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Too Tired and in Too Good of a Mood to Worry About Privacy: Explaining the Privacy Paradox Through the Lens of Effort Level in Information Processing

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Abstract. The confluence of digital transactions, growing cybersecurity threats, and the internet of the future (e.g., web 3.0 and the metaverse) have made information privacy increasingly important to consumers and companies that rely on consumers willingly sharing their personal information. Although information privacy has been of interest to researchers for decades and much has been learned, one thing that perplexes scholars is the privacy paradox, which we define as a mismatch between stated privacy concerns and actual disclosure behaviors. In this paper, we shed light on this phenomenon and show that low-effort information processing triggered by cognitive depletion (Experiment 1), positive mood (Experiment 2), or both (Experiment 3) significantly attenuates the association between stated privacy concerns and disclosure behaviors. These findings do not indicate that individuals do not care about privacy because we find consistent evidence in the three experiments for a significant negative association between stated privacy concerns and disclosure behaviors when individuals have sufficient cognitive capacity (Experiment 1), experience a negative (or neutral) mood (Experiment 2), or have sufficient cognitive capacity coupled with a negative mood state (Experiment 3). Our findings reveal that the paradox is neither an absolute phenomenon nor a myth, but its existence is conditional on contextual factors, including psychological factors related to information processing. We discuss our contribution to privacy theory and provide implications for consumers, companies, and policymakers.

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1. Introduction

In today's information age, the desire to preserve privacy is sometimes difficult because individuals may have no choice but to provide personal information to utilize certain digital technologies. However, there are many situations in which individuals can exercise a choice to preserve privacy in a manner that is consistent with their desire but choose not to do so. When this occurs, it represents "an apparent gap, or dichotomy, between people's self-reported mental states (attitudes, concerns, desires, etc.) regarding privacy and their actual behaviors" (Acquisti et al. 2020, p. 749). This dichotomy is known as the privacy paradox, and it has received considerable scholarly attention in the past two decades because of its profound policy implications on consumer privacy choice and market behaviors (Acquisti et al. 2020). For example, consumers want to share personal information with others. However, they also want to protect their personal information from misuse and unauthorized access. These competing desires may disrupt the efficiency of markets that depend on personal information (e.g., social media, data brokers, and metaverse platforms; Uberti 2022). From a macrolevel view, consumers' demand for sharing and protecting is high. However, the market is skewed toward triggering sharing behaviors and to a much lesser extent toward protecting consumers' personal information. In this study, we examine the privacy paradox to gain insight into how individuals make privacy decisions given their stated privacy concerns. Our aim in doing so is to provide theoretical and practical implications that will be useful in finding the right balance between protecting individuals' privacy and creating economic value for the companies that have built their business models around creative ways to leverage personal information.

Whereas evidence for the privacy paradox abounds (Barth and de Jong 2017, Kokolakis, 2017), the literature is mixed in terms of its ubiquity, and some even argue that the privacy paradox itself is a myth (Solove 2021); thus, there is a lack of clarity around whether individuals truly care about privacy. Acquisti et al. (2020) argue that the mixed views in this area are due to the different conceptual bases used to define the privacy paradox and the various interpretations of the term "paradox." According to Acquisti et al. (2020), occurrences of the paradox do not necessarily indicate that individuals do not care about privacy, and evidence of situations in which privacy mental states match privacy decisions does not necessarily indicate that individuals are always able to act on their desired privacy preferences. Put simply, the paradox is more or less likely to occur depending on many psychological and economic factors that are not necessarily mutually exclusive. Our objective is to add clarity to the scholarly conversation on the privacy paradox by following a systematic approach to uncover some of the conditions under which the association between stated privacy concerns and disclosure behaviors is significantly weakened. Specifically, we test the assumption of high-effort information processing in privacy decisions,[1] which might be compromised by two commonly occurring conditions (i.e., cognitive resource depletion and positive mood). By investigating these conditions, we provide one explanation for why individuals who profess to be concerned about privacy sometimes behave in ways that would suggest otherwise. Our endeavor to provide an explanation of the paradox has important policy implications (Acquisti et al. 2015, 2020; Solove 2021).

One example of the privacy paradox is when people sign up for loyalty cards in which they reveal sensitive personal information even if they have high privacy concerns (Acquisti and Grossklags 2005; also see Acquisti and Gross 2006). Such cases suggest that privacy concerns are a weak predictor of privacy decisions, which may, in turn, provide support for the notion that individuals do not care about privacy. Consistent with Acquisti et al. (2020), however, we argue that such occurrences of the privacy paradox do not necessarily indicate that individuals do not care about privacy. Rather, these findings suggest boundary conditions under which the association between privacy concerns and decisions might be significantly weakened. In this regard, we leverage a systematic approach to identify certain conditions under which privacy concerns are less likely to be associated with disclosure behaviors. We build on three main points to motivate this systematic approach.

First, researchers examine privacy decisions from two distinct yet complementary perspectives: the normative and behavioral privacy perspectives.[2] The normative perspective tends to assume that individuals are rational decision makers who act on their privacy beliefs and perceptions to optimize their privacy decisions (Culnan and Armstrong 1999, Dinev and Hart 2006, Smith et al. 2011). In contrast, the behavioral perspective suggests that numerous privacy-unrelated factors can significantly shape privacy decisions, and hence, it is unrealistic to assume individual rationality (Acquisti 2004; Acquisti et al. 2016, 2017, 2020). It is important to note that the two perspectives are not necessarily mutually exclusive as evidence from both the normative and behavioral literature suggests that privacy decisions can be influenced by both psychological and economic factors and privacy decision making is driven by a combination of normative and nonnormative factors (Acquisti et al. 2015, Dinev et al. 2015, Buck et al. 2022). Notably, the normative perspective is more attentive to privacy beliefs (e.g., privacy concerns) and their effect on self-reported outcomes (e.g., intention to disclose) (e.g., Dinev and Hart 2006, Son and Kim 2008), whereas the behavioral perspective is more focused on contextual cues (e.g., framing and default choices) and their effect on actual decisions (e.g., disclosure behaviors) (e.g., John et al. 2011; Tsai et al. 2011; Acquisti et al. 2012; Adjerid et al. 2016, 2018).[3] Substantial contributions to knowledge have been made by researchers who have taken each of these perspectives. Consistent with Adjerid et al. (2018), we leverage the positive features of each perspective to advance privacy theory. Thus, we account for privacy beliefs (i.e., privacy concerns) and actual privacy decisions (i.e., disclosure behaviors), and we investigate how privacy-unrelated psychological factors (i.e., cognitive depletion and positive mood) moderate the association between privacy concerns and disclosure behaviors.

Second, prior work on disclosure behaviors tends to focus on either cognition (e.g., Alter and Oppenheimer 2009) or affect (e.g., Forgas 2011). Whereas these studies certainly contribute to our understanding, "privacy decisions [disclosure behaviors] … are the outcomes of the collaboration and competition between affective and cognitive assessments in the human mind" (Farahmand 2017, p. 69). Thus, exploring cognition without considering affect or vice versa provides an incomplete picture because cognition and affect are components inherent in the decision-making process (Dolan 2002, Homburg et al. 2006). Accordingly, we consider both components in this study to advance the existing body of knowledge in this area.

Third, it is unclear how the effort level in information processing moderates the association between privacy concerns and disclosure behaviors (Dinev et al. 2015). Some evidence suggests that exerting cognitive effort leads to lower disclosure (Alter and Oppenheimer 2009), whereas some findings suggest otherwise (Balebako et al. 2013). In addition to the mixed findings, research in this area cannot explain the privacy paradox because it is aimed at explaining disclosure behaviors, not the dichotomy between privacy beliefs and privacy decisions, such as disclosure behaviors. We contribute to the existing body of knowledge on how the effort level in information processing can explain possible fluctuations in the association between privacy concerns and disclosure behaviors.

Psychological theories (Petty and Cacioppo 1986, Petty and Briñol 2010) suggest that, under conditions in which information processing is diminished because of cognitive demands or affective experiences, individuals are less likely to make decisions that reflect strongly elaborated beliefs. Thus, to explain and predict the privacy paradox, it is important to account not only for individuals' privacy beliefs (e.g., privacy concerns), but also the amount of effort associated with individuals' information processing. In this study, we use the lens of effort level in information processing to consider some conditions under which privacy concerns are differentially predictive of privacy decisions. Specifically, we demonstrate that the privacy paradox is more likely to manifest under conditions in which information processing is low but that it is less likely to occur under conditions in which information processing is high. Such systematic investigation is timely considering the emerging literature on the privacy paradox.

We adopt the elaboration likelihood model (ELM) as the foundation for our research (Petty and Cacioppo 1986). According to the ELM, there are two processing routes: one requiring high effort (the central route) and the other reflecting low-effort processing (the peripheral route). Many factors can influence whether an individual engages in higher effort central route processing or follows heuristic processing along the peripheral route (Petty and Briñol 2010). In this study, we focus on cognitive resources and mood states, each of which may affect information processing effort in privacy decisions. Our rationale for examining the effects of both cognitive resources and mood states is that (1) they often operate together across a wide variety of different contexts (Middlewood et al. 2016) and (2) there is limited research examining the interactive effect of cognition and affect in privacy contexts (Farahmand 2017). Indeed, people often make privacy decisions without fully reflecting on their privacy beliefs because of the cognitive and affective conditions at the moment of making those decisions. For example, full consideration of privacy choices provided by a website, especially when they are granular (e.g., https://www.theguardian.com/) requires scrolling through many items, and a high degree of cognitive effort is required to consider the choices carefully so as to ensure that one's decisions are consistent with one's privacy beliefs. Further, at the point in time at which such decisions are typically made, an individual might be eagerly anticipating a product or service that would put one in a positive affective state. In such situations, both cognitive and affective conditions may weaken individuals' ability to act on their privacy beliefs, and they may provide personal information even when the choice not to do so exists. Thus, our primary research question is the following: do conditions that reduce effortful information processing attenuate the association between privacy concerns and disclosure behaviors, giving rise to a privacy paradox?

Our findings reveal that low-effort information processing triggered by cognitive depletion (Experiment 1), positive mood (Experiment 2), or both (Experiment 3) significantly attenuates the association between privacy concerns and disclosure behaviors. These findings do not indicate that individuals do not care about privacy because we find consistent evidence in the three experiments for a significant negative association between privacy concerns and disclosure behaviors when individuals have sufficient cognitive capacity (Experiment 1), experience a negative (or neutral) mood (Experiment 2), or have sufficient cognitive capacity coupled with a negative mood state (Experiment 3). In sum, our study identifies conditions that attenuate the association between privacy concerns and disclosure behaviors, supporting the notion of malleability in privacy decisions (Acquisti et al. 2015), and shows that privacy awareness alone on the part of consumers is likely insufficient to protect their desired privacy without effective interventions by companies (e.g., privacy-enhancing technologies) and governments (e.g., regulations) (Acquisti et al. 2015, 2017, 2020).

We contribute to the literature in several ways. First, our study investigates decision making under conditions of low- versus high-effort information processing, thus providing insights for privacy theory when privacy concerns are less or more likely to be associated with disclosure behaviors. In doing so, we present systematic evidence for explaining and predicting possible occurrences of the privacy paradox. These findings have important implications for consumers, companies, and policymakers, which we discuss further in the implications section. Second, this work distinguishes between psychological conditions that are both external (i.e., depleting cognitive tasks) and internal (i.e., mood states) to the individual, and we advance prior privacy research by considering the effects of both cognitive and affective conditions (Farahmand 2017). Dinev et al. (2015) introduce a theoretical model highlighting the role of cognitive depletion and mood in privacy decisions, but the model does not consider the joint effect of cognition and affect. As we show in this study, the joint effect of cognition and affect is pronounced. Moreover, to date, there is no empirical evidence as to whether the theoretical propositions suggested by the Dinev et al. (2015) model hold up under scrutiny. Thus, in addition to testing a number of propositions suggested by the Dinev et al. (2015) enhanced antecedents—privacy concerns—outcomes (e-APCO) model, we theorize and test the joint effect of cognitive depletion and mood on the association between privacy concerns and disclosure behaviors. Third, in addition to capturing individuals' privacy concerns, our experiments assess actual disclosure behaviors rather than self-reported behaviors or stated intentions, which are the usual measures of disclosure in the normative privacy literature. Finally, our study contributes to the psychology literature by demonstrating how cognitive demands and mood states, independently and jointly, influence the associations between attitudes and behaviors.

2. Background and Hypotheses

In this section, we provide background information to derive four hypotheses. We begin by reviewing relevant privacy research (Section 2.1). The first hypothesis is best viewed as a replication of findings from many previous studies that, other things being equal, greater privacy concerns reduce disclosure behaviors. The rationale for replicating this hypothesis is to set up a systematic approach for testing and explaining possible occurrences of the privacy paradox (Section 2.1.1). Specifically, although the effect of privacy concerns on disclosure behaviors may generally exist, this effect may be attenuated (i.e., moderated) under conditions that reduce information processing effort. Next, we offer a brief discussion of the ELM (Section 2.2) followed by a derivation of our new hypotheses (Section 2.3).

2.1. Privacy Concerns and Information Disclosure

Privacy concerns refer to a dispositional belief that reflects the loss of control over personal information (Westin 2003, Solove 2006) and could significantly influence privacy decisions (Smith et al. 1996, 2011). Research shows that individuals who have high privacy concerns are less willing to purchase products online, to use social media, to adopt electronic health records, or to share personal information (Dinev and Hart 2006, Hui et al. 2007, Angst and Agarwal 2009, Xu et al. 2009, Jiang et al. 2013).

Information disclosure refers to the breadth and depth of revelations individuals voluntarily make (Krasnova et al. 2010, Posey et al. 2010). From a theoretical perspective, the association between privacy concerns and disclosure behaviors is largely based on the attitude–intention link suggested by the theory of planned behavior (Ajzen 1991).[4] As a result, the majority of studies in the normative privacy literature rely on a dependent variable that does not necessarily reflect actual behaviors (e.g., intention to disclose) (Smith et al. 2011, Yu et al. 2020). Nevertheless, findings from different disciplines strongly support a negative association between privacy concerns and disclosure-related outcomes (for review, see Li 2011, Smith et al. 2011, Yun et al. 2019). Although there are a few empirical studies in the normative privacy literature that assess actual disclosure (Hui et al. 2007, Sutanto et al. 2013, Keith et al. 2015), we replicate this hypothesis to present evidence for and explain the privacy paradox in a systematic way.

Hypothesis 1. *Privacy concerns are negatively associated with disclosure behaviors.*

2.1.1. The Privacy Paradox. In our study, exceptions to Hypothesis 1 reveal the privacy paradox.[5] However, it is important to note that the privacy paradox is conceptualized by scholars in different ways (Acquisti et al. 2020). For example, some scholars define it as a mismatch between stated disclosure intentions and actual disclosure behaviors (Norberg et al. 2007, Pavlou 2011, Keith et al. 2015).[6] Others argue and empirically show that the paradox is relevant to actual, but not hypothetical, privacy scenarios (Adjerid et al. 2018), suggesting that the paradox is more likely to occur between privacy beliefs and actual disclosure behaviors, not disclosure intentions. Moreover, mismatches between privacy attitudes and stated intentions or actual behaviors are used to define the privacy paradox (for review, see Barth and de Jong 2017, Kokolakis, 2017, Acquisti et al. 2020, Solove 2021). In our study, we define the privacy paradox as a mismatch or dichotomy between stated privacy concerns and actual disclosure behaviors (Smith et al. 2011), and hence, we build on the work of Adjerid et al. (2018) to identify why the paradox may manifest in certain actual scenarios.

The Spiekermann et al. (2001) study is one of the earliest in which a mismatch between stated privacy concerns and disclosure behaviors is observed. In their study, participants interacted with an experimental agent (an anthropomorphic bot in an online shopping store), but their privacy concerns did not determine their disclosure of purchasing preferences to the agent. Acquisti and Grossklags's (2005) study also presents evidence supporting this privacy paradox. Their study reports that a large majority of privacy fundamentalists signed up for a loyalty card in which they revealed sensitive identifying information (Acquisti and Grossklags 2005). Both studies, however, also show a significant association between privacy concerns and decisions. For example, privacy concerns were significantly associated with disclosure of personal information outside the online shopping environment (Spiekermann et al. 2001) and with privacy-protective behaviors (Acquisti and Grossklags 2005).

Several accounts are proposed to explain the privacy paradox in both the normative and behavioral literatures (Acquisti 2004, Acquisti and Grossklags 2005, Dinev and Hart 2006, Barth and de Jong 2017, Kokolakis 2017). However, a comprehensive explanation for the privacy paradox has not emerged for several reasons. First, several contextual (e.g., psychological and economic) factors can explain those situations in which privacy concerns do not predict privacy decisions; this means that several plausible explanations for the paradox exist (Acquisti et al. 2020). Because it is theoretically and empirically challenging to account for all such factors, generating one single explanation for the paradox is unrealistic. Second, the normative and behavioral perspectives represent two distinct streams of literature that focus on privacy decisions from different theoretical and methodological perspectives, making it difficult to reconcile them. As Adjerid et al. (2018, p. 466) point out, "comparisons between the results produced within the two literatures are post hoc, requiring meta-analysis across studies with diverse modeling assumptions and empirical methodologies." Third, many studies that examine privacy concerns or decisions do not focus on the privacy paradox and, thus, tend to measure one or the other but not both privacy concerns and decisions.

For instance, the majority of studies in the normative privacy literature measure privacy concerns but rely on outcomes that do not necessarily reflect actual privacy decisions, such as intention or willingness (e.g., Dinev and Hart 2006, Taddicken 2014, Woodruff et al. 2014, Kehr et al. 2015, Karwatzki et al. 2017, Li et al. 2017). In contrast, the majority of studies in the behavioral privacy literature assess actual privacy decisions but do not assess privacy concerns (e.g., John et al. 2011; Tsai et al. 2011; Acquisti et al. 2012, 2013; Adjerid et al. 2016). It is important to note that the main purpose of many studies within these two streams of literature was not to study the paradox (exceptions include but are not limited to Taddicken 2014, Li et al. 2017, Adjerid et al. 2018) and that is perhaps why they did not seek to account for both privacy concerns and decisions.

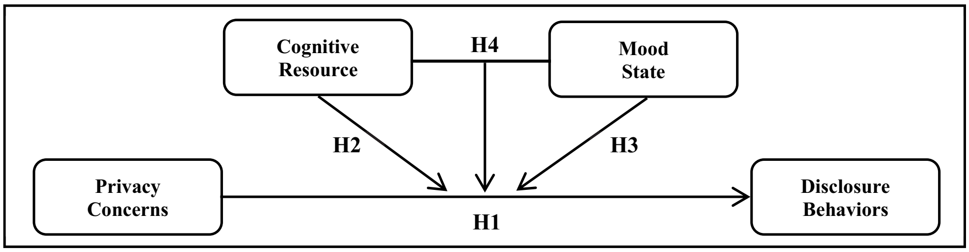
Whereas some studies investigate gaps between attitudes or behavioral intentions and actual decisions, only a handful of studies examine both privacy concerns and decisions. Some of these studies suggest that privacy concerns are significantly associated with privacy decisions (for instance, Hui et al. 2007, Sutanto et al. 2013, Keith et al. 2015). Other studies find privacy concerns not to be associated with decisions (for instance, Spiekermann et al. 2001, Acquisti and Gross 2006, Adjerid et al. 2018). Whereas this might suggest weak empirical evidence for the privacy paradox, we caution against such an interpretation. First, studies that do not measure actual privacy decisions present tentative support for the existence of the privacy paradox. For instance, research shows that individuals weigh affect, enjoyment, or social capital much more than they weigh privacy concerns (Debatin et al. 2009, Wakefield 2013, Kehr et al. 2015, Yu et al. 2015, Sun et al. 2017). Anderson and Agarwal (2011) show that the effect of privacy concerns on willingness to share personal information is conditional on the type of information, intended purpose, or requesting stakeholder. Similarly, the behavioral privacy literature indicates that biases and heuristics can significantly affect privacy decisions (Acquisti et al. 2016, 2017, 2020). Together, such findings provide plausible evidence for the possibility of a mismatch between privacy concerns and decisions given the context effects on privacy concerns and decisions (Xu and Zhang 2022). In the current research, we experimentally manipulate some conditional factors to explore some boundary conditions under which the privacy paradox operates. Boundary conditions are discussed by theorists and empiricists for enhancing the generalizability of a theory and resolving paradoxical phenomena (Whetten 1989, Edwards and Berry 2010, Busse et al. 2017), including privacy-related theories and phenomena (Xu and Zhang 2022). Our systematic approach advances privacy theory in general and enriches our understanding of the privacy paradox by leveraging the ELM and its implications for how the level of information processing affects decision making.

2.2. Elaboration Likelihood Model (ELM)

Our theoretical approach is grounded in the ELM (Petty and Cacioppo 1981, 1986; Petty and Wegener 1998). The ELM is embraced as a prominent psychological theory that explains differences in two important routes involved in decision making: the central and peripheral routes. As explained by Petty and Cacioppo (1981), the central route is more likely to reflect a thoughtful consideration of the merits of the information provided, whereas the peripheral route is likely to be based on simple cues rather than extensive scrutiny of the merits of the information presented. Following Dinev et al. (2015), we refer to the former as "high-effort" processing and the latter as "low-effort" processing.

In order to employ high-effort processes, the ELM holds that an individual must have both the motivation and ability to process relevant information (Petty and Cacioppo 1981, Petty and Wegener 1998). For example, if people are cognitively depleted or performing tasks when mentally fatigued, they are less likely to engage in high-effort information processing (Bodenhausen 1990). One's ability to process information extensively is determined by many factors, such as the extent to which one can devote effortful attention to decision-related information. To the extent that one is low on either motivation or ability to process relevant information, one does not engage in elaborative information processing before acting (e.g., reflecting on well-elaborated beliefs to inform behaviors), and thus, one's actions are more strongly directed by peripheral cues. In this research, we theorize that triggering low-effort information processing, whether as a result of depleted cognitive resources or from being in a positive mood state, attenuates the association between privacy concerns and disclosure behaviors, giving rise to the privacy paradox. Figure 1 depicts our research model.

Figure 1. Research Model



2.3. Cognitive Resource and Mood State

Cognitively demanding tasks can deplete people's working memory capacity, which can reduce their ability to engage in high-effort information processing on subsequent tasks (Baddeley and Hitch 1974, Engle 2002). Just as running a marathon can exhaust an athlete and lead to less effort being expended on a subsequent run, so too can a cognitively taxing activity reduce effortful information processing in a later judgment and decision-making task (Muraven and Baumeister 2000, Beilock et al. 2007). Using techniques (to be described) to manipulate participants into either a low- or high-depletion state, we theorized that participants in a high-depletion condition should, when later asked to disclose personal information, be less able to act in line with their privacy concern beliefs. As a result, the usual linkage between privacy concerns and disclosure behaviors (Hypothesis 1) is attenuated for highly depleted individuals because they do not have sufficient cognitive capacity to enact privacy-related behaviors that are consistent with their long-term goals (e.g., protection of personal information). Thus, when encountering a request to disclose personal information, they are less likely to base the disclosure decision on their dispositional privacy concerns because their cognitive capacity is low. When cognitive capacity is sufficient, however, individuals are more likely to act on their privacy concerns when encountering a request to disclose personal information. In sum, cognitive depletion can influence information processing capacity, which, in turn, moderates the negative association between privacy concerns and disclosure behaviors.

Hypothesis 2. *Cognitive resource depletion moderates the negative association between privacy concerns and disclosure behaviors such that the association is weaker (stronger) when cognitive depletion is high (low).*

We also rely on a second path by which effortful information processing can be influenced: mood state. Mood is an affective state that resides within the person (hence, an internal condition) and reflects a diffuse positive or negative feeling without a clear cause to the individual (Schwarz and Clore 1988, 2007; Morris 1989; Forgas 1995; Zhang 2013).[7] It is widely shown that mood states influence decision making and behavior (Isen et al. 1978; Clark and Isen 1982; Schwarz and Clore 1988, 2007; Schwarz 1990; Forgas 1995, 2017), including those involving attitude-to-behavior processes (Bless et al. 1990, Petty and Wegener 1998). In particular, when people are in a positive mood, they show less effortful information processing and greater reliance on heuristics in their behavior (Bless et al. 1990, Park and Banaji 2000). In short, experiencing a positive mood signals that "everything is okay," and thus, individuals are less interested in thoughtful analysis of their circumstances, and as a result, they do not typically engage in effortful evaluation (Schwarz and Clore 1988, 2007; Wegener and Petty 1994).

There is some support in the privacy literature consistent with the notion that an individual's affective state impacts perception of privacy beliefs and potential risks (Wakefield 2013, Kehr et al. 2015, Yu et al. 2015). For instance, individuals' enjoyment with a website is found to positively predict their privacy protection perceptions of the website and to negatively predict their privacy risk perceptions associated with the website (Li et al. 2011). Another study finds that inducing positive affect leads to underestimations of potential privacy threats (Kehr et al. 2015). These studies, however, do not measure privacy decisions, examine the moderating effect of affect, or consider the level of information processing.

More broadly, our reasoning is consistent with research in psychology suggesting that "moods serve as information," which can influence how people perform cognitive tasks (Clark and Isen 1982; Frijda 1988, 2007, 2010; Sanna et al. 1999). Prior research shows that individuals are more likely to disclose personal information when they are in a positive mood state because they are engaging in low-effort information processing (Forgas 2011). Accordingly, we anticipated that individuals experiencing positive mood states would be less likely to rely on their privacy beliefs when presented with a request to disclose private information because of the low-effort information processing. However, individuals in a negative mood state should be more likely to engage in high-effort information processing and can be expected to act more in line with their privacy concerns when encountering a request to disclose personal information.

Hypothesis 3. *Mood state moderates the negative association between privacy concerns and disclosure behaviors such that the association is weaker (stronger) when mood state is positive (negative).*

In summary, the negative association between privacy concerns and disclosure behaviors (Hypothesis 1) should be attenuated when people employ low-effort information processing because of either cognitive depletion (Hypothesis 2) or positive mood states (Hypothesis 3). Thus, as the level of information processing is diminished by either cognitive depletion or positive mood, there is less utilization of one's privacy beliefs when private information might be disclosed. It is also possible that a condition of both cognitive depletion and positive mood results in even less information processing. That is, the simultaneous presence of a positive mood state in an individual who is already depleted of cognitive resources might result in a state of especially impoverished information processing capacity, producing the greatest attenuation effect on the association between privacy concerns and disclosure behaviors. Thus, we also anticipated that the combined condition of cognitive depletion and positive mood would be especially powerful in robbing individuals of their ability to engage in high-effort information processing, rendering a statistically insignificant association between privacy concerns and disclosure behaviors. However, a nondepleted cognitive resource coupled with negative mood should promote high-effort information processing, giving rise to disclosure behaviors that are especially commensurate with individuals' privacy concerns. In summary, the presence of cognitive depletion and a positive mood state (i.e., producing especially low-effort information processing) results in the weakest or insignificant association between privacy concerns and disclosure behaviors, giving rise to the privacy paradox. However, sufficient cognitive resources coupled with a negative mood state (i.e., producing especially high-effort information processing) results in a significant association between privacy concerns and disclosure behaviors.

Hypothesis 4. *The association between privacy concerns and disclosure behaviors is weakest (strongest) when cognitive depletion is high (low) and mood state is positive (negative).*

We conducted three experiments to test our hypotheses. In each experiment, we measured privacy concerns and disclosure behaviors. Table 1 provides information about the key features of each experiment and the hypotheses that were tested. Next, we describe the three experiments.

3. Experiment 1

3.1. Method

We used two consecutive depletion tasks in a randomized experimental design to induce low or high cognitive depletion. Each depletion task was followed by a set of requests for participants to disclose personal information. We used two depletion tasks to ensure that subjects were depleted for both sets of disclosure requests. We developed a new scale to measure actual disclosure behavior following an approach that was similar to that used by many other privacy scholars (e.g., Norberg et al. 2007, Acquisti et al. 2012, Marreiros et al. 2017, Adjerid et al. 2018). Developing a scale was necessary because our context was different given the cover story we used in the experiment (as subsequently explained). We used established measures for privacy concerns and mood (Mayer and Gaschke 1988, Dinev and Hart 2006). We collected the data from Amazon Mechanical Turk (AMT) and participants could earn up to \$3.00 depending on their performance. The final sample included 150 participants after applying exclusion criteria (i.e., failing attention checks or failing to complete the experimental task) to ensure the quality of responses.[8] The mean age of the participants was 38.2, and 48.7% were female.

3.2. Procedure

We chose the context of a mobile health app and created a cover story involving it to create a realistic environment in which we could assess disclosure behavior. Figure 2 depicts the sequence of tasks involved in Experiment 1. First, participants were asked to respond to four scales: privacy concerns, disclosure intention, need for cognition, and social desirability. Individuals with high disclosure intention are more likely to share personal information; therefore, we controlled for this variable. Need for cognition and social desirability were also included as controls for individual differences in general likelihood to use central route processing overall (i.e., those greater in need for cognition, independent of any manipulations, are more likely to engage in effortful information processing) and to control for individual differences in proclivity to act in socially desirable ways (i.e., those greater in social desirability might be more reticent to disclose information, assuming this might be viewed as problematic behavior). Next, participants were given instructions through which they were led to believe that the tasks involved (i.e., reading, writing, and personal information requests) were central to the app development project, which served as our cover story. This procedure was essential to enable measuring actual disclosure after manipulating depletion. After reading the cover story, participants read a short passage and answered three questions that served as an attention check.[9]

Next, participants were randomly assigned to either a low- or high-depletion condition and asked to perform a commonly used depletion writing task (Schmeichel 2007). In the first writing task, we gave participants six minutes to write a short essay about common health issues without using any word that contained the letters

Table 1. Hypotheses Tested and Key Features of Each Experiment

Experiment	Hypotheses tested	Key features
1	1, 2, 3,[a] 4[a]	Manipulated cognitive depletion (low versus high) Measured mood
2	1, 3	Manipulated mood (neutral versus negative versus positive)
3	1, 4	Manipulated cognitive depletion and mood jointly (low depletion and negative mood versus high depletion and negative mood versus low depletion and positive mood versus high depletion and positive mood)

[a]Because mood was measured and not manipulated in Experiment 1, we were not able to rigorously test Hypotheses 3 and 4 in this experiment, but we did obtain suggestive evidence in support of these hypotheses.

"X" and "Z," which is a fairly easy task (low depletion) or "A" and "N," which is a fairly difficult task (high depletion). After this writing task, all participants were presented with the first set of 12 disclosure items (e.g., "Do you have any chronic disease?") (see Online Appendix B.1 for the entire list of items). Participants were given an option to refuse to provide an answer to any item by choosing "I prefer not to provide this information." Next, participants were given instructions for the second writing task and again given six minutes to work on it. This time, participants were asked to write about one good habit and one bad habit. Those assigned to the low (high) depletion condition in the first writing task were given another easy (difficult) writing task, that involved not using the letters "Q" and "Z" ("E" and "N"). Next, all participants were presented with the second set of disclosure items (see Online Appendix B.1 for the entire list of items). Finally, participants were asked to answer manipulation check questions, report their mood state,[10] provide demographic information, and then were debriefed.

3.3. Manipulation Check

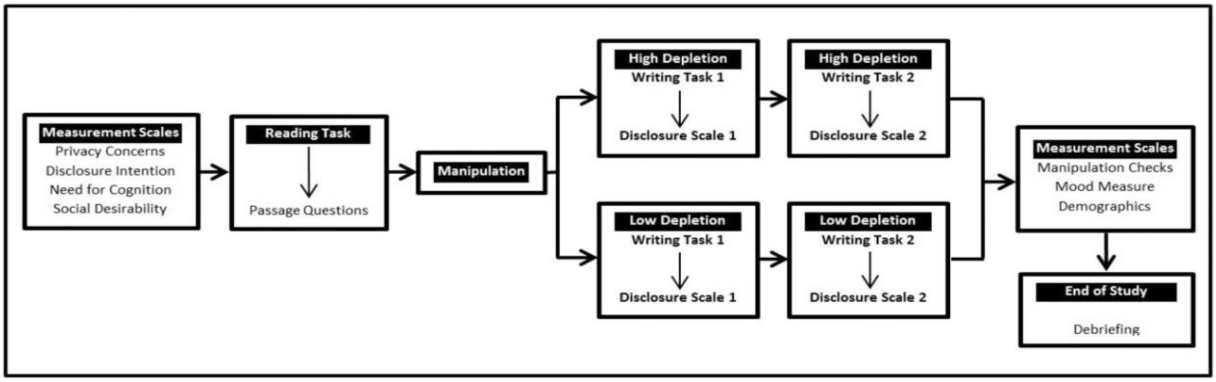
Three items were used to check the depletion manipulation (e.g., "How difficult were the writing tasks?"—1 = not at all difficult to 7 = extremely difficult). Factor analysis and reliability statistics showed convergence of the three items (Cronbach's $\alpha = 0.949$), and a mean score was computed. A t-test ($t = -21.89$; $df = 148$; $p < 0.001$) detected a significant mean difference between the low ($n = 78$, $mean = 2.45$, $s.d. = 1.01$) and high ($n = 72$, $mean = 5.89$, $s.d. = 0.89$) depletion conditions, indicating that the depletion manipulation was successful.

3.4. Measurement Validation

Our main predictors were privacy concerns, cognitive depletion, and mood state. Depletion was dummy coded (low depletion = 0, high depletion = 1). For multi-item constructs, exploratory factor analysis was conducted to verify psychometric properties. The results showed strong support for convergent and discriminant validity, and all Cronbach's α's were well above 0.70 (Online Table A.1.1).

Privacy concern was measured using four items (Dinev and Hart 2006) with a five-point Likert scale (Cronbach's $\alpha = 0.958$), and a mean score was computed. Mood was assessed using the brief mood introspection scale (BMIS) comprising 16 items (1 = definitely do not feel to 7 = definitely feel) (Mayer and Gaschke 1988). In the BMIS, eight adjectives (lively, peppy, active, happy, loving, caring, calm, and content) reflect positive mood, whereas the other eight (drowsy, tired, nervous, gloomy, fed up, sad, jittery, and grouchy) reflect negative mood. The initial factor analysis, however, revealed three factors. The eight positive adjectives, except calm, loaded well on one factor. Six of the negative adjectives loaded well on a second factor, whereas two adjectives (i.e., drowsy and tired) loaded on a third factor. This result was not surprising

Figure 2. Experiment 1 Flowchart Showing Sequence of Activities



considering the nature of the experiment in which the loadings for drowsy and tired would be influenced by the reading and writing tasks. Therefore, we dropped these two items from our mood measure. We also dropped one positive item (i.e., calm) because it cross-loaded on two factors. Following Sanna et al. (1999), we created a mood index after reverse coding the six negative adjectives (Cronbach's $\alpha = 0.924$) and averaging them with the ratings of the seven positive adjectives (Cronbach's $\alpha = 0.945$).

We also measured three other variables (i.e., disclosure intention, need for cognition, and social desirability) to control for individual difference effect. Disclosure intention was measured based on three items (Cronbach's $\alpha = 0.960$) (Malhotra et al. 2004), and a mean score was computed. Need for cognition was measured using 17 items (Cronbach's $\alpha = 0.956$) (Cacioppo and Petty 1982), and a mean score was computed. Social desirability was measured using 17 items. A score for social desirability was computed following the procedure suggested by Stöber (2001) and described in Online Appendix B.1.

3.5. Dependent Variable

Consistent with prior privacy research (e.g., Acquisti et al. 2012), we computed the total sum of the number of items for which each participant provided information.[11] We used a log transformation considering that our measure of disclosure behavior exhibited a nonnormal distribution.[12] Table 2 shows the correlation matrix for all variables along with descriptive statistics.

3.6. Results

Table 3 presents the results of the final model after conducting a series of weighted least squares (WLS) and ordinary least squares (OLS) regression analyses (Online Appendix A.2 presents preliminary analysis, rationale for using WLS regression, and robustness checks).[13] The control variables were dropped from the final model because they did not improve the model and were not statistically significant. We use $Model_{WLS}$ (Table 3) to estimate the coefficients and use the marginal effects (i.e., simple slope tests) (Table 4) to test Hypotheses 1–4. We illustrate the appropriateness of this approach in Online Appendix A.2 (Williams 2012, Dawson 2014, Kingsley et al. 2017).

As shown in Table 4, the main effect of privacy concerns on disclosure behavior is significant ($\beta_{PrivacyConcerns\_ME} = -0.064$, $s.e. = 0.014$, $p < 0.001$) providing support for Hypothesis 1. However, the effect of privacy concerns is only significant under low depletion ($\beta_{PrivacyConcerns\_under\_LowDepletion\_ME} = -0.158$, $s.e. = 0.023$, $p < 0.001$) or negative mood ($\beta_{PrivacyConcerns\_under\_NegativeMood\_ME} = -0.102$, $s.e. = 0.016$, $p < 0.001$) providing support for Hypotheses 2 and 3, respectively. When considering both depletion and mood, the results show that the effect of privacy concerns is only significant under low depletion coupled with negative mood ($\beta_{PrivacyConcerns\_under\_LowDepletion\&NegativeMood\_ME} = -0.177$, $s.e. = 0.025$, $p < 0.001$), thus supporting Hypothesis 4.

3.7. Discussion

In summary, the findings provide support for the prediction that the negative association between privacy concerns and disclosure behaviors is only pronounced under conditions of low depletion and/or negative mood. Whereas privacy concerns are associated with disclosure behaviors overall, the effect of privacy concerns did not reach statistical significance when individuals' effort level in information processing was low because of depleted cognitive resources and/or a positive mood state. These results provide support for the notion that privacy concerns may or may not be associated significantly with disclosure behaviors, depending on contextual factors, such as the level of cognitive depletion and mood state.

One limitation of Experiment 1 is that mood was not manipulated; instead, participants self-reported their mood at the end of the experiment. This design presents a challenge to the validity of the inferences made about the moderation effect of mood, particularly its individual moderation effect (i.e., Hypothesis 3). Also, the depletion manipulation significantly influenced participants' mood such that those assigned to the high-depletion condition reported a less positive mood state ($t = 2.85$, $df = 148$,

Table 2. Experiment 1's Correlation Matrix

	min	max	mean	s.d.	1	2	3	4	5	6
1- log(disclosure behavior)[a]	2.30	3.14	3.08	0.13	1					
2- Privacy concerns	1.00	5.00	3.64	1.09	−0.061	1				
3- Mood[b]	1.46	7.00	5.15	1.16	0.309**	−0.012	1			
4- Need for cognition	1.17	5.00	3.63	0.80	0.124	0.185*	0.311**	1		
5- Disclosure intention[b]	1.00	7.00	4.04	1.68	0.126	−0.526**	0.188*	−0.155	1	
6- Social desirability	0.00	16.00	8.09	4.00	−0.036	0.080	0.303**	0.185*	−0.012	1

[a]Descriptive statistics for nontransformed disclosure: $min = 10$, $max = 23$, $mean = 22.120$, $s.d. = 2.314$. The variance in this measurement is very similar to that found in Acquisti et al. (2012, study 1A), Hui et al. (2007), Marreiros et al. (2017), and Norberg et al. (2007).

[b]A high (low) score in mood reflects a positive (negative) mood. A high (low) score in disclosure intention reflects high (low) intention to disclose personal information.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 3. Experiment 1's Regression Results

Dependent variable: *log (disclosure behavior)*	*Model$_{WLS}$* All disclosure items	
	β (s.e.)	*C.I.*
Constant	3.066*** (0.020)	(3.025, 3.107)
Privacy Concerns	−0.088*** (0.018)	(−0.0126, −0.051)
Depletion (high)	0.009 (0.032)	(−0.054, 0.073)
Mood	0.042** (0.013)	(0.015, 0.068)
Depletion X Mood	−0.039* (0.017)	(−0.074, −0.003)
Privacy Concerns X Depletion	0.075** (0.026)	(0.021, 0.128)
Privacy Concerns X Mood	0.076*** (0.011)	(0.054, 0.098)
Privacy Concerns X Depletion X Mood	−0.060*** (0.014)	(−0.089, −0.032)
F value	23.41***	—
R^2_{OLS} *(Adjusted* R^2_{OLS}*)*[a]	16.60% (12.48%)	—
N	150	—

Note. Both privacy concerns and mood were mean centered before creating the interaction terms.
[a]R^2 obtained from WLS is not meaningful in interpreting the explanatory power of the model because it indicates how much variation in the weighted dependent variable is explained by the weighted independent variables instead of indicating variation explained by the original variables (Wooldridge 2009). For ease of interpretation, we only report OLS R^2 as there is no agreed upon pseudo R^2 for WLS (Willett and Singer 1988).
$^+p < 0.10$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

$p < 0.01$). Although our statistical model accounted for this confounding effect by including all higher level interactions, we wanted to address this research design issue. Therefore, a second experiment manipulated mood to test its individual moderation effect without depletion.

Table 4. Experiment 1's Marginal Effect Estimations

Dependent variable: *log (disclosure behavior)*	All disclosure items
Effect of privacy concerns unconditional (main effect)	Hypothesis 1
	−0.064*** (0.014) (−0.093, −0.035)
Effect of privacy concerns conditional on cognitive depletion	Hypothesis 2
Low depletion	−0.0158*** (0.023) (−0.205, −0.111)
High depletion	−0.027 (0.019) (−0.065, 0.010)
Effect of privacy concerns conditional on mood state	Hypothesis 3
Negative mood	−0.102*** (0.016) (−0.133, −0.070)
Positive mood	−0.002 (0.015) (−0.028, 0.033)
Effect of privacy concerns conditional on cognitive depletion & mood state	Hypothesis 4
Low depletion & negative mood	−0.177*** (0.025) (−0.228, −0.126)
High depletion & negative mood	−0.031 (0.019) (−0.070, 0.007)
Low depletion & positive mood	0.000 (0.019) (−0.039, 0.039)
High depletion & positive mood	0.004 (0.023) (−0.042, 0.051)

Note. The values used to estimate the slopes involving mood are −1 *s.d.* below (for negative mood) and +1 *s.d.* above (for positive mood) the mean.
$^+p < 0.10$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

4. Experiment 2

The main purpose of Experiment 2 was to address the design limitation associated with Experiment 1 by manipulating mood. In doing so, we sought to validate our inference regarding mood state moderating the negative association between privacy concerns and disclosure behaviors using a different experimental design. To further increase generalizability, we used different measures for privacy concerns, disclosure behaviors, and a different population of participants (i.e., Prolific, Peer et al. 2017, Palan and Schitter 2018).

Specifically, we employed a general measure for privacy concerns (Xu et al. 2011) to test whether the results of Experiment 1, which employed a measure for privacy concerns that was specific to the context of health mobile apps, would replicate without a context-specific measure for privacy concerns (Solove 2021). In addition, we measured privacy concerns at the end of Experiment 2 to rule out any priming effect that may have influenced the disclosure baseline in Experiment 1. We also used a different disclosure scale in Experiment 2 because the disclosure scale in Experiment 1 exhibited low variance, which restricted our analytical approach (i.e., it was not feasible to run different analyses for each set of disclosure items or to use a set of highly sensitive versus less-sensitive items because of the low variance observed).[14] By moving to a different approach, we were able to deepen our understanding of the effect of privacy concerns on disclosure behaviors.

4.1. Method

Prior to conducting Experiment 2, we developed a 32-item disclosure scale designed to produce greater variance, and we pilot tested the scale by asking 150 Prolific participants to rate the sensitivity associated with each item (1 = not at all sensitive to 7 = extremely sensitive). The disclosure scale consisted of personal questions related to demographics, health, lifestyle, and ethics (some of the ethics items were adopted from Adjerid et al. 2018). The results from this pilot enabled us to assess the sensitivity of each item and to create different categories for disclosure behavior based on sensitivity level. We used a median split (*median* = 3.62, *mean* = 3.60, *s.d.* = 0.94) to create two sets of disclosure items: low-sensitivity items (e.g., gender, height and weight, number of immediate family members one has) and high-sensitivity items (e.g., health status, income, number of sexual partners) (see Online Table B.2.1 for the sensitivity rating results). Thus, we were able to use three proxies for disclosure in Experiment 2: (1) all items as was done in Experiment 1, (2) low-sensitivity items, and (3) high-sensitivity items.

For the actual experiment, we developed a new writing task to manipulate mood state (neutral versus negative versus positive). The task was pretested using an independent sample of 300 Prolific participants to validate the manipulation prior to conducting Experiment 2 (we describe this in the manipulation check section). Participants earned $1.30 for completing the experiment. The final sample included 278 participants after applying exclusion criteria (i.e., failing attention check, failing to complete the experimental task, or admitting to having falsified any personal information) to ensure the quality of responses.[15] The mean age of the participants was 34.4, and 52.8% were female.

4.2. Procedure

Participants were invited to participate in a study titled "Fill in the Blanks Task." They were informed that they would complete a writing task followed by a number of survey questions. First, participants were randomly assigned to complete one of the fill-in-the-blanks tasks shown in Table 5. The task was designed to prime negative or positive mood by making participants think about their negative or positive experiences as human subjects in other studies on Prolific. The neutral mood condition represents a control in which neither negative nor positive mood was primed. The three conditions required about the same amount of effort (i.e., completing 10 blanks; see Table 5). After completing the task, participants were asked to respond to a set of 32 items designed to capture disclosure behavior. Participants were given an option to refuse to provide an answer to any item by choosing "I prefer not to provide this information." Next, participants were asked whether they falsified any personal information, to provide qualitative feedback to tell us why they decided not to provide any of the information asked, and to respond to the privacy concerns scale.[16] Finally, participants were debriefed (see Online Appendix B.2 for the entire instrument).

4.3. Manipulation Check

The manipulation was validated in a pretest prior to conducting Experiment 2 (i.e., independent sample manipulation check). Specifically, we invited 300 Prolific participants to participate in a study titled "Fill in the Blanks Task." Participants were randomly assigned to one of the three mood conditions. Then, they were asked to report how they felt after completing the task by responding to the positive and negative affect scale (1 = definitely did not feel to 7 = definitely felt) (Watson et al. 1988). The 10 positive (i.e., excited, interested, enthusiastic,

Table 5. Experiment 2's Mood Manipulation Task

Neutral mood condition	Negative mood condition	Positive mood condition
There are (1_______________) different geometric (2_______________) shown below. The one positioned (3_______________) is called a (4_______________). The one positioned (5_______________) is called a (6_______________). The one positioned (7_______________) is called a (8_______________). The one positioned (9_______________) is called a (10_______________). 	Prolific is **torture**! It takes **much** time and effort to earn money from Prolific studies, which is something I (1_______________). As a participant, I especially feel (2_______________) when a study pays **little** for **so much** effort and time. For example, I participated in a study which took (3_______________) minutes and paid (4_______________). This really made me (5_______________). Also, some studies are so **dull,** and I learn **nothing** from them. This just makes me (6_______________). Some researchers **abuse** us by (7_______________). The pandemic made life so hard, **and unfortunately** Prolific (8_______________). Prolific studies not only **damage** us, but also **ruin** true science, and I am very **upset** (9_______________). Working for Prolific is like (10_______________).	Prolific is **awesome**! It takes **little** time and effort to earn money from Prolific studies, which is something I (1_______________). As a participant, I especially feel (2_______________) when a study pays **much** for **so little** effort and time. For example, I participated in a study which took (3_______________) minutes and paid (4_______________). This really made me (5_______________). Also, some studies are so **fun,** and I learn **much** from them. This just makes me (6_______________). Some researchers **help** us by (7_______________). The pandemic made life so hard, **but fortunately** Prolific (8_______________). Prolific studies not only **help** us, but also **advance** true science, and I am very **happy** (9_______________). Working for Prolific is like (10_______________).

attentive, inspired, proud, active, determined, strong, and alert) and 10 negative (i.e., distressed, upset, hostile, irritable, scared, afraid, guilty, ashamed, nervous, jittery) items loaded well on two factors. Following the same procedure in Experiment 1, we created a mood index after reverse coding the 10 negative adjectives (Cronbach's α = 0.946) and averaging them with the ratings of the 10 positive adjectives (Cronbach's α = 0.948). The one-way ANOVA results showed that the manipulation was successful (F = 53.60, df = 297, p < 0.000) with all Bonferroni post hoc pairwise comparisons being significant (p < 0.01) (neutral mood: n = 98, *mean* = 5.16, *s.d.* = 0.74; negative mood: n = 100, *mean* = 4.36, *s.d.* = 1.03; positive mood: n = 102, *mean* = 5.65, *s.d.* = 0.87). This independent sample manipulation check provided evidence for the success of the manipulation. Thus, we did not ask participants in Experiment 2 to report their mood after the fill-in-the-blanks task to reduce possible dissipation of the actual effect of our manipulation.

4.4. Independent Variables

Mood was coded as a categorical variable (neutral mood = 0, negative mood = 1, positive mood = 2). Privacy concern was computed using the same method as in Experiment 1 (Cronbach's α = 0.934). Finally, because we did not fix the amount of time given to complete the task as we did in Experiment 1, we controlled for this variable in the statistical model.

4.5. Dependent Variable(s)

Consistent with Experiment 1, our main dependent variable is computed based on the total sum of the number of items disclosed.[17] By utilizing the sensitivity ratings we gathered from the pilot, we were able to use three proxies for the dependent variable: (1) all items, (2) low-sensitivity items, and (3) high-sensitivity items. Table 6 shows the correlation matrix along with descriptive statistics.

4.6. Results

We conducted OLS multiple regression for each disclosure behavior proxy.[18] As was done in Experiment 1, we use the regression models (Table 7) to estimate the coefficients and rely on the marginal effects (i.e., simple slope tests) (Table 8) to test Hypotheses 1 and 3. As shown in Table 8, the main effect of privacy concerns on disclosure behavior is significant ($\beta_{PrivacyConcerns\_ME} = -1.343$, $s.e.$ = 0.297, p < 0.001) providing support for Hypothesis 1. However, the effect of privacy concerns is only significant under neutral ($\beta_{PrivacyConcerns\_under\_NeutralMood\_ME} = -1.736$, $s.e.$ = 0.736, p < 0.001) or negative mood ($\beta_{PrivacyConcerns\_under\_NegativeMood\_ME} = -2.279$, $s.e.$ = 0.673, p < 0.01), thus providing support for Hypothesis 3. The results are consistent when disclosure is measured using low- or high-sensitivity items.

4.7. Discussion

In summary, the findings indicate that, whereas privacy concerns are associated with disclosure behaviors overall, the effect of privacy concerns did not reach statistical significance when individuals' level of effort was low because of being induced into a positive mood state. The findings provide further support for Hypothesis 3 such that positive mood nullified the association between privacy concerns and disclosure behaviors.

5. Experiment 3

Although the previous experiments provide good causal evidence that depletion (Experiment 1) and mood (Experiment 2) influence the strength of the association between privacy concerns and disclosure behaviors, these experiments were limited in terms of allowing us to make causal inferences about the joint effects of depletion and mood (i.e., Hypothesis 4) because mood was self-reported in Experiment 1 and depletion was not manipulated in Experiment 2. Thus, building on Experiments 1 and 2, we conducted a follow-up experiment in which we jointly manipulated depletion and mood. We took this approach because manipulating depletion and mood independently proved not to be possible.[19] Experiment 3 also adds robustness by demonstrating that the results of Experiment 1, particularly Hypothesis 4, can be replicated using a different measure of disclosure behavior, a different depletion manipulation, and a different experimental design.

5.1. Method

First, we developed a disclosure scale similar to that used in Experiment 2. The scale consisted of 21 items. Prior to Experiment 3, we asked 199 AMT participants to

Table 6. Experiment 2's Correlation Matrix

	min	max	mean	s.d.	1	2	3	4	5
1- Disclosure (all items)	0.00	32.00	25.88	7.93	1				
2- Disclosure (low-sensitivity items)	0.00	16.00	13.46	3.55	0.951**	1			
3- Disclosure (high-sensitivity items)	0.00	16.00	12.42	4.68	0.972**	0.852**	1		
4- Privacy concerns	1.00	7.00	4.50	1.40	−0.225**	−0.237**	−0.201**	1	
5- Task time (in minutes)	0.50	13.51	2.64	2.03	0.022	0.045	0.004	0.058	1

*p < 0.05; **p < 0.01; ***p < 0.001.

Table 7. Experiment 2's Regression Results

Dependent variable: *Disclosure behavior*	Model 1		Model 2		Model 3	
	All items		Low-sensitivity items		High-sensitivity items	
	β (s.e.)	*C.I.*	*β (s.e.)*	*C.I.*	*β (s.e.)*	*C.I.*
Constant	26.33*** (0.897)	(24.560, 28.094)	13.51*** (0.392)	(12.741, 14.283)	12.82*** (0.540)	(11.751, 13.879)
Privacy Concerns	−1.736*** (0.458)	(−2.638, −0.833)	−0.776*** (0.206)	(−1.182, −0.369)	−0.960*** (0.267)	(−1.486, −0.433)
Negative Mood	−2.115^{+} (1.173)	(−4.424, 0.194)	−0.988+ (0.530)	(−2.031, 0.054)	−1.127 (0.696)	(−2.496, 0.243)
Positive Mood	−2.045+ (1.082)	(−4.174, 0.084)	−0.756 (0.471)	(−1.683, 0.170)	−1.289^{+} (0.655)	(−2.577, 0.000)
Privacy Concerns X *Negative Mood*	−0.544 (0.802)	(−2.122, 1.035)	−0.327 (0.381)	(−1.076, 0.422)	−0.217 (0.449)	(−1.100, 0.667)
Privacy Concerns X *Positive Mood*	1.552* (0.632)	(0.307, 2.796)	0.665* (0.275)	(0.124, 1.205)	0.888** (0.378)	(0.143, 1.631)
Task_Time	0.006 (0.004)	(−0.001, 0.014)	0.003* (0.001)	(0.000, 0.006)	0.002 (0.002)	(−0.002, 0.007)
F value	6.42***	—	6.39***	—	5.77***	—
R^2_{OLS} (*Adjusted* R^2_{OLS})	9.04% (7.03%)	—	9.81% (7.81%)	—	7.55% (5.50%)	—
N	278	—	278	—	278	—

Note. Neutral mood is the reference category.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

rate the sensitivity associated with each of the 21 items if they were asked to disclose such information in an AMT study (1 = not at all sensitive to 5 = extremely sensitive). The scale included personal questions related to demographic, contact, financial, health, and other personal information. The results from this pilot work revealed that items related to finance (i.e., yearly income, name of bank, number of bank accounts owned, and number of credit cards owned) were rated as more sensitive (*mean* = 3.14, *s.d.* = 1.31) than health items (*mean* = 2.51, *s.d.* = 1.31), contact items (*mean* = 2.50, *s.d.* = 1.28), demographic items (*mean* = 1.73, *s.d.* = 1.11), or other personal information (*mean* = 1.92, *s.d.* = 1.20) (see Online Table B.3.1 for the sensitivity rating results). Based on these ratings, it appears that finance items are the most sensitive items, contact and health items are moderately sensitive, and demographic and other personal items are the least sensitive items. Therefore, we expanded our proxies for disclosure behavior using a category-based sensitivity level in experiment 3: (1) all items, (2) low-sensitivity items, (3) moderate-sensitivity items, and (4) high-sensitivity items.

For the actual experiment, we developed a new writing task to manipulate depletion (low versus high) and mood (negative versus positive) simultaneously.[20] Experiment 3's procedure was similar to that used in Experiment 2 with the exception that the participants were asked to respond to manipulation check questions after the task and before responding to the disclosure scale. Presenting the manipulation checks items before the disclosure scale was intended to reaffirm the ostensible purpose of the study because participants were informed that this study was about cognitive tasks and mood states. AMT participants earned $0.80 for completing the experiment. The final sample included 153 participants after applying exclusion criteria (i.e., failing attention check, failing to complete the experimental task, or admitting to having falsified any personal information) to ensure the quality of responses.[21] The mean age of the participants was 39.5, and 52.9% were female.

Table 8. Experiment 2's Marginal Effect Estimations

Dependent variable: *Disclosure behavior*	All items	Low-sensitivity items	High-sensitivity items
Effect of privacy concerns unconditional (main effect)		Hypothesis 1	
	−1.343*** (0.297)	−0.636*** (0.136)	−0.706*** (0.171)
	(−1.929, −0.758)	(−0.905, −0.368)	(−1.044, −0.369)
Effect of privacy concerns conditional on mood state		Hypothesis 3	
Neutral mood	−1.736*** (0.736)	−0.776*** (0.206)	−0.959*** (0.267)
	(−2.638, −0.833)	(−1.182, −0.369)	(−1.486, −0.433)
Negative mood	−2.279** (0.673)	−1.103** (0.326)	−1.176*** (0.369)
	(−3.606, −0.952)	(−1.745, −0.460)	(−1.904, −0.448)
Positive mood	−0.183 (0.424)	−0.111 (0.176)	−0.072 (0.260)
	(−1.019, 0.652)	(−0.458, 0.236)	(−0.585, 0.440)

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

5.2. Procedure

Participants were invited to participate in a study titled "Cognitive Tasks and Mood States." They were informed that they would complete a writing task followed by a number of survey questions. First, participants were asked to complete a task that involved typing a series of statements with which we provided them. The task required participants to either type a set of positive (positive mood condition) or negative (negative mood condition) statements with which we provided them with (low depletion condition) or to decipher and then type the statements (high depletion condition). The task was designed to induce, at the same time, low or high depletion and negative or positive mood state.[22] For example, participants in the low-depletion and positive mood condition were presented with a set of positive statements (e.g., "I have only two kinds of days: happy and hysterically happy") and were asked to simply type the statements in a text box. Those in the high-depletion and positive mood condition were presented with the same statements but with each word presented backward (e.g., "I evah ylno owt sdnik fo syad: yppah dna yllaciretsyh yppah"). Thus, participants in the high-depletion condition had to exert more cognitive effort because they had to decipher each word before they could type it. A set of negative statements was used for the negative mood condition (e.g., "I have only two kinds of days: sad and suicidal sad" (low depletion) and "I evah ylno owt sdnik fo syad: das dna ladicius das" (high depletion)). Participants were randomly assigned to one of the four treatment conditions. After the writing task, participants were asked to respond to manipulation check questions. Then, participants were asked to respond to a set of 21 items designed to measure their disclosure behavior (e.g., year of birth, gender, phone area code, number of credit cards owned, risky diseases, religion, sexual orientation, etc.), and they were allowed to refuse to provide an answer to any item by choosing "I prefer not to provide this information." Next, participants were asked whether they falsified any personal information, to provide qualitative feedback to tell us why they decided not to provide any of the information asked, and to respond to the privacy concerns scale.[23] Finally, participants were debriefed (see Online Appendix B.3 for the entire instrument).

5.3. Manipulation Check

The same three items used in Experiment 1 to check the depletion manipulation were again used. Factor analysis and reliability statistics showed convergence of the three items (Cronbach's $\alpha = 0.950$). A mean score was computed, and the t-test ($t = -5.58$, $df = 151$, $p < 0.001$) detected a significant mean difference between the low ($n = 81$, $mean = 2.14$, $s.d. = 1.45$) and high ($n = 72$, $mean = 3.58$, $s.d. = 1.72$) depletion conditions, indicating that the depletion manipulation was successful. Consistent with Experiment 1, we used the BMIS as a manipulation check for mood state. After creating a mood index, applying the same method used in Experiment 1, we tested whether the mood manipulation was successful. The t-test ($t = -4.67$, $df = 151$, $p < 0.001$) detected a significant mean difference between the negative ($n = 69$, $mean = 4.15$, $s.d. = 1.24$) and positive ($n = 84$, $mean = 5.11$, $s.d. = 1.27$) mood conditions, indicating that the mood manipulation was successful. As a robustness check, we tested whether the depletion manipulation unintentionally influenced mood state and whether the mood manipulation unintentionally influenced cognitive depletion (i.e., to test for spillover effect). The t-test results confirmed that there was no spillover effect (i.e., the depletion (mood) manipulation did not significantly influence mood state ($t = -0.23$, $df = 151$, $p = 0.81$) (cognitive depletion) ($t = 1.04$, $df = 151$, $p = 0.29$)). Therefore, we concluded that our task successfully manipulated both cognitive depletion and mood state as intended.

5.4. Independent Variables

The depletion–mood experimental variable was coded as a categorical variable (low depletion and negative mood = 0, high depletion and negative mood = 1, low depletion and positive mood = 2, high depletion and positive mood = 3). Privacy concern was measured and computed using the same method as in Experiment 1 (Cronbach's $\alpha = 0.959$). Finally, because we did not fix the amount of time given to complete the task as we did in Experiment 1, we controlled for this variable in the statistical model.

5.5. Dependent Variable(s)

Consistent with Experiments 1 and 2, our main dependent variable was computed based on the total sum of the number of items disclosed.[24] In Experiment 3, we used four proxies for the dependent variable: (1) all items, (2) low-sensitivity items (demographics and others), (3) moderate-sensitivity items (contact and health items), and (4) high-sensitivity items (finance items). Table 9 shows the correlation matrix along with descriptive statistics.

5.6. Results

We conducted OLS multiple regression for each disclosure behavior proxy.[25] As was done in Experiments 1 and 2, we use the regression models (Table 10) to estimate the coefficients and rely on the marginal effects (i.e., simple slope tests) (Table 11) to test Hypotheses 1 and 4.

As shown in Table 11, the main effect of privacy concerns on disclosure behavior is significant ($\beta_{PrivacyConcerns\_ME} = -0.859$, $s.e. = 0.262$, $p < 0.01$) providing support for Hypothesis 1. However, the effect of privacy concerns is only significant under low depletion coupled with negative mood ($\beta_{PrivacyConcerns\_under\_LowDepletion\&NegativeMood\_ME} = -1.445$, $s.e. = 0.350$, $p < 0.001$), thus providing support for

Table 9. Experiment 3's Correlation Matrix

	min	max	mean	s.d.	1	2	3	4	5	6
1- Disclosure (all items)	0.00	21.00	15.56	5.295	1					
2- Disclosure (low-sensitivity items)	0.00	10.00	8.67	2.20	0.862***	1				
3- Disclosure (moderate-sensitivity items)	0.00	7.00	4.86	2.33	0.921***	0.662***	1			
4- Disclosure (high-sensitivity items)	0.00	4.00	2.01	1.49	0.825***	0.539***	0.719***	1		
5- Privacy concerns	1.00	7.00	4.33	1.71	−0.263**	−0.236**	−0.195*	−0.277***	1	
6- Task time (in minutes)	1.14	15.24	3.61	2.12	0.086	0.073	0.025	0.158	0.006	1

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Hypothesis 4. The results are very consistent when disclosure is measured using low-, moderate-, or high-sensitivity items.

5.7. Discussion

In summary, the findings provide confirming evidence that, although privacy concerns can significantly predict disclosure behaviors when individuals are able to employ high-effort information processing, privacy concerns may not be predictive of disclosure behaviors when individuals employ low-effort information processing because of a depleted cognitive resource coupled with a positive mood state.

6. General Discussion

The purpose of this study was to examine privacy decisions under low- versus high-effort information processing. Table 12 summarizes the results from the three experiments that were conducted.

In a theoretical paper, Dinev et al. (2015) proposes that the association between privacy concerns and decisions can be disrupted depending on the effort level in information processing. Our results support their proposition that, if high-effort processing is present, privacy decisions are processed in a manner consistent with stated privacy concerns. However, if low-effort processing is present, the negative association between privacy concerns and privacy decisions can break down. Consistent with Acquisti et al. (2020), our findings suggest that gaps between stated privacy concerns and actual disclosure behaviors can arise because of nonnormative factors, such as cognitive depletion and mood state.

6.1. Theoretical Implications

Our theoretical approach and empirical findings provide a systematic explanation for the privacy paradox. Specifically, the privacy paradox is more (less) likely to manifest when the information processing effort is compromised (sufficient) because of many contextual factors, including cognitive or affective states. Privacy concerns and disclosure behaviors were consistently associated in our three experiments (i.e., Hypothesis 1). This provides strong evidence that individuals who care about privacy generally act on their privacy concerns when making disclosure decisions. By going deeper into the conditional analysis (i.e., marginal effects), however, we observe that the association between privacy concerns and disclosure behaviors is not necessarily homogenous in the data. The association was weak to insignificant under certain conditions (i.e., high depletion and/or positive mood) and strong and significant under other conditions (i.e., low depletion and/or negative mood) within the same data in which we found a significant main effect of privacy concerns. Our findings reveal that the privacy paradox is neither an absolute phenomenon nor a myth (Solove 2021), but that its existence is conditional on contextual factors—including psychological and economic factors (Acquisti et al. 2020)—that influence information processing (Dinev et al. 2015), thus supporting the notion of malleability in privacy decisions (Acquisti et al. 2015).

We borrowed our psychological factors from the e-APCO model (Dinev et al. 2015, p. 643), which suggests that "as processing effort moves from high to low, the impact of extraneous influences becomes greater, possibly to the point that they dominate decision making." We further show that not only external (i.e., cognitive resource), but also internal factors (i.e., mood state) can alter privacy decisions. The e-APCO model uses processing effort as a high-level theoretical lens but does not make specific predictions about the moderating effects of the various psychological and economic factors. In the current work, we validate two major propositions from the e-APCO model (i.e., the depletion and mood two-way interaction effect) and theorize and test their joint effect to advance the extant privacy literature, namely, the consideration of both cognition and affect (Farahmand 2017).

Our study also contributes to the depletion literature because we show that depletion effects play a significant role in attenuating the association between privacy concerns and disclosure behaviors. Furthermore, we demonstrate how cognition and affect interact to influence behavior, supporting the Hagger et al. (2010) suggestion that poorer performance in self-control tasks could be due to both factors.

Our findings relating to mood are consistent with predictions suggested by the affect infusion model (Forgas 1995, 2017). Although analyzing our data from a pure affect perspective was not the main objective, our results are in line with the notion that a positive (negative) mood is associated with higher (lower) level of disclosure,

Table 10. Experiment 3's Regression Results

Dependent variable: *Disclosure behavior*	Model 1 All items *β (s.e.)*	Model 1 All items *C.I.*	Model 2 Low-sensitivity items *β (s.e.)*	Model 2 Low-sensitivity items *C.I.*	Model 3 Moderate-sensitivity items *β (s.e.)*	Model 3 Moderate-sensitivity items *C.I.*	Model 4 High-sensitivity items *β (s.e.)*	Model 4 High-sensitivity items *C.I.*
Constant	15.063*** (1.013)	(13.060, 17.065)	8.342*** (0.409)	(7.533, 9.151)	5.090*** (0.446)	(4.207, 5.973)	1.630*** (0.285)	(1.066, 2.193)
Privacy Concerns	−1.445*** (0.350)	(−2.138, −0.751)	−0.481** (0.152)	(−0.782, −0.180)	−0.531*** (0.147)	(−0.823, −0.239)	−0.432*** (0.100)	(−0.631, −0.234)
High Depletion & Negative Mood	0.346 (1.215)	(−2.056, 2.749)	0.348 (0.493)	(−0.627, 1.324)	−0.165 (0.560)	(−1.273, 0.942)	0.163 (0.369)	(−0.565, 0.893)
Low Depletion & Positive Mood	−1.052 (1.154)	(−3.335, 1.229)	−0.0214 (0.496)	(−1.196, 0.766)	−0.630 (0.508)	(−1.635, 0.375)	−0.207 (0.311)	(−0.824, 0.408)
High Depletion & Positive Mood	−0.332 (1.085)	(−2.476, 1.812)	0.255 (0.441)	(−0.616, 1.127)	−0.402 (0.503)	(−1.397, 0.591)	−0.184 (0.311)	(−0.799, 0.430)
Privacy Concerns X High Depletion & Negative Mood	0.312 (0.756)	(−1.182, 1.806)	−0.109 (0.272)	(−0.647, 0.427)	0.304 (0.371)	(−0.429, 1.038)	0.117 (0.244)	(−0.364, 0.600)
Privacy Concerns X Low Depletion & Positive Mood	0.577 (0.714)	(−0.834, 1.989)	0.096 (0.270)	(−0.437, 0.630)	0.358 (0.334)	(−0.303, 1.019)	0.123 (0.196)	(−0.265, 0.511)
Privacy Concerns X High Depletion & Positive Mood	1.356* (0.544)	(0.279, 2.43)	0.525* (0.200)	(0.129, 0.922)	0.401 (0.249)	(−0.092, 0.895)	0.428* (0.165)	(0.102, 0.755)
Task_Time	0.003 (0.003)	(−0.002, 0.010)	0.001 (0.001)	(−0.001, 0.003)	0.000 (0.001)	(−0.002, 0.003)	0.002* (0.000)	(0.000, 0.004)
F value	3.90***	—	3.60***	—	3.66***	—	4.18***	—
R^2_{OLS} (*Adjusted* R^2_{OLS})	11.68% (6.78%)	—	10.53% (5.56%)	—	6.62% (1.44%)	—	15.02% (10.30%)	—
N	153	—	153	—	153	—	153	—

Note. Low depletion and negative mood is the reference category.
$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

consistent with Forgas's (2011) findings. Still, our research provides additional insights in that the effect of positive mood on disclosure occurs even when people express high privacy concerns.

Our overall theoretical contribution involves both theory testing (i.e., testing some propositions from the e-APCO model) and theory building (i.e., identifying a new moderating effect) (Colquitt and Zapata-Phelan 2007). Sutton and Staw (1995) emphasize the importance of conducting empirical research to test theoretical assertions. Because of the need for empirical support for the e-APCO model, we advance research by testing its main theoretical statements and also theorizing and testing the joint effect of cognition and affect.

6.2. Limitations and Directions for Future Research

All studies have limitations, and ours is no exception, but these limitations also suggest avenues for future research. First, we used two populations (AMT and Prolific) in which people are conditioned to share personal information on a daily basis. These subject populations might have biased the disclosure baseline in our experiments upward. This possible bias does not, however, challenge the causality of effects we observed in that we showed these effects occurred when participants were randomly assigned to experimental conditions. In fact, one can argue that testing our hypotheses in such populations represents a conservative test because of the high disclosure tendency in such populations. Nonetheless, future research is needed to validate our results in other populations (e.g., users of web 3.0 technologies).

Second, we only focused on two conditions that could explain the privacy paradox. Future research is needed to examine other factors (e.g., specific emotions, herding, time constraints, motivations; see Dinev et al. 2015, Acquisti et al. 2020) to explain the paradox we examine and whether our results could vary because of idiosyncratic individual factors. Third, whereas we focus on behaviors, which represents a strength of our study, we did not test how our experimental manipulations affected the association between privacy concerns and disclosure intentions. We did, however, observe in Experiment 1 that privacy concerns were associated more strongly with disclosure intentions as compared with disclosure behaviors (see Table 2). This observation is consistent with findings reported by Adjerid et al. (2018). Future research may investigate how low-effort information processing moderates the association between privacy concerns and disclosure intentions as well as behaviors.

Another direction for future research is to identify ways to reduce the unfavorable effect of low-effort information processing to reverse the privacy paradox. For example, whether privacy alerts prior to a behavioral task can counteract the effect of reduced information processing is an empirical question worth investigating.

Table 11. Experiment 3's Marginal Effect Estimations

Dependent variable: *Disclosure behavior*	All items	Low-sensitivity items	Moderate-sensitivity items	High-sensitivity items
Effect of privacy concerns unconditional (main effect)		Hypothesis 1		
	−0.859** (0.262)	−0.339*** (0.092)	−0.259* (0.127)	−0.260** (0.078)
	(−1.378, −0.339)	(−0.522, −0.155)	(−0.512, −0.006)	(−0.415, −0.105)
Effect of privacy concerns conditional on cognitive depletion & mood state		Hypothesis 4		
Low depletion & negative mood	−1.445*** (0.350)	−0.481** (0.152)	−0.531*** (0.147)	−0.432*** (0.100)
	(−2.138, −0.751)	(−0.782, −0.180)	(−0.823, −0.239)	(−0.631, −0.234)
High depletion & negative mood	−1.133+ (0.670)	−0.591* (0.228)	−0.226 (0.340)	−0.315 (0.221)
	(−2.458, 0.192)	(−1.042, −0.140)	(−0.899, 0.445)	(−0.753, 0.122)
Low depletion & positive mood	−0.867 (0.622)	−0.0385+ (0.222)	−0.173 (0.300)	−0.309+ (0.168)
	(−2.097, 0.362)	(−0.825, 0.055)	(−0.766, 0.420)	(−0.643, 0.024)
High depletion & positive mood	−0.088 (0.408)	0.044 (0.127)	−0.129 (0.198)	−0.004 (0.129)
	(−0.895 0.718)	(−0.206, 0.296)	(−0.522, 0.263)	(−0.259, 0.251)

$^{+}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Nudges in the form of "distracting pop-up alerts" might be used to capture people's attention at critical moments, increasing their motivation to attend to information more carefully before committing to privacy disclosures and encouraging central route processing at key moments in the decision-making process (Petty and Brinñol 2010, Acquisti et al. 2017). Note that our inferences only apply to situations in which privacy choices exist; that is, there is an option *not* to provide personal information and still use the service.

Finally, our study shows that negative affect leads individuals to be consistent with their privacy preferences when requested to disclose personal information, yet security research shows that negative affect (e.g., frustration) leads individuals to violate security policies (Ormond et al. 2019). This suggests that specific negative emotions may be beneficial in one arena but not the other. Future research examining the influence of affect in both security and privacy decisions would add substantial value to these overlapping literatures.

6.3. Practical Implications

In today's information age, organizations can create significant value from personal and behavioral data to an extent that is inconceivable to the average person (Zuboff 2015). Privacy scholars emphasize the imbalance between individuals' privacy desires and the market's thirst for personal data and that individuals' actions alone will probably not work to address this imbalance (Acquisti et al. 2020). We believe that the different stakeholders involved (i.e., individuals, companies, and policymakers) all share some responsibility with respect to addressing the privacy imbalance.

Individuals need to enhance their awareness about the impact that psychological, economic, and environmental factors have on privacy decisions and how such factors can easily lead to privacy decisions that are undesirable in the long term or inconsistent with privacy preferences. The challenge for individuals is that the effects of these factors are quite nuanced and can be hard to discern. One possible solution is privacy education, training, and awareness (PETA) programs (Alashoor and Aldawood 2022). These programs, however, assume that people engage in effortful information processing, and the current findings demonstrate that, under some conditions (e.g., cognitive depletion, positive moods), this is not likely to occur. Therefore, it is important that PETA programs are enriched with knowledge and implications

Table 12. Summary of Results

	Experiment 1 Depletion manipulated mood self-reported	Experiment 2 Mood manipulated	Experiment 3 Depletion and mood jointly manipulated
Hypothesis 1: Individuals with high levels of privacy concerns are less likely to disclose personal information	Supported	Supported	Supported
Hypothesis 2: Cognitive depletion attenuates individuals' ability to act on their privacy concerns	Supported	Not tested	Not tested
Hypothesis 3: Positive mood attenuates individuals' ability to act on their privacy concerns	Supported	Supported	Not tested
Hypothesis 4: Cognitive depletion and positive mood together further attenuate individuals' ability to act on their privacy concerns	Supported	Not tested	Supported

from the behavioral economics stream of privacy literature.

Policymakers must consider what policies and regulations should be enacted to strike an appropriate balance between protecting individuals' privacy and creating economic value for the companies that have built their business models around creative ways to leverage personal information (e.g., Acxiom). Whereas governmental efforts are considered slow in terms of addressing the privacy issue, the enaction of the General Data Protection Regulation, the California Consumer Privacy Act, and recently the Colorado Privacy Act, all represent important regulatory steps toward instilling the notion of privacy protection in the public sphere. The effects of these types of initiatives on individuals' privacy awareness and behavior are uncertain, are likely to be nuanced, and take time to sort out.

Companies obviously play a role that is of the utmost importance in achieving the right balance between individuals' desire for privacy and the economic possibilities that stem from leveraging individuals' data. Recently, some companies (e.g., Apple, DuckDuckGo, and MetaMask) have used privacy to brand themselves or to differentiate what they are doing in comparison with their competitors. Such organizational practices both capitalize on individuals' privacy concerns and, at the same time, likely increase privacy awareness among the general public. It is time that companies take real steps to improve privacy awareness and create other strategies for data collection (e.g., data as property; Acquisti et al. 2020). Today, we see evidence of various types of creative and easy-to-use privacy-enhancing technologies when consumers first visit a website. For example, https://www.theguardian.com/ requires its visitors to make easy but very granular privacy choices before allowing them to browse the website. This provides some anecdotal evidence that privacy regulation is having some effects that impact consumers even if the companies that are following such regulations are not necessarily doing so with the express aim of enhancing individuals' privacy or privacy awareness. Further, the fact that companies are required to follow certain regulations suggests that the public will benefit not only from better privacy protection, but that individuals' privacy awareness will likely increase as well with time. Future research and time will tell how the hurdles to achieve a privacy balance are resolved.

7. Conclusion

Although a growing body of research has emerged to examine factors and contexts associated with privacy decisions, evidence for the existence of the privacy paradox and the boundary conditions that govern when it may occur have remained elusive. In this study, we find that employing low-effort information processing as a result of cognitively depleting tasks and/or positive moods leads to privacy paradoxical decisions such that individuals' stated privacy concerns no longer predict their disclosure behaviors. We hope that our study inspires further work aimed at enhancing consumer privacy choice and addressing the imbalance between consumer privacy and market behaviors.

Acknowledgments

The authors dedicate this publication in memory of H. Jeff Smith, a respected and valued colleague who began this journey with them but sadly passed away on October 27, 2018.

Endnotes

[1] This assumption is implicitly or explicitly made in the normative privacy literature as is subsequently discussed in more detail.

[2] These are hereafter referred to as the normative and behavioral perspectives.

[3] Some studies in the normative literature also examine contextual factors, but their outcome measures are based on intentions or willingness (e.g., Angst and Agarwal 2009, Anderson and Agarwal 2011, Lowry et al. 2012).

[4] For a review of other theories adopted in this literature, see Li (2012).

[5] "Exceptions to Hypothesis 1" refers to conditions under which the association between privacy concerns and disclosure behaviors is weakened to the point of statistical insignificance, which may, in turn, suggest a privacy paradox.

[6] Similarly, this "mismatch" refers to conditions under which the association between a privacy-related determinant (e.g., disclosure intentions) and a privacy-related outcome (e.g., disclosure behaviors) is weakened to the point of statistical insignificance.

[7] Affect or core affect is an umbrella term for both moods and emotions (Forgas 1995, Zhang 2013). Moods are "low-intensity, diffuse and relatively enduring affective states without a salient antecedent cause and therefore little cognitive content (e.g., feeling good or feeling bad)," whereas emotions "are more intense, short-lived and usually have a definite cause and clear cognitive content" (Forgas 1995, p. 41). In this study, we focus on moods because they are more common and normally subconscious, and individuals are generally unaware of their effects, whereas emotions are context-specific, conscious feelings, and individuals are often aware of them when making decisions (Forgas 1995, Zhang 2013).

[8] The exclusion criteria did not impact the success of the randomization as the descriptive statistics for all variables (before and after applying the exclusion criteria) show the same patterns with no significant differences. In addition, there was no significant correlation (*Chi-square* = 0.00, $p > 0.10$) between the experimental variable (i.e., depletion) and the exclusion criteria. See Online Appendix C for descriptive statistics and statistical tests. Note that the depletion manipulation significantly influenced participants' mood after applying the exclusion criteria such that those assigned to the high-depletion condition reported a less positive mood state ($t = 2.85$, $df = 148$, $p < 0.01$). Although we statistically deal with this issue in Experiment 1 by including all higher level interactions in the model, to address the issue further, we conducted Experiment 2 in which we manipulate mood.

[9] The reading task was also used to conceal the main purpose of the study and to enable a realistic measure of actual disclosure behavior at a later stage of the experiment. It also served to reduce the

possibility that the privacy concerns scale, which was used early in the experiment, could result in a privacy priming effect.

[10] In the depletion literature, mood is measured either after the depletion task (Gino et al. 2011) or after the performance task (disclosure decision in our case) (Barber and Smit 2014). We chose to measure mood at the end of the experiment to avoid attenuation of the depletion effect and because mood changes can interact with the depletion state to affect subsequent task performance (Hagger et al. 2010).

[11] The two sets of disclosure items were combined in the final analysis.

[12] The substantive conclusions of the results reported remain consistent when using the original variable.

[13] We used WLS to correct for heteroskedasticity in the OLS model. After applying several robustness checks, the results from the WLS model remained consistent with those from the OLS model (for more details, see Online Appendix A.2).

[14] Note that low variance reduces statistical power, and hence, detecting a significant moderation effect with low variance in Experiment 1's disclosure scale provided a conservative test of the moderation effect (Aguinis et al. 2017).

[15] The exclusion criteria did not impact the success of the randomization as the descriptive statistics for privacy concerns and disclosure (before and after applying the exclusion criteria) show the same patterns with no significant differences. In addition, there was no significant correlation (*Chi-square* = 4.20, $p > 0.10$) between the experimental variable (i.e., mood) and the exclusion criteria. See Online Appendix C for descriptive statistics and statistical tests.

[16] There was high consistency between the qualitative feedback and the privacy concerns score. Those who decided not to disclose some or all personal information used privacy concerns in their qualitative feedback as a justification, and they also scored higher on the privacy concerns scale. Such observation confirms that dispositional privacy concerns impact disclosure behaviors and not vice versa.

[17] In Experiment 2, there was no need to log transform the dependent variable (as we did in Experiment 1) because the new disclosure scale exhibited sufficient variance and acceptable distribution. Nonetheless, we ran all the analyses after log transforming the dependent variables. The results remained consistent with those based on the untransformed dependent variable.

[18] The homoskedasticity of the variance of residuals was not violated. Therefore, we relied on OLS.

[19] To the best of our knowledge, there is no previous research that manipulates depletion and mood independently. Nonetheless, we designed and conducted several experiments (not reported here) to manipulate depletion and mood independently, but we were unable to do so without encountering problems, such as spillover and dissipation effects. Therefore, we opted for a joint manipulation task that eliminates dissipation effects by design because depletion and mood are manipulated simultaneously. Our joint manipulation task successfully manipulated participants into the four intended treatment conditions without any significant spillover effect (see Section 5.3).

[20] Given that Experiment 2 showed no significant differences between the neutral and negative mood conditions in terms of their moderation effect, we did not include a neutral mood condition in Experiment 3 (Forgas 1999, Albarracin and Hart 2011).

[21] The exclusion criteria did not impact the success of the randomization as the descriptive statistics for privacy concerns and disclosure (before and after applying the exclusion criteria) show the same patterns with no significant differences. In addition, there was no significant correlation (*Chi-square* = 4.16, $p > 0.10$) between the experimental variable (i.e., depletion and mood) and the exclusion criteria. See Online Appendix C for descriptive statistics and statistical tests.

[22] The statements were presented in a jpg format so that participants could not simply cut and paste the words but would have to actually type them.

[23] Consistent with Experiment 2, there was high consistency between the qualitative feedback and the privacy concerns score. Those who decided not to disclose some or all personal information used privacy concerns in their qualitative feedback as a justification, and they also scored higher on the privacy concerns scale. Such observation confirms that dispositional privacy concerns impact disclosure behaviors and not vice versa.

[24] Consistent with Experiment 2, there was no need to log transform the dependent variable (as we did in Experiment 1) because the new disclosure scale exhibited sufficient variance and acceptable distribution. Nonetheless, we ran all the analyses after log transforming the dependent variables. The results remained consistent with those based on the untransformed dependent variable

[25] The homoskedasticity of the variance of residuals was not violated. Therefore, we relied on OLS.

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