as the reference category.

Data Analysis

In addition to computing descriptive statistics, we conducted path analyses using the *lavaan* package in R (Rosseel, 2012) with observed and latent variables. We performed mediation analyses for H1–H4 and moderation analyses with product terms for H5–H8.

Across all models, we specified separate paths for each behavior—searching for information, expressing opinions, and disclosing personal information—using the corresponding measures for each behavior. We adopted this approach because such measures pertain to specific, concrete, and narrow behaviors (Allen et al., 2022), and to allow us to assess whether the theoretical assumptions of the chilling effects process operate consistently or vary across different types of behaviors, given limited behavior-specific comparative evidence (e.g., Penney, 2017). Privacy concerns and sociodemographic variables were included as covariates to account for their associations with chilling effects found in prior research, while keeping the model specifications aligned with our theory-informed hypotheses.

For the mediation models, maximum likelihood estimation with bootstrap standard errors (5000 bootstrap samples) was used to estimate indirect effects (Hayes, 2022). *Salience* and *privacy concerns* were specified as latent variables. A combined confirmatory factor analysis (CFA) of both variables showed good global fit (Hooper et al., 2008; Hu & Bentler, 1999): χ^2 (19, $N = 889$) =

49.116, $p < .001$, Robust CFI (comparative fit index) = .991, Robust RMSEA (root mean square error of approximation) = .043, SRMR (standardized root mean square residual) = .027.²

For the moderation models, maximum likelihood estimation with robust Huber-White standard errors was used. We mean-centered the independent and moderator variables prior to conducting the moderation analyses to facilitate interpretation (Hayes, 2022), with covariates kept in their original scale. *Salience* was operationalized as a mean index score of all *salience* items (Cronbach's $\alpha = 0.81$, $M = 3.19$; $SD = 0.92$), rather than as a latent variable accounting for measurement error; effect-size estimates from the mediation and moderation models should be compared with caution. The use of single-item measures, including moderators, may also have attenuated sensitivity to detecting interaction effects (Busemeyer & Jones, 1983).

Missing data were handled using full-information maximum likelihood with the complete survey dataset for all models. Missing data accounted for less than 4% of the full survey dataset and the subset including the measures used in our models.³ The Supplemental Material includes item wordings and frequencies, R scripts, descriptive statistics, model outputs, robustness checks, and item correlation matrices.⁴

Results

We begin by presenting the main descriptive statistics. Next, we present our mediation models, which assess the associations between the variables involved in the theoretical process (Büchi et al., 2022) of chilling effects of dataveillance (H1–H4) for each digital communication behavior. We then introduce our moderation models, which examine separately (H5–H8) the exploratory moderating effect of need- and norm-based motives on these associations for each behavior.

Descriptive Statistics: Chilling Effects Variables and Need- and Norm-Based Motives

Participants reported an average perceived salience of dataveillance of 3.19 ($SD = 0.92$) across items, suggesting that they tend to notice dataveillance practices on a monthly basis. Table 1 reports the means of the other measures by behavior. On average, participants reported lower need- and norm-based motives, more expected negative consequences, and greater self-inhibition of their opinion expression and personal information disclosure compared to information search.

Table 2 presents the frequency distributions of need- and norm-based motives for digital communication. Most participants reported strong need-based motives (86.9%) and norm-based motives (65.3%) to search for information, indicating they selected 4 or 5 on both 5-point scales.

Table 1. Item Mean and Standard Deviation by Digital Communication Behavior.

Items	Searching for Information <i>M</i> (<i>SD</i>)	Expressing Opinions <i>M</i> (<i>SD</i>)	Disclosing Personal Information <i>M</i> (<i>SD</i>)
Expectations of negative consequences	2.55 (1.04)	3.76 (0.95)	3.81 (0.96)
Need-based motive	4.42 (0.77)	1.75 (0.94)	1.85 (0.95)
Norm-based motive	3.77 (1.16)	1.79 (0.99)	1.9 (1.01)
Self-reported self-inhibition	2.44 (0.92)	3.04 (1.3)	3.19 (1.24)

Table 2. Frequencies of Response Options for Need- and Norm-Based Motives by Digital Communication Behavior^a.

	1 %	2 %	3 %	4 %	5 %	NA %
Need-based motive						
(1 = does not apply at all to 5 = fully applies)						
Searching for information	0.56	1.22	10.58	30.96	55.9	0.78
Expressing opinions	50.78	29.96	13.36	3.56	1.67	0.67
Disclosing personal information	44.21	33.41	15.92	3.79	1.89	0.78
Norm-based motive						
(1 = is not expected at all to 5 = is strongly expected)						
Searching for information	7.02	5.79	20.49	34.97	30.29	1.44
Expressing opinions	50.89	24.61	16.48	4.57	1.56	1.89
Disclosing personal information	44.99	27.51	19.04	5.57	1.67	1.22

Note. ^aN = 898. NAs include “No answer” and “Don’t know” answers.

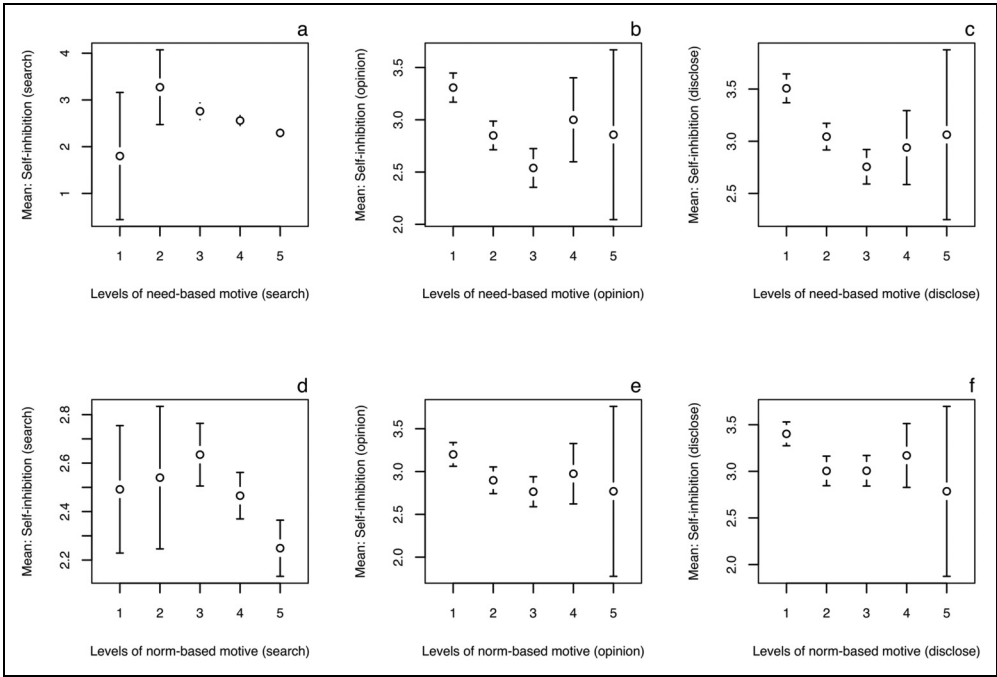


Figure 2. Means with confidence intervals of self-reported self-inhibition across levels of need- and norm-based motives by digital communication behavior, representing unadjusted bivariate descriptive results and not indicating moderation.

In contrast, less than 8% indicated strong need- and norm-based motives for opinion expression and personal information disclosure.

Figure 2 shows average self-reported self-inhibition across levels of need- and norm-based motives. Overall, the tendency to self-inhibit decreases as need- and norm-based motives for

each behavior increase when excluding extreme response options (low motives for searching information: 1 or 2; high motives for expressing opinions and disclosing personal information: 4 or 5). The figure presents bivariate descriptive results unadjusted for other variables, including covariates, and should not be interpreted as evidence of moderation as tested in H5–H8.

Process of Chilling Effects of Dataveillance

Mediation models were estimated separately for information search, opinion expression, and personal information disclosure. Table 3 reports the models' output and global fit, controlling for privacy concerns and sociodemographic characteristics. All models showed good fit. For *information search*, perceived salience of dataveillance was significantly associated with self-reported self-inhibited digital communication (H1) and expectations of negative consequences from digital communication (H2); expectations of negative consequences were also related to self-inhibition (H3), and mediated the relationship between perceived salience and self-inhibition (H4) as indicated by the significant indirect effects ($p < .05$). For *opinion expression*, only the relationships between perceived salience of dataveillance (H1) and expectations of negative consequences (H3) and self-inhibition were significant; H2 and H4 were not supported. For *personal information disclosure*, perceived salience was significantly associated with self-inhibition (H1) and expectations of negative consequences (H2); expectations of negative consequences were also related to self-inhibition (H3), but no mediation was found (H4 not supported). The total effects of perceived salience on self-inhibition were significant in all models.

Role of Need- and Norm-Based Motives in Mitigating Chilling Effects of Dataveillance

Moderation models were estimated separately for each of the four hypothesized moderation paths. In each model, we specified separate paths for each digital communication behavior. All models, reported in Table 4, showed acceptable to good fit. Neither the need-based motive (models 1–2; H5–H6) nor the norm-based motive (models 3–4; H7–H8) to engage in digital communication significantly and negatively moderated the relationship between each independent variable—perceived salience of dataveillance and expectations of negative consequences from digital communication—and self-reported self-inhibition for all behaviors. The results did not support exploratory H5–H8 when controlling for privacy concerns and sociodemographic characteristics.

Robustness Checks

We conducted robustness checks⁵ to assess whether the skewed distributions of the need- and norm-based motives influenced our null moderation findings. Because most participants reported stronger motives for searching for information and lower motives to express opinions and disclose personal information, we recoded the 5-point motive scales. First, we created binary measures using (1) median splits and (2) cutoffs based on distributional tendencies (1–4 as low and 5 as high for the search behavior; 1 as low and 2–5 as high for the opinion expression and disclosure behaviors). Moderation path analyses using these binary measures showed overall no significant interactions.⁶ Second, we treated motives as categorical measures in OLS models, using either the highest motive (5) or lowest motive (1) as the reference category. This approach produced no consistent evidence of moderation; only a few interaction terms were significant, and model comparisons showed that adding categorical interaction terms did not improve model fit relative to baseline models without interactions.

Discussion

In today's data-driven digital society, where being online is both a need and a norm, self-inhibited digital communication when feeling subjected to dataveillance may limit access to opportunities digitalization offers. Drawing on chilling effects, U&G and social norms scholarship, this study asks whether need- and norm-based motives to engage in digital communication mitigate socially undesirable chilling effects of dataveillance across three prevalent behaviors—searching for information, expressing opinions, and disclosing personal information—using survey data from a representative Swiss-German internet population sample analyzed through mediation and moderation path analyses. We report three main findings. First, being strongly motivated to engage in digital communication does not seem to weaken associations between variables involved in the chilling effects process in this study. Second, in line with the chilling effects theoretical model (Büchi et al., 2022), perceived salience of dataveillance and expectations of negative consequences from digital communication are both significantly associated with self-inhibition. Third, descriptive results show distinct response patterns for information search compared to opinion expression and personal information disclosure; the latter two behaviors also show similar patterns in terms of need- and norm-based motives.

Our first finding, based on exploratory moderation analyses, is that the associations examined in the chilling effects process do not seem to depend on stronger motives to engage in free digital communication. Insights from the U&G and social norms approaches suggest that engagement in (media use) behaviors is motivated by need satisfaction and perceived norms to do so (Chung & Rimal, 2016; Katz et al., 1973a). Prior empirical studies also showed that internet users' needs, use motivations, and perceived norms are associated with engagement in digital communication behaviors and self-disclosure, especially on social media (Masur et al., 2023; Wang et al., 2012; Zillich & Müller, 2019). We find little evidence supporting a moderating role of need- and norm-based motives, a pattern consistent across all behaviors examined. Regardless of how strongly users reported felt needs or perceived norms to engage online, higher perceived salience of dataveillance and expected negative consequences from digital communication were overall associated with higher self-reported self-inhibition. This pattern underscores the perceived risks users may associate with dataveillance and suggests that chilling effects may operate relatively consistently in everyday life. Yet these null findings should be interpreted considering methodological limitations and the study design's sensitivity. Moderation remains inherently challenging to detect in non-experimental designs (McClelland & Judd, 1993). The skewed distributions and single-item measurement of the motive variables may have reduced sensitivity (Busemeyer & Jones, 1983); small interaction effects may have remained undetected. Nonetheless, the findings remained consistent in robustness checks using binary and categorical motive specifications. While these checks do not fully resolve limitations regarding vulnerability to measurement error and limited variance, they suggest that the null findings are not specific to the specification of the motive variables.

Accordingly, the lack of evidence supporting moderation suggests a refinement in how motives should be theorized in the chilling effects process: mitigating chilling effects may depend more on situational than stable motives. In our examples, Anna might generally report a strong need to search for information and Max a strong expectation to comment on social media in their everyday life; yet these stable motives may not reduce self-inhibition in momentary situations when they feel subjected to dataveillance, for instance when searching or commenting on sensitive topics. This interpretation resonates with theoretical calls to pay attention to situational factors, such as needs and perceived norms (Masur, 2023; Schnauber-Stockmann et al., 2025a), and with evidence suggesting that situational factors can explain more variance in media use and self-disclosure than

stable ones (Masur, 2019; Schnauber-Stockmann et al., 2025b). It is possible that situational, within-person motives may be more strongly associated with variation in self-inhibition than stable, between-person motives. Furthermore, the moderation models reveal significant negative direct effects of both motives on self-inhibition. While we cannot offer a definitive interpretation due to our conditional outcome variable, this suggests that the potential mitigating effect of motives may be more clearly captured as direct predictors of general self-inhibition. Lastly, a more tentative interpretation is that users may not consciously reflect on their general motivations when deciding whether to self-inhibit. In complex dataveilled environments, bounded rationality may limit people's capacity to "process all relevant information" and make them "rely on simplified mental models, approximate strategies, and heuristics" (Acquisti & Grossklags, 2005, p. 27). Self-inhibition may appear as the safest response where dataveillance is perceived as salient and consequences uncertain, even among those who need or are expected to engage online. In sum, this finding helps clarify how motives may (not) mitigate chilling effects and motivates future longitudinal and experimental research.

A second key finding is that we find empirical evidence broadly aligning with the theoretical model of the chilling effects of dataveillance (Büchi et al., 2022). While most individual hypothesized associations are supported, support for the full mediation models remains partial and behavior-specific. First, when expectations of negative consequences are not accounted for, all models show significant total effects, demonstrating a clear association between perceived salience of dataveillance and self-inhibition. Perceived salience and expected negative consequences from digital communication are also each directly associated with self-inhibition across behaviors. Given the conditional wording of our outcome variable, these associations refer to *surveillance-related* rather than general self-inhibition. Second, behavior-specific differences emerge: all direct paths are significant in the information search and personal information disclosure models, while only the *cp* and *b* paths (from perceived salience and expectations of negative consequences to self-inhibition) are significant in the opinion expression model. The only significant indirect effect—the association between perceived salience and self-inhibition through expected negative consequences—was observed for information search. Given our cross-sectional design, this result should be interpreted as an indirect association consistent with the theoretical process of chilling effects. It suggests that expectations of negative consequences may play a more central role in chilling effects for information search than for opinion expression and personal information disclosure, where other intervening variables may be more influential. Recent works suggest distinguishing between people's experiences and perceptions related to institutional and social surveillance online (Bartol et al., 2026), and relatedly, between concerns and constructs linked to vertical (institutional) and horizontal (social) privacy (Quinn & Epstein, 2023). A tentative interpretation is that behavior-specific differences in indirect effects may relate to the types of digital traces users actively leave behind and to whether these traces are perceived as visible to different surveilling actors, including peers. In networked environments such as social media, digital traces may be visible to multiple audiences (Marwick & boyd, 2014). Expected negative consequences may be shaped by considerations related to institutional but also social surveillance, as suggested by research on online political expression drawing on the spiral of silence theory (Matthes et al., 2018; Stoycheff, 2016). Environmental factors, such as audience size, trust and closeness with other people, or level of access to the content or identity of the discloser, may likewise play a role in self-disclosure (Masur, 2019, 2023, p. 57). For information search, expected negative consequences may be more directly tied to institutional dataveillance. Predictors of behavior-specific differences in chilling effects remain underexplored (e.g., Penney, 2017) and should be tested in future research.

These mediation findings underscore the importance of contextual factors, such as the type of behavior, when investigating behavioral responses to perceptions of dataveillance (e.g.,

Daoust-Braun et al., 2025; Kappeler et al., 2023). Self-inhibition is only one possible response; in other digital contexts, users feeling watched may adopt alternative strategies, such as obfuscation (Brunton & Nissenbaum, 2011), to pursue their online aims while limiting data collection and analysis. Our results offer new evidence consistent with the chilling effects process in everyday digital communication (Kappeler et al., 2023), extending previous works beyond political, sensitive, or advertising contexts (Penney, 2016; Stoycheff, 2023; Strycharz & Segijn, 2024b; Stubenvoll & Binder, 2024). Privacy concerns, modeled as a covariate, are also significantly associated with self-inhibition, aligning with past chilling effects research (Kim & Zo, 2025; Strycharz & Segijn, 2024a). Nonetheless, coefficient estimates and R^2 values across our models remain relatively small. This is in line with prior cross-sectional studies on chilling effects (Strycharz & Segijn, 2024a) and with media effects research more broadly, potentially indicating varying individual susceptibilities (Valkenburg et al., 2016) to chilling effects. Although limited explained variance limits practical significance and warrants investigation into other contributing variables, the findings from our quota-based population sample align with theoretical expectations and concern behaviors central to civic and democratic participation (Büchi et al., 2022).

Our third finding highlights distinctive behavior-specific patterns in how respondents reported motives and chilling effects variables, informing future work measuring attitudes and behaviors in response to dataveillance. First, need- and norm-based motives showed similar response patterns for opinion expression and personal information disclosure, with comparable frequency distributions, relatively strong correlations ($r_{\text{opinion}} = 0.59$; $r_{\text{disclose}} = 0.54$), and moderate shared variance ($r^2_{\text{opinion}} = 0.35$; $r^2_{\text{disclose}} = 0.30$). This similarity may be consistent with the idea that media-related needs are shaped by socially learned processes and expectations (Blumler, 1979; Lichtenstein & Rosenfeld, 1984) or a stronger interplay between the social environment and individual social needs (Grady et al., 2022) in driving these behavior types. Second, while most internet users reported strong motives for information search, only a minority did so for opinion expression and personal information disclosure. On average, participants also reported lower expected negative consequences and less frequent self-inhibition for information search compared to the other behaviors. These patterns suggest that items related to opinion expression and personal information disclosure may capture a shared underlying construct linked to digital traces that may be perceived as visible to different types of surveilling actors, which may involve more complex assessments of possible consequences, as discussed above. The skewed motive-item distributions can inform instrument development to better capture variance in behavior-specific motivations to engage online and, given our representative sample, may also reflect population tendencies in Switzerland. Prior research, for instance, has shown cross-national variation in chilling effects between American and Dutch respondents in advertising contexts (Strycharz & Segijn, 2024a, 2024b). The present findings should therefore be interpreted in relation to the Swiss context, including its stable democratic environment, strong civil rights, data protection framework, and considerable shares of internet users reporting privacy concerns (about 40%) and self-inhibition (over 70%) (Latzer et al., 2025). These contextual factors may have shaped variance in the key variables and may help explain a potential broader cultural or normative reluctance to express opinions and disclose personal information, although this interpretation remains tentative given our single-country, cross-sectional design. Future research should examine whether these patterns hold in other national contexts and develop validated multi-item measures for behavior-specific constructs accordingly.

These insights come with limitations. While our models were theory-derived, equivalent models specifying alternative directional paths might lead to different interpretations (MacCallum et al., 1993). For instance, individuals more likely to self-inhibit may, as a result, be more likely to expect negative consequences. Importantly, our cross-sectional design does not permit causal inference.

We refrain from making any causal claims about mediation without temporal precedence. Additionally, observed and self-reported variables collected in the same survey assume measurement without error, and potential biases, including common-method, recall, and social desirability biases, cannot be ruled out. Prior participation in the longitudinal field experiment may have slightly heightened participants' sense of dataveillance relative to the general population, which should be considered a constraint when interpreting and generalizing the findings. Finally, future studies could design more nuanced measures differentiating referent groups and social norm types (Shulman et al., 2017) to assess the role of norms in self-inhibition.

Conclusion

The chilling effects of dataveillance can limit full participation in digitally dependent societies, yet little is known about what makes them less likely. This study contributes to understanding whether need- and norm-based motives to engage in digital communication mitigate socially undesirable chilling effects. Theoretically, the originality of our work lies in examining how individual responses to dataveillance relate to motivational factors driving digital communication, opening the door to future research. We advance this line of inquiry by integrating U&G and social norms approaches into chilling effects and user-centered dataveillance research, an underexplored intersection. Empirically, we do not find evidence supporting that need- nor norm-based motives negatively moderate chilling effects in this study. This finding helps refine the empirical understanding of the boundary conditions of chilling effects, suggesting that this phenomenon may not vary as a function of stable need- and norm-based motives driving free digital communication. Although self-reported cross-sectional data may introduce bias and cannot establish causality, our work provides representative evidence broadly aligning with the theoretical process of chilling effects (Büchi et al., 2022). Finally, we demonstrate the importance of behavior-specific analyses for a more nuanced investigation and measurement of chilling effects. Our descriptive results show distinct response patterns: compared to information search, participants reported more expected negative consequences, more frequent self-inhibition, and lower motives for opinion expression and personal information disclosure. These contributions underscore the potential gravity of dataveillance effects in everyday life. Returning to our examples, Anna and Max's strong motives to search for political information and comment on social media would not override the negative effect that reading or hearing about dataveillance would have on their free digital communication.

Acknowledgments

The authors thank Céline Odermatt for reviewing the translation and members of the Media Change & Innovation Division, Department of Communication and Media Research (IKMZ), University of Zurich, for their feedback and assistance in the development of this study.

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Ethical Considerations

This study was approved by the Ethics Committee of the Faculty of Arts and Social Sciences of the University of Zurich (no approval number).

Consent to Participate

All participants provided written informed consent to voluntarily participate in the study.

Consent for Publication

All participants provided written informed consent for publication of their anonymized data.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was funded by the Swiss National Science Foundation (grant number 201176). Sarah Daoust-Braun was also supported by the Social Sciences and Humanities Research Council (Canada Graduate Research Scholarship—Doctoral).

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability Statement

Detailed information on the sample, item wording and frequencies, R scripts, descriptive statistics, and model outputs are available on the Open Science Framework: https://osf.io/ugjsf/overview?view_only=d3b4d665c7e346c8b7255aac1c51d11e

Supplemental Material

Supplemental material for this article is available online (https://osf.io/ugjsf/overview?view_only=d032330864664326a7641baece7e6b11).

Notes

1. See the Supplemental Material for sample details: https://osf.io/ugjsf/overview?view_only=d3b4d665c7e346c8b7255aac1c51d11e
2. Nine respondents with missing data on all CFA items were excluded, resulting in $N = 889$.
3. Participants who selected “no answer” or “don’t know” options were treated as missing data. Apart from this, our measures have no nonresponse, except for one participant who did not provide sociodemographic information. Among our model measures, the items *salience_netuse* (5.7%), *chilling_opinion* (7.9%), and *chilling_disclose* (5.3%) have higher missing data rates.
4. https://osf.io/ugjsf/overview?view_only=d3b4d665c7e346c8b7255aac1c51d11e
5. https://osf.io/ugjsf/overview?view_only=d3b4d665c7e346c8b7255aac1c51d11e
6. Under the binary specifications, the association between perceived salience of dataveillance and self-inhibition was significantly moderated by the need-based motive for opinion expression in the direction opposite to our hypothesis. In two models, exogenous variables were treated as fixed because the variance-covariance matrix was not positive definite under the initial specification.

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Appendix

Table 3. Parameter Estimates of Mediation Models by Digital Communication Behavior^a.

Searching for Information				Expressing Opinions			
Latent variables	λ [95% CIs]	SE	Z	p	λ (std.)	SE	Z
saliency							
saliency_netuse	1 [1.00, 1.00]				0.636		
saliency_think	1.13 [1.01, 1.26]	0.064	17.567	<.001	0.838	0.064	17.652
saliency_talk	0.77 [0.67, 0.88]	0.053	14.498	<.001	0.895	0.052	14.642
saliency_news	0.77 [0.68, 0.87]	0.05	15.271	<.001	0.676	0.049	15.49
privacy							
privacyconcern_abuse	1 [1.00, 1.00]				0.849		
privacyconcern_safe	1 [0.94, 1.06]	0.032	31.623	<.001	0.849	0.032	31.552
privacyconcern_foreign	1.05 [0.99, 1.12]	0.034	30.658	<.001	0.817	0.034	30.831
privacyconcern_share	1.02 [0.97, 1.08]	0.029	34.792	<.001	0.859	0.029	35.061
Regressions	b [95% CIs]	SE	Z	p	β	SE	Z
Outcome: expect_search							
saliency (a)	0.157 [0.06, 0.26]	0.052	3.003	.003	0.134	0.046	1.345
privacy	0.316 [0.23, 0.41]	0.045	6.964	<.001	0.27	0.043	5.908
age	-0.006 [-0.01, -0.00]	0.002	-2.545	.011	-0.086	0.002	-2.553
gender_female	0.135 [0.01, 0.27]	0.067	2.023	.043	0.065	0.063	0.189
educationlevel	-0.144 [-0.26, -0.03]	0.059	-2.431	.015	-0.081	0.056	2.663
Outcome: chilling_search							
saliency (cp)	0.141 [0.05, 0.23]	0.046	3.043	.002	0.136	0.061	2.046
expect_search (b)	0.162 [0.10, 0.23]	0.034	4.715	<.001	0.184	0.054	3.29
privacy	0.213 [0.13, 0.29]	0.04	5.368	<.001	0.207	0.059	5.003
age	0.004 [0.00, 0.01]	0.002	2.004	.045	0.069	0.003	5.013
gender_female	0.126 [0.01, 0.24]	0.058	2.187	.029	0.068	0.087	2.977
educationlevel	-0.148 [-0.25, -0.04]	0.052	-2.827	.005	-0.094	0.074	0.46
Indirect effect (a*b)	0.025 [0.01, 0.05]	0.011	2.413	.016	0.025	0.009	1.188
Total effect (cp+a*b)	0.167 [0.08, 0.26]	0.047	3.539	<.001	0.161	0.061	2.224
R ² expect_search = 0.137							
R ² chilling_search = 0.170							
Model fit							
χ^2 (55, N = 898) = 173.886, p < .001, robust CFI = .968, robust RMSEA = .050, SRMR = .043							

(continued)

Outcome: expect_opinion

saliency (a)	0.061 [-0.03, 0.15]	0.046	1.345	.179	0.057
privacy	0.253 [0.17, 0.34]	0.043	5.908	<.001	0.236
age	-0.006 [-0.01, -0.00]	0.002	-2.553	.011	-0.087
gender_female	0.012 [-0.11, 0.13]	0.063	0.189	.85	0.006
educationlevel	0.149 [0.04, 0.26]	0.056	2.663	.008	0.091
Outcome: chilling_opinion					
saliency (cp)	0.124 [0.01, 0.24]	0.061	2.046	.041	0.085
expect_opinion (b)	0.179 [0.07, 0.28]	0.054	3.29	.001	0.132
privacy	0.293 [0.18, 0.41]	0.059	5.003	<.001	0.202
age	0.015 [0.01, 0.02]	0.003	5.013	<.001	0.167
gender_female	0.26 [0.09, 0.43]	0.087	2.977	.003	0.1
educationlevel	0.034 [-0.11, 0.18]	0.074	0.46	.646	0.015
Indirect effect (a*b)	0.011 [-0.00, 0.03]	0.009	1.188	.235	0.008
Total effect (cp+a*b)	0.135 [0.02, 0.26]	0.061	2.224	.026	0.093
R ² expect_opinion = 0.083					
R ² chilling_opinion = 0.127					
Model fit					
χ^2 (55, N = 898) = 161.480, p < .001, robust CFI = .971, robust RMSEA = .047, SRMR = .043					

Table 3. Continued.

Disclosing Personal Information		Latent Variables		λ [95% CIs]		SE	Z	p	λ (std)
salience		salience_netuse		1 [1.00, 1.00]					0.641
		salience_think		1.12 [1.01, 1.25]		0.063	17.678	<.001	0.839
		salience_talk		0.76 [0.66, 0.87]		0.052	14.687	<.001	0.69
		salience_news		0.76 [0.67, 0.86]		0.049	15.539	<.001	0.676
privacy		privacyconcern_abuse		1 [1.00, 1.00]					0.85
		privacyconcern_safe		1 [0.94, 1.06]		0.032	31.506	<.001	0.848
		privacyconcern_foreign		1.05 [0.99, 1.12]		0.034	30.746	<.001	0.815
		privacyconcern_share		1.02 [0.97, 1.08]		0.029	34.883	<.001	0.86
Regressions				b [95% CIs]		SE	Z	p	β
Outcome: expect_disclose		salience (a)		0.092 [0.00, 0.18]		0.045	2.03	.042	0.086
		privacy		0.23 [0.15, 0.32]		0.043	5.28	<.001	0.214
		age		−0.006 [−0.01, −0.00]		0.002	−2.774	.006	−0.096
		gender_female		0.037 [−0.08, 0.16]		0.062	0.6	.548	0.019
		educationlevel		0.119 [0.00, 0.23]		0.058	2.042	.041	0.073
Outcome: chilling_disclose		salience (cp)		0.184 [0.07, 0.30]		0.059	3.128	.002	0.134
		expect_disclose (b)		0.155 [0.06, 0.24]		0.046	3.361	.001	0.12
		privacy		0.278 [0.17, 0.39]		0.058	4.839	<.001	0.202
		age		0.012 [0.01, 0.02]		0.003	4.401	<.001	0.139
		gender_female		0.203 [0.04, 0.36]		0.082	2.488	.013	0.082
		educationlevel		0.044 [−0.09, 0.18]		0.069	0.649	.516	0.021
		Indirect effect (a*b)		0.014 [0.00, 0.03]		0.008	1.685	.092	0.01
		Total effect (cp+a*b)		0.199 [0.08, 0.32]		0.059	3.342	.001	0.144
		R ² expect_disclose = 0.079							
		R ² chilling_disclose = 0.131							
Model fit									
χ^2 (55, N = 898) = 162.049, $p < .001$, robust CFI = .971, robust RMSEA = .047, SRMR = .043									

Note. *CIs = confidence intervals; SE = standard error; salience = perceived salience of dataveillance; privacy = privacy concerns; expect = expectations of negative consequences when engaging in the behavior; chilling = self-reported self-inhibition of the behavior.

$p < .05$ are in bold.

Table 4. Parameter Estimates of Moderation Models by Digital Communication Behavior^a.

Model 1: Moderation Salience * Need					
Latent Variable	λ [95% CIs]	SE	Z	p	λ (std.)
privacy					
privacyconcern_abuse	1 [1.00, 1.00]				0.851
privacyconcern_safe	0.99 [0.93, 1.05]	0.031	31.758	<.001	0.846
privacyconcern_foreign	1.05 [0.98, 1.12]	0.035	30.24	<.001	0.817
privacyconcern_share	1.02 [0.96, 1.08]	0.029	34.773	<.001	0.859
Regressions					
	b [95% CIs]	SE	Z	p	β
Outcome: chilling_search					
salience_c	0.155 [0.08, 0.23]	0.036	4.245	<.001	0.156
need_search_c	-0.188 [-0.27, -0.11]	0.041	-4.576	<.001	-0.16
salience_c x need_search_c	-0.031 [-0.12, 0.06]	0.046	-0.671	.502	-0.026
privacy	0.267 [0.20, 0.34]	0.036	7.336	<.001	0.263
age	0.003 [-0.00, 0.01]	0.002	1.588	.112	0.056
gender_female	0.139 [0.02, 0.25]	0.058	2.389	.017	0.077
educationlevel	-0.135 [-0.24, -0.03]	0.055	-2.464	.014	-0.087
Outcome: chilling_opinion					
salience_c	0.127 [0.03, 0.23]	0.051	2.479	.013	0.091
need_opinion_c	-0.206 [-0.28, -0.13]	0.038	-5.355	<.001	-0.15
salience_c x need_opinion_c	0.065 [-0.00, 0.13]	0.035	1.857	.063	0.053
privacy	0.317 [0.21, 0.42]	0.054	5.872	<.001	0.222
age	0.011 [0.01, 0.02]	0.003	4.013	<.001	0.133
gender_female	0.2 [0.03, 0.37]	0.085	2.354	.019	0.078
educationlevel	-0.007 [-0.15, 0.14]	0.073	-0.09	.928	-0.003
Outcome: chilling_disclose					
salience_c	0.204 [0.11, 0.30]	0.049	4.185	<.001	0.153
need_disclose_c	-0.219 [-0.29, -0.14]	0.038	-5.794	<.001	-0.171
salience_c x need_disclose_c	0.003 [-0.07, 0.07]	0.036	0.071	.943	0.002
privacy	0.302 [0.20, 0.41]	0.054	5.572	<.001	0.222
age	0.009 [0.00, 0.01]	0.003	3.615	<.001	0.115
gender_female	0.181 [0.03, 0.34]	0.079	2.295	.022	0.075
educationlevel	0.035 [-0.10, 0.17]	0.068	0.516	.606	0.017
Model fit					
R ² chilling_search = 0.130					
R ² chilling_opinion = 0.106					
R ² chilling_disclose = 0.119					
Model fit					
Scaled χ^2 (63, N = 898) = 183.576, $p < .001$, robust CFI = .962, robust RMSEA = .047, SRMR = .050					

(continued)

Table 4. Continued.

Model 2: Moderation Salience * Norm					
Latent Variable	λ [95% CIs]	SE	Z	p	λ (std.)
privacy					
privacyconcern_abuse	1 [1.00, 1.00]				0.851
privacyconcern_safe	0.99 [0.93, 1.05]	0.031	31.796	<.001	0.846
privacyconcern_foreign	1.05 [0.98, 1.12]	0.035	30.25	<.001	0.817
privacyconcern_share	1.02 [0.96, 1.08]	0.029	34.806	<.001	0.859
Regressions					
	b [95% CIs]	SE	Z	p	β
Outcome: chilling_search					
salience_c	0.148 [0.08, 0.22]	0.036	4.075	<.001	0.149
norm_search_c	-0.071 [-0.12, -0.02]	0.025	-2.801	.005	-0.091
salience_c $\times$ norm_search_c	0.014 [-0.04, 0.07]	0.028	0.51	.61	0.018
privacy	0.277 [0.20, 0.35]	0.037	7.485	<.001	0.273
age	0.003 [-0.00, 0.01]	0.002	1.342	.18	0.047
gender_female	0.138 [0.02, 0.25]	0.058	2.369	.018	0.076
educationlevel	-0.144 [-0.25, -0.04]	0.054	-2.646	.008	-0.092
Outcome: chilling_opinion					
salience_c	0.122 [0.02, 0.22]	0.051	2.394	.017	0.087
norm_opinion_c	-0.134 [-0.20, -0.07]	0.035	-3.84	<.001	-0.103
salience_c $\times$ norm_opinion_c	0.019 [-0.04, 0.08]	0.032	0.59	.555	0.016
privacy	0.325 [0.22, 0.43]	0.055	5.945	<.001	0.226
age	0.012 [0.01, 0.02]	0.003	4.156	<.001	0.139
gender_female	0.238 [0.07, 0.41]	0.086	2.768	.006	0.093
educationlevel	0.013 [-0.13, 0.16]	0.073	0.173	.863	0.006
Outcome: chilling_disclose					
salience_c	0.196 [0.10, 0.29]	0.049	4.006	<.001	0.147
norm_disclose_c	-0.14 [-0.21, -0.07]	0.034	-4.172	<.001	-0.116
salience_c $\times$ norm_disclose_c	-0.02 [-0.08, 0.04]	0.032	-0.633	.527	-0.017
privacy	0.308 [0.20, 0.42]	0.055	5.63	<.001	0.225
age	0.009 [0.00, 0.01]	0.003	3.533	<.001	0.115
gender_female	0.199 [0.04, 0.36]	0.08	2.488	.013	0.081
educationlevel	0.04 [-0.09, 0.17]	0.069	0.581	.561	0.019
Model fit					
R ² chilling_search = 0.118					
R ² chilling_opinion = 0.098					
R ² chilling_disclose = 0.105					
Scaled χ^2 (63, N = 898) = 201.290, $p < .001$, robust CFI = .956, robust RMSEA = .051, SRMR = .050					

(continued)

Table 4. Continued.

Model 3: Moderation Expect * Need				
Latent Variable	λ [95% CIs]	SE	Z	p
privacy				
privacyconcern_abuse	1 [1.00, 1.00]			
privacyconcern_safe	0.99 [0.93, 1.05]	0.031	31.796	<.001
privacyconcern_foreign	1.05 [0.98, 1.12]	0.035	30.258	<.001
privacyconcern_share	1.02 [0.96, 1.08]	0.029	34.829	<.001
Regressions				
	b [95% CIs]	SE	Z	β
Outcome: chilling_search				
expect_search_c	0.159 [0.10, 0.22]	0.032	4.947	<.001
need_search_c	-0.146 [-0.23, -0.06]	0.043	-3.425	.001
expect_search_c x need_search_c	0.045 [-0.04, 0.13]	0.044	1.026	.305
privacy	0.258 [0.19, 0.33]	0.035	7.336	<.001
age	0.004 [-0.00, 0.01]	0.002	1.907	.057
gender_female	0.081 [-0.03, 0.19]	0.058	1.405	.16
educationlevel	-0.093 [-0.20, 0.01]	0.054	-1.715	.086
Outcome: chilling_opinion				
expect_opinion_c	0.162 [0.08, 0.25]	0.043	3.77	<.001
need_opinion_c	-0.164 [-0.24, -0.09]	0.039	-4.24	<.001
expect_opinion_c x need_opinion_c	-0.022 [-0.09, 0.05]	0.037	-0.583	.56
privacy	0.322 [0.22, 0.43]	0.053	6.09	<.001
age	0.012 [0.01, 0.02]	0.003	4.277	<.001
gender_female	0.178 [0.01, 0.34]	0.084	2.115	.034
educationlevel	-0.001 [-0.14, 0.14]	0.073	-0.009	.993
Outcome: chilling_disclose				
expect_disclose_c	0.131 [0.05, 0.21]	0.041	3.156	.002
need_disclose_c	-0.186 [-0.26, -0.11]	0.038	-4.885	<.001
expect_disclose_c x need_disclose_c	-0.023 [-0.09, 0.04]	0.034	-0.684	.494
privacy	0.336 [0.23, 0.44]	0.053	6.345	<.001
age	0.01 [0.00, 0.02]	0.003	3.766	<.001
gender_female	0.142 [-0.01, 0.30]	0.08	1.783	.075
educationlevel	0.064 [-0.07, 0.20]	0.07	0.922	.357
Model fit				
R ² chilling_search = 0.137				
R ² chilling_opinion = 0.111				
R ² chilling_disclose = 0.119				
Scaled χ^2 (77, N = 898) = 212.169, $p < .001$, robust CFI = .958, robust RMSEA = .045, SRMR = .062				

(continued)

Table 4. Continued.

Model 4: Moderation Expect * Norm					
Latent Variable	λ [95% CIs]	SE	Z	p	λ (std.)
privacy					
privacyconcern_abuse	1 [1.00, 1.00]				0.851
privacyconcern_safe	0.99 [0.93, 1.05]	0.031	31.817	<.001	0.846
privacyconcern_foreign	1.05 [0.98, 1.12]	0.035	30.273	<.001	0.817
privacyconcern_share	1.02 [0.96, 1.08]	0.029	34.841	<.001	0.859
Regressions					
	<i>b</i> [95% CIs]	SE	Z	p	β
Outcome: chilling_search					
expect_search_c	0.178 [0.12, 0.24]	0.031	5.65	<.001	0.205
norm_search_c	-0.061 [-0.11, -0.01]	0.026	-2.319	.02	-0.078
expect_search_c $\times$ norm_search_c	-0.008 [-0.06, 0.04]	0.026	-0.32	.749	-0.012
privacy	0.259 [0.19, 0.33]	0.035	7.345	<.001	0.257
age	0.004 [-0.00, 0.01]	0.002	1.689	.091	0.06
gender_female	0.09 [-0.02, 0.20]	0.058	1.555	.12	0.05
educationlevel	-0.095 [-0.20, 0.01]	0.054	-1.772	.076	-0.061
Outcome: chilling_opinion					
expect_opinion_c	0.18 [0.10, 0.26]	0.043	4.169	<.001	0.134
norm_opinion_c	-0.115 [-0.18, -0.05]	0.035	-3.316	.001	-0.088
expect_opinion_c $\times$ norm_opinion_c	0.005 [-0.06, 0.07]	0.033	0.144	.886	0.004
privacy	0.318 [0.21, 0.42]	0.053	5.979	<.001	0.222
age	0.013 [0.01, 0.02]	0.003	4.455	<.001	0.15
gender_female	0.212 [0.05, 0.38]	0.085	2.5	.012	0.083
educationlevel	0.017 [-0.13, 0.16]	0.073	0.23	.818	0.008
Outcome: chilling_disclose					
expect_disclose_c	0.151 [0.07, 0.23]	0.041	3.698	<.001	0.118
norm_disclose_c	-0.124 [-0.19, -0.06]	0.034	-3.688	<.001	-0.102
expect_disclose_c $\times$ norm_disclose_c	0.043 [-0.02, 0.10]	0.03	1.423	.155	0.035
privacy	0.329 [0.22, 0.43]	0.054	6.136	<.001	0.24
age	0.01 [0.00, 0.02]	0.003	3.747	<.001	0.123
gender_female	0.157 [-0.00, 0.31]	0.08	1.955	.051	0.064
educationlevel	0.069 [-0.07, 0.21]	0.07	0.991	.322	0.033
R^2 chilling_search = 0.130					
R^2 chilling_opinion = 0.106					
R^2 chilling_disclose = 0.106					
Model fit					
Scaled χ^2 (77, N = 898) = 221.003, $p < .001$, robust CFI = .954, robust RMSEA = .047, SRMR = .062					

Note. ^aCIs = confidence intervals; SE = standard error; *privacy* = privacy concerns; *salience_c* = perceived salience of dataveillance; *expect_c* = expectations of negative consequences; *need_c* = need-based motive; *norm_c* = norm-based motive; *chilling* = self-reported self-inhibition of the behavior. Independent and moderator variables (*salience_c*, *expect_c*, *need_c*, *norm_c*) were mean-centered. $p < .05$ are in bold.