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# Role of "Likes" and "Dislikes" in Influencing User Behaviors on Social Media

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**ABSTRACT**

Two recent changes on social media platforms include (1) allowing users to mask the number of "likes" on others' posts, aimed at reducing social comparisons and consequent technology-mediated dangerous behaviors (TMDBs), such as disclosing private information, and (2) adding a "dislike" reaction, aimed at increasing engagement. Nevertheless, the effects of these changes on user behaviors are unclear. In this paper, we seek to address this gap by integrating risk-sensitivity theory (RST) and prospect theory. First, we explain that while masking others' "likes" may reduce social comparison, based on the "homeostatic violation" concept, people also make internal comparisons to expectations. Undesirable deviations from users' expectations of "likes" and "dislikes" (e.g., too few "likes" or too many "dislikes") can motivate TMDBs that users believe can alleviate the undesirable deviations. Thus, we argue that, in addition to social comparison mechanisms, there is an internal comparison mechanism that can motivate TMDBs. We test these claims via five randomized controlled experiments (total n = 1,594). Results show that, beyond social comparison mechanisms, receiving too few "likes" or too many "dislikes," compared to internal expectations, can motivate TMDBs. Moreover, we found that losses loom larger than gains as users are more likely to engage in TMDBs to avoid excess "dislikes" than to avoid deprivation of "likes." These findings make novel contributions to social media research and practice by pointing to an internal comparison mechanism as a potent motivator of TMDBs beyond social comparison processes and to the higher "toxicity" of "dislikes" than "likes" in terms of inciting TMDBs on social media.

**KEYWORDS**

Social media; online "like"; online "dislike"; risk sensitivity; prospect theory; technology-mediated dangerous behavior; problematic behavior online; toxicity online

## Introduction

"Likes" and "dislikes" are two forms of, respectively, positive and negative reactions on social media that allow users to engage with online content [32]. They are one-click paralinguistic digital affordances that allow users to express their delight or dismay toward specific content without using natural language. "Likes" are a common and popular reaction functionality on social media platforms. Facebook users, for example, post over 4.5 billion "likes" per day, and 50 percent of users "like" at least one post per day [14].

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"Likes" often serve as *appetitive stimuli*, that is they reinforce behaviors [56]. This is because they are rewarding and people forage for "likes" on social media in a way that is similar to animals' foraging for food to satisfy a range of needs [70]. Given the appetitive nature of "likes," people are willing to engage in technology-mediated dangerous behaviors (TMDBs) to satisfy their need for them [70]. TMDBs are actions taken by users aimed at increasing gratifications by accumulation of rewards (reward-seeking) or reducing pains (pain avoidance, such as alleviating ostracism) that are mediated via technology and are probabilistically associated with adverse outcomes [70]. Examples of TMDBs are posting racy, sexy, or risky selfies and disclosing private and sensitive information on social media. It is important to study TMDBs because they can lead to undesirable outcomes for users [70].

The negative effects of "likes" are captured by the concept of "toxicity." For instance, New York City recently designated social media a public health hazard for its toxic effects on youth mental health [2]. Likewise, the Royal Society for Public Health has argued that "likes" are the most toxic feature of social media [61]. Social comparison is one key mechanism that drives this toxicity. It involves users comparing themselves to others who are in a better (i.e., an upward comparison) or a worse position (i.e., a downward comparison) than theirs [70]. Recognizing the need to reduce social comparisons, some social media platforms have allowed users to hide the "like" counters for others [73]. A case in point is Instagram's decision to hide "like" counts on others' posts: "The idea [of hiding "like" counts] is to try and depressurize Instagram, make it less of a competition" [Adam Mosseri, Head of Instagram, November 2019] [52].

In contrast to the "like," the "dislike" feature is not commonplace on social media platforms, although it has been consistently used on some platforms such as YouTube and Reddit. In contrast to "likes," "dislikes" typically serve as *aversive stimuli* in the sense that they are unpleasant [56]. On YouTube, for example, "disliking" a video is quite common, with many videos having over a million "dislikes" [24]. Considering its popularity, other social media platforms, such as Facebook, Twitter, and TikTok, have contemplated or decided to add a "dislike" reaction [4, 62, 63, 68]. Given its stimulating nature, "dislike" counts appear to also motivate social comparison mechanisms. For instance, YouTube recently announced that they will hide "dislike" counts of others [69].

Two notable gaps in our understanding of users' interactions on social media platforms stem from these recent changes. First, it is not clear if minimizing explicit social comparison mechanisms by hiding others' "likes" (or "dislikes") is sufficient to eliminate the toxicity of social media reactions. While recent research on social media has demonstrated that social comparisons drive people to forage for more "likes," in part, by engaging in TMDBs [70], social comparison mechanisms may not be *the only driver* of TMDBs on social media platforms. An important case in point is Instagram's reversal of their aforementioned November 2019 policy to hide "like" counts because "It turned out that it didn't actually change nearly as much about . . . how people felt, or how much they used the experience as we thought it would" [Adam Mosseri, Head of Instagram, May 2021] [52]. This suggests that despite the importance of social comparisons in motivating TMDBs, there may be other mechanisms beyond social comparison that can motivate TMDBs. Second, the consequences of adding a "dislike" reaction and its implications for users are still largely unknown.

One possible explanation for users' motivation to act in response to "likes" and "dislikes," in the absence of explicit social comparison enablers, such as others' reaction counts, is rooted in the homeostatic balance (homeostasis) idea, which states that people generally strive to maintain their inner peace and psychological equilibria [65]. Due to unmet needs and desires, homeostatic violations can rattle one's homeostasis and create a sense of urgency to act in order to restore the balance [65]. Given the sense of urgency, preferred choices can include dangerous behaviors that have high potential rewards [54, 55]. On this basis, it can be argued that users might encode undesirable deviations from expected number of "likes" and "dislikes" (too few "likes" or too many "dislikes") as violating their homeostasis; and such violations can motivate actions aimed at restoring it. Thus, there may be an internal comparison mechanism (in addition to social comparison mechanisms) that may also drive user behaviors, including TMDBs. Notably, homeostatic violations can arise in different directions in the case of "likes" and "dislikes." In the case of "likes," they represent receiving *fewer* of them than expected, which prospect theory calls "gain deprivation" [29]. In contrast, in the case of "dislikes," they capture receiving *more* of them than expected, which prospect theory calls "excess loss" [29]. Against this backdrop, we put forward two research questions (RQs):

(RQ1): How does the internal comparison mechanism (i.e., contrasting received "likes"/"dislikes" against one's expectations) drive TMDBs?

(RQ2): Do gain deprivation in the context of "likes" and excess loss in the context of "dislikes" have differential effects on TMDBs?

We address these research questions by integrating risk sensitivity theory (RST) [46] and prospect theory [29]. In line with RST, this integrative perspective suggests that people with unmet expectations, as in not receiving enough "likes" or receiving too many "dislikes," are likely to have a stronger risk appetite than people whose expectations are met or exceeded. Consequently, they are expected to be more inclined to engage in TMDBs. Adding prospect theory ideas, the integrative perspective posits that the shift in risk preferences will be larger in the case of undesirable deviations in "dislikes" than in "likes," because losses loom larger than gains.

We test and validate this integrative theory via five randomized controlled experiments with social media users ($n_1 = 300$, $n_2 = 480$, $n_3 = 400$, $n_4 = 214$, $n_5 = 200$). In the experiments, we manipulate the undesirable deviation from the expected number of reactions (No/Yes; Studies 1-5) and the reaction type: "likes" (Studies 1-5) and "dislikes" (Studies 2-5). We focus on three TMDBs, which were identified via two preliminary studies as high-risk/high-reward acts. In Studies 1, 2, and 4, we focus on (a) intention to post a risky selfie (TMDB 1), defined as planning to publish a selfie that can compromise a person's long-term goals and success if taken out of context or circulated, and (b) preference for high-risk/high-reward (hereafter called "high-risk/reward") selfies (TMDB 2), defined as favoring selfies that are risky yet can produce more "likes" (or fewer "dislikes") over mundane and safe photos. Together, intention and preference reflect the user's orientation toward TMDBs. In Study 3, we focus on disclosing private information on one's social media profile (TMDB 3), which may compromise the user's desired state if circulated. This reflects an actual behavior, manifested in the users' likelihood of engaging in a TMDB. Together, our choice of three TMDBs provides a comprehensive view of the effects of internal comparison mechanisms on users' decisions.

Overall, the findings show that internal comparisons that contrast expected and actual (received) "likes" (or "dislikes") can cause undesirable deviations, that is, homeostatic violations, that motivate TMDBs. They further suggest that "dislikes" are more toxic than "likes" and may present a new threat to social media users in that they can more strongly motivate TMDBs. These findings extend prior works and inform the understanding of user responses to social media affordances in three ways. First, they account for unexplored drivers of TMDBs, beyond social comparison mechanisms, namely internal comparisons. Second, they consider the relatively novel context of negative reactions such as "dislikes." Third, they show that "dislikes" are more toxic than "likes" as they have higher potency for motivating TMDBs. From a practical standpoint, these findings offer important insights to social media platforms about the risks of "dislike" and "like" affordances, and to users about the effects of their responses to social media reactions.

## Theoretical Background and Hypotheses

### *Technology-Mediated Dangerous Behaviors (TMDBs)*

TMDBs represent a family of information technology (IT)-mediated actions that can have adverse consequences for users [70]. Examples of TMDBs include clicking on phishing links [58], disclosing private information to strangers online [70], using mobile phones while driving [71], taking risky selfies (e.g., on the edge of a cliff) [70], and doing dangerous challenges on social media (e.g., "Benadryl challenge" on TikTok) [11]. While the adverse consequences of TMDBs may not always be realized, there is a considerable risk when they are enacted; hence, they are considered "dangerous" [70].

Prior works have consistently conceptualized TMDBs as intrinsically or extrinsically rewarding behaviors. Intrinsic rewards are in the form of satisfying internal needs, such as one's curiosity (e.g., when receiving a new message notification on social media) or alleviating painful states, such as boredom [58]. Extrinsic rewards are in the form of external gratifications, including gain attainments, such as receiving attention, admiration, affection, and social status (e.g., receiving "likes" or "followers" on social media), or loss avoidance, such as avoiding online ostracism and disapproval [58]. Notably, avoiding or alleviating pain (i.e., loss avoidance) is rewarding in the sense that it is desirable and motivates human action [1]. Indeed, studies show that pain relief is pleasurable, is encoded in the same brain regions in which gain attainments are encoded, and, like gain attainment, manifests in the dopamine release [51]. In addition, economic theory suggests that while weighted differently, people are motivated by both accumulating gains and avoiding losses, which together are summarized as expected rewards and are encoded against a reward threshold to decide whether to act on them [60]. Lastly, disorders that manifest in excess pain have overlapping etiology with disorders that manifest in reduced ability to process gains (e.g., major depression) [59]. All in all, both economic and neuroscientific views consider both gain attainment and loss avoidance as rewarding.

Notably, seeking rewards, whether in the form of gain attainment or loss avoidance, is a potent driver of engaging in the TMDBs [58, 70]. Users are often aware of the danger of TMDBs [70]. For example, most users know that taking selfies on the edge of a cliff can be dangerous [80]. However, prior research shows that in certain circumstances, users may act less rationally and engage in TMDBs despite the risks. For example, Qahri-Saremi and Turel

[58] found that in certain situations, such as high online ostracism or source likability, users may engage with phishing messages on social media despite their overall awareness of the risks. Similarly, users who voice privacy concerns may disclose private information that contradicts their voiced concerns [64]. In this paper, we focus on an *internal comparison mechanism*, namely *homeostasis violation gauging*, as a potential driver of TMDBs on social media. This mechanism, we posit, is driven by undesirable deviations from one's internal expectations for "likes" and "dislikes" [81].

### Prior Information Systems (IS) Research on "Likes" and "Dislikes"

To provide a proper overview of prior research on "likes" and "dislikes" in the context of TMDBs, we performed a systematic search of literature for papers with "likes," "dislikes," and "technology-mediated dangerous behaviors" in the titles and abstracts. We specifically searched all AIS Senior Scholars' Basket of Journals.[1] This search produced 241 papers. However, most uses of the words "like" and "dislike" did not relate to social media "likes" and "dislike." Filtering out these papers left us with 22 relevant papers (see Table 1) that offer several important insights: (1) as a dependent variable, "likes" are often used as a proxy for engagement,; (2) as independent variables, "likes" and "dislikes" signal information, such as quality and virality; and (3) the use of "likes" and its effects are context dependent. These studies also point to three notable research gaps. First, although "dislikes" are becoming more common, our insights about them are much more limited as compared to "likes." Second, the knowledge about whether and how users react differentially to "likes" versus "dislikes" is limited. Third, mechanisms, beyond social comparisons, through which common social media reactions can influence TMDBs are not fully understood. That is, from a practical standpoint, the limited effectiveness of the elimination of social comparison mechanisms merits novel theorizing.

### Risk Sensitivity Theory and Hypotheses

Originated in studies on animal foraging behavior, RST explains that animals seek to minimize the chances of aversive outcomes that deviate from their needs by shifting their risk appetite; this leads to preferring higher-risk/reward options under conditions of deprivation [49]. The essence of RST is the idea that animals are motivated to maximize their net energy intake by increasing the chances of finding nutrients, minimizing search costs, and reducing the danger of becoming another animal's prey in this process [44]. It further posits that in normal conditions (i.e., sufficient energy budget), animals are goal-oriented actors that strategically select foraging fields, approaches, and times [67]. However, when their energy budgets are low (i.e., they do not have enough food), animals can develop an irrational shift in risk preferences and choose high-risk/reward foraging activities, which, despite their bigger reward potentials in terms of food intake, they involve much higher risks [67].

Recent lines of work have extended RST from animals to humans by focusing on humans' unmet higher-order needs, such as financial and hedonic reward needs [53]. For example, Payne et al. [55] showed that people shift their financial risk appetite in response to financial inequality. Drawing on RST, Payne et al. [55] found that higher inequality in the outcomes of an experimental economic game led participants toward

**Table 1.** A summary of prior IS research on "likes" and "dislikes."

| Paper | "Likes" | "Dislikes" | Specification | Findings |
|---|---|---|---|---|
| Bapna et al. [7] | ✓ | | IV & DV | Firm posts with desirable attributed (e.g., credibility) increase "likes", but mostly for early-stage brands. "Likes," in turn, drive subsequent community size. |
| Bhattacharyya and Bose [9] | ✓ | | IV | A higher volume of "likes" increases attitude toward advertised products, visiting linked sites, purchasing the product, and recommending it. |
| Chen et al. [15] | ✓ | | IV | "Likes" on ads increase impulse buying. |
| Chesney [16] | ✓ | | IV | "Likes" can signal information and relate to virality. |
| Dewan et al. [19][a] | ✓ | | IV | Indicators that peers and the community "favorite" a song drive one's music preferences. Community influence is salient for narrow-appeal music. Peer influence is more dominant. |
| Ding et al. [20] | ✓ | | IV | Movie prerelease "likes" predict box-office success. |
| Garvey et al. [23] | ✓ | | DV | It is feasible to design a system to generate Tweet components aimed at increasing engagement in form of "likes." |
| Heimbach and Hinz [26] | ✓ | | IV | "Like" is more ambiguous than "recommend" and thus often mismatches one's needs and results in lower sharing behavior. |
| Jin et al. [27] | ✓ | | IV | "Likes" on Facebook can signal quality and underlie herding, and they ultimately increase the likely success of crowdfunding. |
| Kim and Dennis [33] | ✓ | | DV | People are more likely to "like" articles that align with their beliefs and that they believe are true. |
| Kim et al. [34] | ✓ | | DV | Believability of articles drives "liking" the article. |
| Kuan et al. [35] | ✓ | | IV | "Like" information increases intentions to buy a product. |
| Lee et al. [36] | ✓ | | IV | "Likes" increase traffic and sales, predominantly in certain contexts, such as when buying experience good and from independent stores. |
| Meire et al. [47] | ✓ | | IV | "Likes" increase the likelihood of positive sentiment in a post. |
| Moravec et al. [50] | ✓ | | DV | Believability of articles drives "liking" the article. |
| Turel [70] | ✓ | | IV | Inequality in "likes" triggers social comparison mechanisms that drive people to feel deprived of "likes" and engage in TMDBs. |
| Wang et al. [74][a] | ✓ | ✓ | IV | Liking emoticons increase perceived good intention of feedback provider and reduce perceived feedback negativity only when feedback is specific. The reverse is true for disliking emoticons, but only when feedback is unspecific. |
| Wessel et al. [75] | ✓ | | IV | Fake "likes" increase crowdfunding backing in the short run, but then lead to a larger decline, leading to an overall loss. |
| Xu et al. [77] | ✓ | | DV | Task characteristics (e.g., information needs), symbol sets (included image), and their fit predict "liking" a post. |
| Yang et al. [78] | ✓ | | DV | On business pages, social complains receive more "likes" than quality or money complaints, and positive posts receive more "likes" than negative ones. |
| Zalmanson et al. [81] | ✓ | ✓ | IV | A like/dislike button is a social cue that increases social perceptions and information disclosure, but only on trusted websites. |
| Zhang and Moe [82] | ✓ | | IV | "Likes" and textual comments can be combined to inform brand favorability. |

[a]These studies did not use the "like" and "dislike" functions as is. Instead, they used proxies that convey the same information, like emoticons and "favorite" indicators. IS, information systems; IV, independent variable; DV, dependent variable; TMDBs, technology-mediated dangerous behaviors.

greater risks to achieve higher outcomes. This effect was driven by upward social comparisons. Payne et al. [55] also found that risk-taking was higher in the states with greater income inequality, an effect driven by inequality at the upper end of the income distribution. Similarly, Mishra and Lalumière [49] demonstrated that young people behave as predicted by RST, shifting from risk-aversion to risk-proneness in situations of high need. In the same vein, Turel [70] argued that RST can be extended to the social media context where users forage the "fields of social media" for social-hedonic rewards. They found that social media users change their risk appetite toward more dangerous behaviors with higher rewards for increasing the probability of obtaining "likes" when they perceive that others have more "likes" than they do (i.e., upward social comparison).

However, social comparison information is not always available or explicitly enabled by system design. For example, Instagram and YouTube allow users to hide others' "likes" and "dislikes" counts, respectively. In this paper, we contend that without a formal social comparison mechanism, users can still experience an unmet need based on the number of reactions they receive in relation to *what they anticipate or expect to receive* [49]. Humans are generally irritated by such undesirable deviations from expectations, which motivate action. This disturbance of one's inner peace is encapsulated by the homeostatic violation concept [65]. It is also expressed in many theoretical accounts that postulate an internal comparison mechanism between current and desired states, including expectation-disconfirmation [8], social cognitive [6], ambivalence [57,58], and cognitive dissonance [22] theories. The common thread in all these theories is that humans do not like to be in a state that violates their homeostasis [54]. Therefore, they consciously or subconsciously act to amend this situation.

Extending this view, RST suggests that attempts to restore homeostasis get riskier and less rational as the deficit in what is needed grows larger [46]. This idea has been supported in the contexts of financial risk-taking [49, 55] and engaging in TMDBs [70, 81]. It is reasonable to apply RST to social media reactions ("likes" and "dislikes") because such reactions fulfill basic human needs, and deprivation from expected reactions can drive dangerous online behaviors [70]. Because humans satisfy higher-order needs by accumulating "likes" in a similar way to animals' food foraging, based on RST, we can expect social media users to present a shift in risk preferences when they are deprived of the expected number of "likes." Note that while not all users are expected to act in a risky and dangerous manner in response to deviations from their desired reactions, we can expect users in a deprivation state to present a stronger risk appetite, on average, compared to users whose reaction needs are met.

Given the risks of engaging in high-risk/reward TMDBs that users might well be aware of, there might be a difference between user orientation toward (i.e., intention and preferences for) such TMDBs and their likelihood of actual engagement in them. While users may have a strong orientation toward high-risk/reward TMDBs to mitigate their homeostatic violation, the risks of engaging in TMDBs may prevent some users, particularly those with lower risk propensity, from engaging in the actual behavior. Thus, there may be a gap between users' orientation and actual behaviors in the case of TMDBs. As such, to provide a more comprehensive view of users' decisions in the face of homeostatic violations, in our hypotheses, we investigate both user orientation toward (i.e., their intention and preference for) TMDBs and their likelihood of engaging in an actual TMDB:

> (H1) (the "gains zone"[2]hypothesis): Gain deprivation (i.e., receiving fewer "likes" than expected) increases (a) user orientation toward, and (b) the likelihood of engaging in TMDBs.

Because "dislikes" are *aversive stimuli*, people are dismayed by them and try to avert them [56]. In fact, receiving "dislikes" is significantly more aversive for people than being ignored, because receiving "dislikes" weakens one's sense of belonging and self-esteem more than ostracizing them does [43]. Despite this potency of "dislikes," the RST and IS research streams have thus far focused primarily on "likes" and their effects on users' behaviors (see Table 1). People, however, prefer riskier choices when their needs are not met not only in the "gains zone" (e.g., saving more lives, making more money), but also in the "losses zone" (e.g., trying to avoid life loss, or losing money) [48]. To illustrate, drug addicts prefer riskier choices to avoid unpleasant states, such as withdrawal [10], and animals gravitate toward riskier behaviors to avoid predators [79].

As such, we contend that RST can be generalized from its original appetitive focus to theorize about the need to avoid aversive states. After all, deviations from expected states, whether the deviation is in the form of "lower-than-expected" in an appetitive context or "more-than-expected" in an aversive context, are unpleasant and manifest in undesired homeostatic violations [10]. In support of this view, it has been shown that when people try to minimize the possibility of loss, such as death, they are more likely to select riskier options than safe options [48]. Following this logic, we expect that when people receive more "dislikes" than expected, they will experience a homeostatic violation and, consequently, will be more willing to amend the situation through dangerous choices (TMDBs in our case), compared to when they receive a lower-than-expected number of "dislikes." On this basis, we hypothesize:

(H2) (the "losses" zone hypothesis): Excess loss (i.e., receiving more "dislikes" than expected) increases (a) users' orientation toward, and (b) the likelihood of engaging in TMDBs.

## *Prospect Theory and Hypotheses*

The core ideas of prospect theory are: (1) people encode gains and losses based on deviations from expected values, (2) people's utility functions are convex in the domain of losses and concave in the domain of gains, and (3) losses loom larger than gains; an attribute that renders people more loss-averse than gain-appetitive [29]. That is, people have an inherent preference for loss avoidance compared to a similar magnitude of gain attainment. This theory has been validated across different contexts as it is more realistic than utility maximization theories that assume similar reactions to gains and losses [38].

Prospect theory has been used in several IS models, such as in the contexts of privacy [3], escalation of commitment in IS projects [30], and responses to IS threats and risks [39]. In this paper, based on prospect theory, we posit that the RST-prescribed shift in risk preference should be larger in aversive contexts, namely excess of "dislikes," as compared to appetitive contexts, namely deprivation of "likes." This follows from the key idea of prospect theory that people are more motivated to prevent losses (i.e., receiving fewer "dislikes") than to generate the same amount of gains (i.e., receiving more "likes") [45]. Against this backdrop, we hypothesize:

(H3) (the "risk aversion" hypothesis): Compared to gain deprivation (i.e., receiving fewer "likes" than expected), excess loss (i.e., receiving more "dislikes" than expected) has a stronger effect on (a) users' orientation toward, and (b) the likelihood of engaging in TMDBs.

## Research Design

We report two preliminary studies followed by five randomized controlled experiments to test our hypotheses and assess the robustness of our findings.

### Preliminary Studies

We conducted two preliminary studies aiming to identify TMDBs that are perceived as dangerous by social media users and can produce more "likes" or fewer "dislikes" for them (i.e., they represent high-risk/reward choices). Before conducting the preliminary studies, a focus group of 10 social media users agreed that posting nature and/or food photos was a common, mundane, and safe behavior on social media. We used such behaviors as a reference point.

In Preliminary Study 1, 100 Amazon Mechanical Turk (MTurk) workers reported what they perceived to be common TMDBs on social media, rated their danger, and indicated their confidence in receiving more "likes" and fewer "dislikes" for these actions compared to posting a nature image. The responses pointed to two TMDBs that represent high-risk /reward acts: (1) sharing risky photos of themselves (i.e., sexy/racy, risky, and rebellious selfies), and (2) disclosing private/sensitive information about themselves.

In Preliminary Study 2, data collected from 14 IS scholars (i.e., faculty members and Ph.D. students in a university located in the Southeastern United States) who were social media users confirmed that the two proposed TMDBs are indeed perceived to be more dangerous ($p < .001$) and with a higher reward potential (more likely to produce "likes") ($p < .027$) than the safe behaviors (i.e., posting nature and food photos). We, therefore, concluded that posting sexy/risky/rebellious selfies and disclosing sensitive/private information are appropriate TMDBs in the context of social media (see Online Supplemental Appendix 1 for more details about the two preliminary Studies). These findings are consistent with TMDBs used in Turel [70]. Thus, we adapted the same scales for operationalizing TMDBs in our studies.

### Main Studies

We used a multi-study design to test our hypotheses. Study 1 aimed to examine H1a. Study 2 sought to validate Study 1 findings and examine H2a and H3a using a different sample. Study 3 extended these findings from user orientation toward TMDBs to an actual TMDB and tested H1b, H2b, and H3b. We ensured the robustness of our findings in Studies 4 and 5 by replicating Studies 2 and 3, respectively, while directly accounting for the extent of social (upward and downward) comparisons. This ensured that our proposed internal comparison mechanism influences users' decisions beyond (after accounting for) the effects of the social comparison mechanisms.

Studies 1, 2, and 4 focus on user *orientation* toward TMDB, which, based on the results of the preliminary studies, was operationalized using (1) intention to post a risky selfie (TMDB 1) and (2) preference for high-risk/reward selfie (TMDB 2). Studies 3 and 5 focus on users' likelihood of engaging in an actual TMDB (i.e., actual behavior), which, based on the results of the preliminary studies, was operationalized using disclosing private and sensitive information, including users' full name, birthdate, city of residence, political affiliation, and love for alcohol and partying (TMDB 3). Treating this information as private and sensitive is consistent with prior studies [40, 70].

Samples for Studies 1-3 were independently drawn from social media users residing in the United States, using the CloudResearch MTurk Toolkit [41] to recruit MTurk workers. This allowed for obtaining representative samples of social media users [37, 66]. We implemented several attention-check questions and data quality screening facilitated by CloudResearch [41] to automatically exclude careless respondents [18]. To ensure the naivete of participants, we excluded the top 4 percent of MTurk respondents, who usually respond to 50 percent of MTurk surveys. This is consistent with guidelines for addressing the non-naivete concerns with MTurk samples [5]. Participants with complete responses were paid $3.00 for their time (~20 minutes). For improved generalization and minimizing reliance on the same platform for data collection (i.e., MTurk) [21], samples for Studies 4 and 5 were collected using the CloudResearch Connect platform, which has been used in prior studies [25, 31]. We implemented similar attention check questions and data quality features in Studies 4 and 5 as those in Studies 1-3 to avoid careless responses.

The true purpose of the studies was not revealed to the participants. Rather, they were told that the purpose of the study was to test a new social media concept platform that allows posting profile pictures and interacting with other users via "likes" or "dislikes," depending on the condition the participants were assigned to. The procedure included three seamlessly integrated components: (1) a pre-task survey in which we measured demographics, descriptive information, and control variables; (2) interaction on an ostensible social media platform, adapted from Wolf et al. [76] and Qahri-Saremi and Turel [58], where we manipulated the number of "likes" or "dislikes" (depending on the condition) that the participant received; and (3) a post-task survey in which we measured manipulation checks and TMDBs. Participants were debriefed after the data collection was over.

In the pre-task survey in each study, we measured participants' privacy and risk beliefs toward the TMDBs that we are focusing on, their overall risk propensity, social comparison orientation, gender, age, and number of hours per day of social media use, which were used as control variables (see Online Supplemental Appendix 2 for the scales). At the end of the pre-task survey, participants were instructed that they would be redirected to a new social media forum where they would create a profile for themselves and interact with 11 other people who are also participants in this study. They were told that on a social media platform, they would be able to see other participants' profiles, read their introductions, and give and receive "likes" (and "dislikes," depending on the condition they were assigned to). Finally, they were asked how many "likes" (or "dislikes," depending on the condition) they *expect* to receive on their profile (possible range: 0-11).

Next, participants entered the task component of the experiments, which involved interaction on the ostensible social media platform, adapted from Wolf et al. [76] and Qahri-Saremi and Turel [58]. To increase the realism of this step, participants were asked to wait for other participants to join the platform. However, in reality, only one participant at a time was on the platform, and the rest of the participants (n = 11) were pre-programmed bots. As a first step in the task, the person was asked to choose an avatar (out of 82 options) and write a clear introduction of themselves (at least 400 characters). The descriptions and avatars of the bots ensured race, age, and gender diversity. Next, they entered the social media forum where they could interact with the bots by only giving and receiving "likes" (or "dislikes"), using the typical Facebook "like" button (or the thumbs down button for "dislike"). For three minutes, participants were asked to read others' profiles and "like" (or "dislike" when relevant) as many profiles as they wanted. In all studies, participants could only view the number of "likes" (or "dislikes") that they have received and could not see others' "likes" or "dislikes" counts. This intentional design was to minimize the effects of the social comparison mechanism (see Online Supplemental Appendix 3).

After task completion, participants were seamlessly redirected to the post-task survey, where they responded to questions for manipulation checks and measuring TMDBs (see Online Supplemental Appendix 2 for the scales). The participants were told they would be given another chance to visit the social media forum, and they could make changes to their profile and add information to it if they wished. Participants were told that they needed to wait for others to join the social media forum, and in the meantime, they could specify the changes they would like to make to their profiles via the next few pages. The next few pages in the survey captured TMDBs, depending on the Study. Next, participants were presented with manipulation check questions, which concluded the experiment. Participants were debriefed via a message attached to their compensation after the conclusion of the experiment. In all studies, the pre-task and post-task surveys were based on existing valid scales, which were pilot-tested with a separate sample of 120 MTurk workers who were social media users residing in the United States (similar to our main samples in Studies 1-3). The procedures were free of glitches, the cover story and task were perceived as realistic (i.e., participants were naïve to the true purpose of the study and thought it was about testing a new social media site), and the scales were internally consistent (Cronbach's $\alpha \geq .70$).

## Study 1

### *Participants, Procedure, and Measures: Study 1*

The sample included 300 social media users, of which 207 were women (69 percent). The average age was 35.07 (SD = 10.52), and median social media use was 2 hours/day. The pre-task survey captured age, gender (female = 0, male = 1), social media use hours/day, privacy and risk beliefs about the target TMDB, risk propensity, and social comparison orientation. We aimed at observing gain deprivation effects on TMDB, after accounting for these controls. These control variables were selected because social media use can provide learning opportunities about TMDBs, and risk propensities and risk and privacy beliefs can influence tendencies to engage in TMDBs [70]. Moreover, we included social comparison orientation as a control variable to account for its possible confounding effect.

In the task part, we manipulated the number of "likes" a participant received. We randomly assigned participants to one of the two conditions: *gain attainment* and *gain deprivation*. Participants in the gain attainment condition received at least the expected number of "likes," with a maximum of 11 "likes" (the number of other "participants" in the forum). Participants in the gain deprivation condition received fewer "likes" than expected (between 0 and one less than the expected number of "likes"). In the post-task survey, we validated the manipulation (the sense of gain deprivation) and measured the target TMDBs, that is, respondents' intention to replace their avatar with a risky selfie (TMDB 1) and the preference for a high-

**Table 2.** Descriptive statistics and between-condition differences: Study 1[a]

| | Overall (n = 300) | Condition 1: Gain Attainment (n = 150) | Condition 2: Gain Deprivation (n = 150) | *p*-Value for Difference |
|---|---|---|---|---|
| Pre-task Survey | | | | |
| Age | 35.07 (10.52) | 34.48 (10.57) | 35.66 (10.46) | .332 |
| Gender (F = Female, M = Male) | 207 F/ 93 M | 105 F/ 45 M | 102 F/ 48 M | .709 |
| Social Media Hours/Day | 4.05 (1.56) | 4.19 (1.60) | 3.91 (1.51) | .129 |
| Privacy Beliefs toward Risky Selfies[b] | .000 (1.00) | .020 (.97) | -.021 (1.03) | .715 |
| Risk Beliefs toward Risky Selfies[b] | .00 (1.00) | -.06 (.97) | .06 (1.03) | .336 |
| Risk Propensity (α = .88) | 3.01 (1.14) | 3.02 (1.14) | 2.99 (1.15) | .790 |
| Social Comparison Orientation | 4.37 (1.44) | 4.34 (1.42) | 4.40 (1.47) | .680 |
| Post-task Survey | | | | |
| Perceived Gain Deprivation (α = .92) | 2.00 (1.16) | 1.57 (.86) | 2.43 (1.25) | <.001 |
| TMDB 1: Intention to Post a Risky Selfie[b] | .00 (1.00) | -.11 (1.01) | .11 (.98) | .054 |
| TMDB 2: Preference for High-risk/reward Selfie[b] | .00 (1.00) | -.14 (.99) | .14 (1.00) | .015 |

[a]Numbers represent mean, and SD (in parentheses). [b]Principal components due to formative specification using z-score scales. *p*<.05 values for the difference between conditions are in bold. TMDB, technology-mediated dangerous behavior.

risk/reward selfie (TMDB 2). We presented the manipulation checks at the end to eliminate possible effects on participants' responses to TMDBs. Notably, because the risky selfie TMDB was operationalized based on different types of selfies (i.e., racy/sexy, risky, and rebellious), we specified privacy and risk beliefs as well as the intention and preference for this TMDB as formative constructs and used their principal component analysis (PCA) scores in the analysis.[3]

### Results: Study 1

Descriptive statistics, reliabilities, and comparisons between the conditions are provided in Table 2. Results indicate that there were no prior differences between the randomly assigned conditions in their demographic, privacy and security beliefs, risk propensity, social media use, and social comparison orientation. The results further show that people in the Gain Deprivation condition felt significantly more deprived than people in the Gain Attainment condition (small effect). Thus, the results provide preliminary support for H1a.

To further probe H1a in the presence of control variables, we ran a regression model with the condition as the predictor and intention to post a risky selfie as the dependent variable (TMDB 1). As shown in Table 3, users who were deprived of "likes" had significantly stronger intentions to replace their avatar with a risky selfie ($\beta = .12$, $p = .029$). Privacy beliefs toward risky selfies ($\beta = -.31$, $p < .001$) and risk propensity ($\beta = .14$, $p = .016$) were the only significant control variables. The model explained 21.8 percent of the variance in TMDB 1 and had a medium effect size ($f^2 = .28$). Repeating the analyses with TMDB 2, also depicted in Table 3, explained 16.4 percent of the variance and had a medium effect size ($f^2 = .20$). This model showed that users who were deprived of "likes" had a significantly stronger preference for high-risk/reward selfies ($\beta = .15$, $p = .005$). Gender ($\beta = .18$, $p = .001$), social media hours/day ($\beta = .18$, $p = .002$), and privacy beliefs toward risky selfies ($\beta = -.27$, $p < .001$) were significant control variables.

**Table 3.** Tests of H1a for TMDB 1 (intention to post a risky selfie) and TMDB 2 (preference for high-risk/reward selfie) (Study 1)[a]

| | | TMDB 1: Intention to Post a Risky Selfie (n = 300) | TMDB 2: Preference for High-risk /reward Selfie (n = 300) |
|---|---|---|---|
| Controls Only | Age | .05 (.340) | -.01 (.838) |
| | Gender (0 = Female, 1 = Male) | .10 (.074) | **.18 (.002)** |
| | Social Media Hours/Day | .04 (.501) | **.17 (.004)** |
| | Privacy Beliefs | **-.32 (<.001)** | **-.28 (<.001)** |
| | Risk Beliefs | -.08 (.239) | .04 (.571) |
| | Risk Propensity | **.13 (.018)** | .05 (.366) |
| | Social Comparison Orientation | .04 (.425) | .03 (.579) |
| | $R^2$ ($f^2$ in parentheses) | 20.5 percent (.26) | 14.1 percent (.16) |
| Controls & Main Effects | Age | .05 (.400) | -.02 (.721) |
| | Gender (0 = Female, 1 = Male) | .10 (.066) | **.18 (.001)** |
| | Social Media Hours/Day | .05 (.388) | **.18 (.002)** |
| | Privacy Beliefs | **-.31 (<.001)** | **-.27 (<.001)** |
| | Risk Beliefs | -.09 (.177) | .03 (.726) |
| | Risk Propensity | **.14 (.016)** | .06 (.334) |
| | Social Comparison Orientation | .04 (.458) | .03 (.628) |
| | Undesirable Deviation | **.12 (.029)** | **.15 (.005)** |
| | $R^2$ ($f^2$ in parentheses) | 21.8 percent (.28) | 16.4 percent (.20) |
| | $\Delta R^2$ (*p-value* in parentheses) | 1.3 percent (.029) | 2.3 percent (.005) |

[a]Numbers represent standardized coefficients, and p-values (in parentheses). p < .05 values are in bold. TMDB, technology-mediated dangerous behavior.

### *Discussion: Study 1*

Findings supported H1a and demonstrated that people who received fewer "likes" than expected, regardless of what others received (invisible to them, which minimized the effects of social comparison), had elevated intentions to post risky selfies (TMDB 1) and stronger preferences for high-risk/reward selfies (TMDB 2), compared to people who received enough "likes." This reaffirms the applicability of RST to the social media context and extends its theoretical basis beyond social comparison. It points to an overlooked internal comparison mechanism, which considerably broadens our knowledge of the factors that motivate TMDBs.

## Study 2

### *Participants, Procedure, and Measures: Study 2*

The Study 2 sample included 480 social media users, of which 344 were women (72 percent). The average age was 35.21 (SD = 10.43), and median social media use was 2 hours/day. The pre-task survey was identical to the one in Study 1. In the task part, we employed a 2 (*Reaction Type*: "likes" vs. "dislikes") × 2 (*Undesirable Deviation*: "No, expectations are met" vs. "Yes, undesirable deviation from expectation") between-subjects factorial design. Each participant was randomly assigned to one of these four conditions. The first factor was manipulated by creating two parallel social media forums: one with a "like" functionality and another with a "dislike" functionality. The second factor was manipulated like in Study 1: participants reported their expected number of "likes" or "dislikes," and we experimentally controlled the number of "likes" or "dislikes" they received. For example, in the "dislikes" condition, a participant who expected to receive 5 "dislikes" and was assigned to the "undesirable deviation" condition received between 6 and 11 "dislikes" (i.e., above expectation). The post-task survey had one difference from Study 1: In the "dislikes" condition, we modified scales to focus on "dislikes." For the "likes" condition, we used the same survey items as those in Study 1 (see Online Supplemental Appendix 2). Construct specifications and operationalizations were similar to those of Study 1.

## Results: Study 2

Descriptive statistics, reliabilities, and comparisons between the conditions are provided in Table 4. The results demonstrate several prior cross-conditional differences between the groups. Thus, we control for these factors in subsequent analyses. Results suggest that, as expected, participants in the undesirable deviation condition, regardless of the reaction type to which they were exposed ("likes" vs. "dislikes"), reported significantly higher perceived deprivation, intentions to post a risky selfie (TMDB 1), as well as stronger preference for high-risk/reward selfies (TMDB 2). The "Reaction Type" factor produced significant differences in perceived deprivation: it was significantly higher in the "dislikes" condition. It produced no differences in intentions to post a risky selfie (TMDB 1) and preference for high-risk/reward selfies (TMDB 2), likely because reaction-type conditions lump together undesirable deviation and no undesirable deviation from expectations.

To test H1a and H2a with these data, we split the sample into the corresponding gains ("likes") and losses ("dislikes") datasets. We then regressed intentions to post a risky selfie (TMDB 1; see Table 5) and preference for high-risk/reward selfies (TMDB 2; see Table 6) on the control variables and the predictor (no undesirable deviation = 0, undesirable deviation = 1) in each dataset. To test H3a, an extended regression model, including the reaction type (1 = "dislikes," 0 = "likes") and an interaction term for the conditional effect of reaction type, was estimated on the whole dataset.

**Table 4.** Descriptive statistics and between-condition differences for Study 2.[a]+

| | | Factor: Undesirable Deviation | | | Factor: Reaction Type | | |
|---|---|---|---|---|---|---|---|
| Pre-task Survey | Overall (n = 480) | No Undesirable Deviation (n = 240) | Undesirable Deviation (n = 240) | *p*-Value | "Likes" (n = 240) | "Dislikes" (n = 240) | *p*-Value |
| Age | 35.21 (10.43) | 35.54 (10.86) | 34.87 (10.00) | .482 | 35.83 (10.61) | 34.58 (10.24) | .191 |
| Gender (F = Female, M = Male) | 344 F 136 M | 177 F 63 M | 167 F 73 M | .312 | 162 F 78 M | 182 F 58 M | **.043** |
| Social Media Hours/Day | 3.96 (1.43) | 3.99 (1.40) | 3.93 (1.47) | .655 | 4.00 (1.49) | 3.92 (1.37) | .524 |
| Privacy Beliefs[b] | .00 (1.00) | .14 (.95) | -.14 (1.03) | **.002** | -.01 (.97) | .01 (1.03) | .807 |
| Risk Beliefs[b] | .00 (1.00) | .11 (1.02) | -.11 (.97) | **.015** | -.03 (.98) | .03 (1.02) | .458 |
| Risk Propensity | 2.89 (1.06) α = .86 | 2.80 (1.01) | 2.98 (1.11) | .059 | 2.94 (1.10) | 2.85 (1.02) | .365 |
| Social Comparison Orientation | 4.55 (1.39) α = .83 | 4.52 (1.39) | 4.58 (1.40) | .607 | 4.50 (1.41) | 4.60 (1.37) | .412 |
| Post-task Survey | | | | | | | |
| Perceived Deprivation | 2.47 (1.50) α = .93 | 2.01 (1.22) | 2.94 (1.60) | **<.001** | 2.07 (1.20) | 2.88 (1.65) | **<.001** |
| TMDB 1: Intention to Post a Risky Selfie[b] | .00 (1.00) | -.34 (.95) | .34 (.93) | **<.001** | .001 (.97) | -.001 (1.03) | .992 |
| TMDB 2: Preference for High Risk/ Reward Selfie[b] | .00 (1.00) | -.32 (.93) | .32 (.97) | **<.001** | -.015 (.96) | .015 (1.04) | .736 |

[a]Numbers represent mean, and SD (in parentheses). [b]Principal components due to formative specification based on z-score scales. p < .05 values for difference between conditions are in bold. TMDB, technology-mediated dangerous behavior.

**Table 5.** Tests of H1a-H3a for TMDB 1: Intention to post a risky selfie (Study 2).[a]

| | | Test H1a: "Likes" (Gains Zone) (n = 240) | Test H2a: "Dislikes" (Losses Zone) (n = 240) | Test H3a: All Data (n = 480) |
|---|---|---|---|---|
| Controls Only | Age | -.02 (.695) | .04 (.480) | .01 (.854) |
| | Gender (0 = Female, 1 = Male) | .08 (.187) | .02 (.775) | .05 (.239) |
| | Social Media Hours/Day | .02 (.788) | .00 (.968) | .00 (.950) |
| | Privacy Beliefs | **-.22 (.006)** | **-.25 (.007)** | **-.23 (<.001)** |
| | Risk Beliefs | -.14 (.065) | -.12 (.187) | -.13 (.028) |
| | Risk Propensity | **.17 (.012)** | .11 (.105) | **.14 (.003)** |
| | Social Comparison Orientation | -.01 (.942) | .11 (.073) | .06 (.208) |
| | $R^2$ ($f^2$ in parentheses) | 18.5 percent (.23) | 15.6 percent (.19) | 16.3 percent (.20) |
| Controls, Main, & Interaction Effects | Age | -.04 (.575) | .10 (.089) | .03 (.499) |
| | Gender (0 = Female, 1 = Male) | .09 (.146) | -.03 (.560) | .03 (.455) |
| | Social Media Hours/Day | .03 (.657) | -.02 (.791) | .01 (.884) |
| | Privacy Beliefs | **-.20 (.010)** | **-.20 (.012)** | **-.20 (<.001)** |
| | Risk Beliefs | **-.16 (.044)** | -.07 (.403) | -.11 (.057) |
| | Risk Propensity | **.16 (.014)** | .08 (.178) | **.12 (.005)** |
| | Social Comparison Orientation | -.00 (.972) | .07 (.202) | .04 (.375) |
| | Undesirable Deviation | **.15 (.010)** | **.45 (<.001)** | **.29 (<.001)** |
| | Reaction Type [0 = Likes, 1 = Dislikes] | | | .01 (.731) |
| | Undesirable Deviation x Reaction Type | | | **.14 (<.001)** |
| | $R^2$ ($f^2$ in parentheses) | 20.8 percent (.26) | 33.6 percent (.51) | 26.1 percent (.35) |
| | $\Delta R^2$ (*p-value* in parentheses) | 2.3 percent (.010) | 18.0 percent (<.001) | 9.8 percent (<.001) |

[a]Numbers represent standardized coefficients, and p-values (in parentheses). p < .05 values are in bold. TMDB, technology-mediated dangerous behavior.

Results of the "likes" model support H1a and, therefore, replicate the results of Study 1. Results of the "dislikes" model support H2a. They show that undesirable deviations in the "losses" zone also increase intentions to post risky selfies and lead to a stronger preference for high-risk/reward selfies. Lastly, the significant positive interaction terms support H3a. They show that the undesirable deviation effect is stronger with "dislikes" (coded 1) than with "likes" (coded 0). Models generated medium ($f^2 > .21$) to large ($f^2 > .51$) effect sizes.

## *Discussion: Study 2*

Results show that undesirable deviations from expected reactions operate as expected in both the "gains" and "losses" zones of prospect theory. That is, people sensed undesirable deviation when they did not receive the number of "likes" they expected *or* when they received more "dislikes" than they expected. This undesirable deviation stimulated them to engage in high-reward but riskier and more dangerous actions to amend the situation, as compared to people who did not sense such a deviation. This is consistent with prior findings on the effects of the homeostatic violation mechanism and the core ideas of RST [55]. It also extends these perspectives from the "gains" zone of prospect theory to the "losses" zone [29]. Consistent with prospect theory, results further demonstrate that the effects of undesirable deviations are stronger in the case of excess of losses (i.e., too many "dislikes") as compared to deprivation of gains (i.e., too few "likes"); that is, "dislikes" are more toxic than "likes."

**Table 6.** Tests of H1a-H3a for TMDB 2: Preference for high-risk/reward selfie (Study 2).[a]

| | | Test H1a: "Likes" (Gains Zone) (n = 240) | Test H2a: "Dislikes" (Losses Zone) (n = 240) | Test H3a: All Data (n = 480) |
|---|---|---|---|---|
| Controls Only | Age | -.10 (.116) | -.05 (.444) | -.08 (.071) |
| | Gender (F=Female, M=Male) | **.18 (.005)** | .06 (.334) | **.12 (.006)** |
| | Social Media Hours/Day | **.22 (<.001)** | .06 (.370) | **.12 (.007)** |
| | Privacy Beliefs | **-.22 (.008)** | **-.21 (.025)** | **-.22 (<.001)** |
| | Risk Beliefs | .05 (.555) | -.05 (.571) | .00 (.993) |
| | Risk Propensity | .05 (.462) | -.03 (.702) | .00 (.930) |
| | Social Comparison Orientation | -.12 (.074) | .02 (.717) | -.04 (.401) |
| | $R^2$ ($f^2$ in parentheses) | 14.4 percent (.17) | 8.0 percent (.09) | 9.7 percent (.11) |
| Controls, Main, & Interaction Effects | Age | -.11 (.08) | .00 (.999) | -.06 (.155) |
| | Gender (F=Female, M=Male) | **.18 (.003)** | .01 (.815) | **.10 (.015)** |
| | Social Media Hours/Day | **.23 (<.001)** | .04 (.480) | **.13 (.003)** |
| | Privacy Beliefs | **-.20 (.013)** | **-.17 (.046)** | **-.19 (.001)** |
| | Risk Beliefs | .03 (.663) | -.00 (.975) | .02 (.713) |
| | Risk Propensity | .04 (.514) | -.05 (.390) | -.01 (.871) |
| | Social Comparison Orientation | -.11 (.076) | -.02 (.782) | -.06 (.189) |
| | Undesirable Deviation | **.17 (.006)** | **.44 (< .001)** | **.29 (<.001)** |
| | Reaction Type [0=Likes, 1= Dislikes] | | | .03 (.497) |
| | Undesirable Deviation x Reaction Type | | | **.14 (.001)** |
| | $R^2$ ($f^2$ in parentheses) | 17.1 percent (.21) | 25.1 percent (.34) | 19.7 percent (.25) |
| | $\Delta R^2$ (*p-value* in parentheses) | 2.7 percent (.006) | 17.0 percent (<.001) | 10.0 percent (<.001) |

[a]Numbers represent standardized coefficients, and p-values (in parentheses). p < .05 values are in bold. TMDB, technology-mediated dangerous behavior.

## Study 3

### *Participants, Procedure, and Measures: Study 3*

The sample included 400 social media users, of which 283 were women (71 percent). The average age was 34.86 (SD = 9.91), and median social media use was 2 hours/day. The pre-task survey had one difference from Studies 1 and 2. Because the TMDB of interest here was publicly disclosing private information on one's profile (TMDB 3), we adjusted the privacy and risk belief scales to focus on context-relevant concerns. For control purposes, we measured whether participants perceived their full name (including middle name), birthdate, city of residence, political affiliations, and love for alcohol and partying as private and their online public disclosure as risky (see Online Supplemental Appendix 2). These factors were specified as formative, and we used their PCA score in analyses.[4]

The task employed the same 2 (*Reaction Type*) × 2 (*Yes/No Undesirable Deviation*) factorial between-subjects design as in Study 2. In the post-task survey, we captured TMDB 3 (posting a new profile with private information disclosed in it) and checked the manipulation using the same approach as in Study 2. TMDB 3 was binary: 1 = participants shared private information on their new profiles, 0 = they did not. Participants who chose to share private information were asked to write a new introduction for their social media profile, including the private information (see examples in Online Supplemental Appendix 4). The authors manually checked the texts of positive responses to ensure that users actually provided private information. No exclusions were made based on these checks. Note that none of the initial profiles contained the types of sensitive information we focus on.

## Results: Study 3

Descriptive statistics, reliabilities, and comparisons between the conditions are provided in Table 7.

To test H1b-H3b, we followed the procedures similar to those in Study 2: testing H1b with the “likes” subset, H2b with the “dislikes” subset, and H3b with the whole dataset. One difference from Study 2 was that we used a binary logistic regression model because TMDB 3 was a binary variable (see Table 8). The results of the “likes” model did not support H1b: in the “likes” condition, the undesirable deviation was not strong enough to drive posting a new profile with private information. However, the results of the “dislikes” model supported H2b and extended Study 2’s findings in the “dislikes” condition to actual behavior (i.e., TMDB 3). Lastly, the significant interaction term in the “All Data” model supported H3b. This means that undesirable deviation in “dislikes” (coded as 1) was significantly more potent than in “likes” (coded as 0) in driving TMDB 3. These models generated small ($f^2 > .07$) to medium ($f^2 > .17$) effect sizes.

## Discussion: Study 3

Study 3 extended the findings of Study 2 to an actual behavior. Results provide support for H2b and H3b, but not for H1b. Testing the “likes” and “dislikes”

**Table 7.** Descriptive statistics and between-condition differences for Study 3.[a]

| | | Factor: Undesirable Deviation | | | Factor: Reaction Type | | |
|---|---|---|---|---|---|---|---|
| Pre-task Survey | Overall (n = 400) | No Undesirable Deviation (n = 200) | Undesirable Deviation (n = 200) | *p*-Value | “Likes” (n = 200) | “Dislikes” (n = 200) | *p*-Value |
| Age | 34.86 (9.91) | 34.69 (10.18) | 35.04 (9.65) | .724 | 34.88 (9.72) | 34.84 (10.11) | .968 |
| Gender (F = Female, M = Male) | F: 283 M: 117 | F: 147 M: 53 | F: 136 M: 64 | .154 | F: 137 M: 63 | F: 146 M: 54 | .228 |
| Social Media Hours/ Day | 3.94 (1.41) | 3.98 (1.38) | 3.90 (1.45) | .572 | 3.97 (1.48) | 3.90 (1.35) | .621 |
| Privacy Beliefs* | .00 (1.00) | .10 (1.00) | -.10 (1.00) | .050 | -.03 (.99) | .03 (1.02) | .608 |
| Risk Beliefs* | .00 (1.00) | .10 (.96) | -.10 (1.03) | .054 | -.02 (.94) | .02 (1.05) | .681 |
| Risk Propensity | 2.91 (1.05) α = .86 | 2.79 (.98) | 3.03 (1.11) | **.020** | 2.91 (1.08) | 2.91 (1.03) | .951 |
| Social Comparison Orientation | 4.52 (1.43) α = .85 | 4.54 (1.39) | 4.50 (1.47) | .753 | 4.51 (1.43) | 4.53 (1.46) | .861 |
| Post-task Survey | | | | | | | |
| Perceived Deprivation | 2.49 (1.50) α = .93 | 2.07 (1.25) | 2.92 (1.61) | **<.001** | 2.12 (1.24) | 2.87 (1.64) | **<.001** |
| TMDB 3: Disclosing Private Information | No: 240 Yes: 160 | No: 135 Yes: 65 | No: 105 Yes: 95 | **.002** | No: 131 Yes: 69 | No: 109 Yes: 91 | **.025** |

[a]Numbers represent mean, and SD (in parentheses); * principal components due to formative specification based on z-score scales. p < .05 values for difference between conditions are in bold. TMDB, technology-mediated dangerous behavior.

**Table 8.** Tests of H1b-H3b on TMDB 3: Disclosing private information on profile (Study 3).[a]

| | | Test H1b: "Likes" (Gains Zone) (n = 200) | Test H2b: "Dislikes" (Losses Zone) (n = 200) | Test H3b: All Data (n = 400) |
|---|---|---|---|---|
| **Controls Only** | Constant | **-2.96 (.014) [.05]** | -1.18 (.301) [.31] | **-1.76 (.027) [.17]** |
| | Age | **.04 (.014) [1.04]** | -.01 (.521) [.99] | .01 (.225) [1.01] |
| | Gender (F = Female, M = Male) | -.29 (.402) [.75] | .17 (.623) [1.18] | -.12 (.602) [.89] |
| | Social Media Hours/Day | .08 (.459) [1.09] | **.28 (.014) [1.33]** | .13 (.078) [1.14] |
| | Privacy Beliefs | -.02 (.931) [.98] | .09 (.689) [1.10] | .01 (.942) [1.01] |
| | Risk Beliefs | -.19 (.434) [.83] | **-.55 (.018) [.58]** | **-.36 (.025) [.70]** |
| | Risk Propensity | .25 (.094) [1.29] | -.09 (.580) [.92] | .08 (.421) [1.09] |
| | Social Comparison Orientation | -.04 (.753) [.96] | .10 (.373) [1.10] | .03 (.708) [1.03] |
| | Cox & Snell $R^2$ ($f^2$ in parentheses) | 6.1 percent (.07) | 9.5 percent (.11) | 4.0 percent (.4) |
| Controls, Main, & Interaction Effects | Constant | **-2.94 (.015) [.053]** | -1.50 (.200) [.22] | **-2.31 (.005) [.10]** |
| | Age | **0.04 (.013) [1.04]** | -0.01 (.765) [1.00] | 0.02 (.125) [1.02] |
| | Gender (F = Female, M = Male) | -0.29 (.399) [.75] | 0.01 (.986) [1.01] | -0.17 (.473) [.84] |
| | Social Media Hours/Day | 0.08 (.467) [1.09] | **0.27 (.023) [1.31]** | 0.14 (.078) [1.15] |
| | Privacy Beliefs | -0.02 (.924) [.98] | 0.15 (.533) [1.16] | 0.02 (.891) [1.02] |
| | Risk Beliefs | -0.18 (.449) [.83] | **-0.51 (.033) [.60]** | **-0.32 (.049) [.73]** |
| | Risk Propensity | 0.26 (.090) [1.29] | -0.17 (.279) [.84] | 0.05 (.653) [1.05] |
| | Social Comparison Orientation | -0.04 (.744) [.963] | 0.08 (.472) [1.08] | 0.02 (.788) [1.02] |
| | Undesirable Deviation | -0.11 (.727) [.90] | **1.11 (< .001) [3.03]** | **0.59 (.006) [1.81]** |
| | Reaction Type [1 = Dislikes, 0 = likes] | | | **0.48 (.027) [1.61]** |
| | Undesirable Deviation x Reaction Type | | | **0.27 (.015) [1.31]** |
| | Cox & Snell $R^2$ ($f^2$ in parentheses) | 6.1 percent (.07) | 14.7 percent (.17) | 8.6 percent (.09) |
| | Δ Cox & Snell $R^2$ | 0.0 percent | 5.2 percent | 4.6 percent |

[a]Numbers represent unstandardized coefficients, p-values (in parentheses), and exp(B) in square brackets. p < .05 are in bold. TMDB, technology-mediated dangerous behavior.

datasets separately (the first two columns in Table 8) demonstrated that undesirable deviations in the losses zone, but not in the gains zone, are efficacious in increasing the likelihood of engaging in the effortful addition of private information to one's profile. The differences between the "likes" and "dislikes" models highlight the potentially stronger toxicity of "dislikes."

The *exp(B)* values and the third model in Table 8 show that undesirable deviations in "likes" and "dislikes" increase the odds of posting a new profile with private information in very different magnitudes: .90-fold and 3.03-fold, respectively. Such effects, especially the larger magnitude in the "dislikes" condition, are consistent with the idea that homeostatic violation due to undesirable deviations in digital reactions can have considerable action potential. In our case, such actions included a TMDB in the form of disclosing private information on social media. The third model in Table 8, and the significant positive interaction term support the integrative theoretical perspective (as expressed in H3b). While Study 2 also supported this perspective with respect to TMDBs 1 and 2, in Study 3, we extend this to actual behavior. Together, these findings, in line with prospect theory, suggest that "dislikes" are significantly more potent than "likes" in motivating TMDBs aimed at restoring homeostasis.

## Robustness Check Studies (Studies 4 & 5)

We conducted two robustness check studies, that is, Studies 4 and 5, to ensure the robustness of our findings in Studies 1-3. Specifically, in Studies 1-3, we masked the number of "likes"/"dislikes" that others (i.e., programmed bots) received, which was expected to considerably reduce the extent of social comparisons [70]. In addition, we controlled for participants' social comparison orientation. Nevertheless, the procedures in these studies required participants to pay attention to others' (i.e., programmed bots') profiles in the social media forum. This procedure might have unintentionally led our participants to compare their profiles with those of others they perceived as better off (i.e., upward social comparison) and/or worse off (i.e., downward social comparison) than themselves. As such, they might have still engaged in some degrees of social (i.e., upward and/or downward) comparisons despite the absence of others' "likes"/"dislikes" counters.

In Studies 4 and 5, we sought to rectify this potential confound by directly measuring and accounting for social comparison mechanisms and examining whether our hypothesized internal comparison mechanism holds beyond the potential effects of social comparisons. To that end, Studies 4 and 5 replicated Studies 2 and 3, respectively, but included direct measures of upward and downward social comparisons that participants might have engaged in. Study 4 adapted and sought to corroborate the findings of Study 2 (i.e., TMDBs 1 and 2), and Study 5 strived to do the same for Study 3 (i.e., TMDB 3).

### *Study 4*

The Study 4 sample included 214 social media users, of which 102 were women (48 percent). The average age was 37.33 (SD = 11.94), and median social media use was 2 hours/day. The experiment design and procedure were similar to those of Study 2, except that in the post-task survey, we measured respondents' extent of upward and downward social comparisons using Van der Zee and colleagues' scales [72] adapted to our context (see Online Supplemental Appendix 2). To avoid potential carry-over effects, these additional measures were placed after the TMDBs and manipulation check questions in the post-task survey.

Descriptive statistics and reliabilities are provided in Table 9. Similar to Studies 1-3, the manipulation check was successful as those who were randomly assigned to the undesirable deviation condition showed significantly higher levels of perceived deprivation ($d = 1.35$, $p < 0.001$).

To test H1a-H3a, we followed similar procedures to those in Study 2: testing H1a with the "likes" subset, H2a with the "dislikes" subset, and H3a with the whole dataset. Upward and downward social comparisons were included as control variables in all analyses.[5]

The results, presented in Table 10 and Table 11, replicated the findings in Study 2, supporting H1a, H2a, and H3a for both TMDB 1 and TMDB 2. Similar to Study 2, they show that undesirable deviations in both the gains and the losses zones increase intentions to post risky selfies (TMDB 1) and lead to a stronger preference for high-risk/reward selfies (TMDB 2). Moreover, we found significant positive interaction terms between the reaction type (i.e., "likes"/ "dislikes") and undesirable deviation (Yes/No) for TMDBs 1 and 2, supporting H3a. These results corroborate our earlier findings that the undesirable deviation effect is indeed stronger in the losses zone ("dislikes," coded 1) than in the gains zone

**Table 9.** Descriptive Statistics and Between-Condition Differences for Study 4.[a]

| | | Factor: Undesirable Deviation | | | Factor: Reaction Type | | |
|---|---|---|---|---|---|---|---|
| Pre-task Survey | Overall (n = 214) | No Undesirable Deviation (n = 107) | Undesirable Deviation (n = 107) | *p*-Value | "Likes" (n = 110) | "Dislikes" (n = 104) | *p*-Value |
| Age | 37.33 (11.94) | 37.91 (12.27) | 36.75 (11.62) | .479 | 37.25 (11.84) | 37.40 (12.10) | .927 |
| Gender (F = Female, M = Male) | 102 F 112 M | 51 F 56 M | 51 F 56 M | 1.00 | 52 F 58 M | 50 F 54 M | .907 |
| Social Media Hours/Day | 3.87 (1.65) | 3.93 (1.66) | 3.80 (1.63) | .562 | 3.85 (1.66) | 3.88 (1.64) | .894 |
| Privacy Beliefs[b] | -.01 (.95) | .11 (.95) | -.14 (.93) | **.048** | -.02 (.91) | -.01 (.99) | .909 |
| Risk Beliefs[b] | -.03 (-.07) | .06 (.99) | -.13 (1.00) | .158 | -.02 (0.96) | -.05 (1.04) | .819 |
| Risk Propensity | 2.70 (1.04) α=.88 | 2.71 (.96) | 2.69 (1.12) | .910 | 2.67 (1.05) | 1.74 (1.03) | .643 |
| Post-task Survey | | | | | | | |
| Upward Social Comparison | 4.17 (1.40) α=.92 | 2.39 (1.45) | 2.97 (1.65) | **.007** | 2.35 (1.46) | 3.03 (1.62) | **.001** |
| Downward Social Comparison | 4.55 (1.39) α=.95 | 4.45 (1.37) | 3.89 (1.38) | **.004** | 4.20 (1.46) | 4.14 (1.34) | .758 |
| Perceived Deprivation | 2.75 (1.57) α=.92 | 2.08 (1.23) | 3.43 (1.59) | **<.001** | 2.23 (1.32) | 3.31 (1.63) | **<.001** |
| TMDB 1: Intention to Post a Risky Selfie[b] | 0.03 (.96) | -.32 (.79) | .38 (.99) | **<.001** | .07 (.99) | -.014 (.94) | .507 |
| TMDB 2: Preference for High Risk/ Reward Selfie[b] | .04 (.97) | -.31 (.85) | .38 (.96) | **<.001** | -.12 (.93) | .21 (.97) | **.012** |

[a]Numbers represent mean, and SD (in parentheses). [b]Principal components due to formative specification based on z-score scales. p < .05 values for difference between conditions are in bold. TMDB, technology-mediated dangerous behavior.

("likes," coded 0). The effects of newly added control variables on TMDBs were mostly non-significant ($p > .05$), except for the effect of downward social comparison on TMDB 2 in the gains zone ($p = .036$). Nevertheless, these results show that the internal comparison mechanism can motivate TMDBs above and beyond the effects of the social comparison mechanisms when there are no "likes" or "dislikes" counters for other participants. Altogether, our models generated medium ($f^2 > .21$) to large ($f^2 > .51$) effect sizes.

## *Study 5*

For Study 5, we collected an additional independent sample of 200 social media users, including 110 women (55 percent), an average age of 38.4 ($SD = 11.90$), and a median of 2 hours/day of social media use. The experiment design and procedure were similar to those in Study 3, except that, similar to Study 4, we measured respondents' extent of upward and downward social comparisons in the post-task survey, using Van der Zee and colleagues' scales [72] adapted to our context (Online Supplemental Appendix 2). Descriptive statistics and reliabilities are reported in Table 12. Similar to Studies 1-4, the manipulation was effective as those who were randomly assigned to the undesirable deviation condition showed significantly higher levels of perceived deprivation ($d = 1.26$, $p < 0.001$).

**Table 10.** Tests of H1a-H3a for TMDB 1: Intention to post a risky selfie (Study 4).[a]

| | | Test H1a: "Likes" (Gains Zone) (n = 110) | Test H2a: "Dislikes" (Losses Zone) (n = 104) | Test H3a: All Data (n = 214) |
|---|---|---|---|---|
| **Controls Only** | Age | -.01 (.942) | -.15 (.112) | -.06 (.350) |
| | Gender (0 = Female, 1 = Male) | .09 (.347) | .05 (.577) | .07 (.295) |
| | Social Media Hours/Day | -.08 (.460) | -.13 (.220) | -.11 (.141) |
| | Privacy Beliefs | -.08 (.557) | **-.26 (.027)** | -.16 (.064) |
| | Risk Beliefs | -.16 (.222) | -.12 (.351) | -.13 (.130) |
| | Risk Propensity | .14 (.169) | **.31 (.001)** | **.22 (.001)** |
| | Upward Social Comparison | **.22 (.023)** | .11 (.238) | **.15 (.028)** |
| | Downward Social Comparison | .13 (.182) | -.02 (.804) | .05 (.414) |
| | $R^2$ ($f^2$ in parentheses) | 14.7 percent (.17) | 30.6 percent (.44) | 18.9 percent (.23) |
| **Controls, Main & Interaction Effects** | Age | .00 (.997) | -.11 (.152) | -.05 (.432) |
| | Gender (0 = Female, 1 = Male) | .11 (.244) | .01 (.869) | .06 (.321) |
| | Social Media Hours/Day | -.06 (.595) | -.15 (.094) | -.10 (.124) |
| | Privacy Beliefs | -.04 (.771) | **-.23 (.024)** | -.12 (.129) |
| | Risk Beliefs | .16 (.191) | .10 (.337) | .12 (.133) |
| | Risk Propensity | .16 (.099) | **.25 (.003)** | **.21 (<.001)** |
| | Upward Social Comparison | .16 (.090) | .07 (.419) | .11 (.086) |
| | Downward Social Comparison | .17 (.080) | .05 (.520) | .11 (.077) |
| | Undesirable Deviation | **.22 (.025)** | **.46 (<.001)** | **.33 (<.001)** |
| | Reaction Type [0 = Likes, 1 = Dislikes] | | | -.07 (.225) |
| | Undesirable Deviation x Reaction Type | | | **.12 (.045)** |
| | $R^2$ ($f^2$ in parentheses) | 18.9 percent (.23) | 49.5 percent (.98) | 31.1 percent (.45) |
| | $\Delta R^2$ (*p-value* in parentheses) | **4.2 percent (.025)** | **18.9 percent (<.001)** | **12.2 percent (<.001)** |

[a]Numbers represent standardized coefficients, and p-values (in parentheses). p < .05 values are in bold. TMDB, technology-mediated dangerous behavior.

We used the same procedures as in Study 3 for testing H1b-H3b: testing H1b with the "likes" subset, H2b with the "dislikes" subset, and H3b with the whole dataset. Upward and downward social comparisons were included as control variables in all analyses.[6]

The results, presented in Table 13, reproduced the findings in Study 3. They show that while undesirable deviations increase the likelihood of disclosing private information (TMDB 3) in the losses zones, supporting H2b, there is no such an effect in the gains zone, rejecting H1b. Moreover, like Study 3, we found that losses ("dislikes," coded 1) loomed larger than gains ("likes," coded 0), and the interaction term between the reaction type (i.e., "likes"/ "dislike") and undesirable deviation (Yes/No) was significant, supporting H3b. The effects of newly added control variables (i.e., upward and downward social comparisons) on TMDB 3 were non-significant ($p > .05$). These results corroborate our findings in Study 3. They show that the internal comparison mechanism can motivate disclosing private information in the losses zone, but not in the gains zone, and this happens above and beyond the effects of the social comparison mechanisms afforded when there are no reaction counters for other participants. Altogether, our models generated medium ($f^2 > .15$) effect sizes.

**Table 11.** Tests of H1a-H3a for TMDB 2: Preference for high-risk/reward selfie (Study 4).[a]

| | | Test H1a: "Likes" (Gains Zone) (n = 110) | Test H2a: "Dislikes" (Losses Zone) (n = 104) | Test H3a: All Data (n = 214) |
|---|---|---|---|---|
| **Controls Only** | Age | -.04 (.712) | -.08 (.412) | -.05 (.452) |
| | Gender (0 = Female, 1 = Male) | .03 (.731) | .17 (.101) | .10 (.124) |
| | Social Media Hours/Day | .15 (.151) | .08 (.467) | .11 (.154) |
| | Privacy Beliefs | -.20 (.124) | .05 (.725) | -.06 (.501) |
| | Risk Beliefs | .18 (.159) | -.25 (.075) | -.04 (.689) |
| | Risk Propensity | .12 (.201) | .03 (.806) | .11 (.100) |
| | Upward Social Comparison | **.23 (.013)** | .09 (.413) | **.21 (.002)** |
| | Downward Social Comparison | .16 (.100) | -.05 (.612) | .06 (.388) |
| | $R^2$ ($f^2$ in parentheses) | 18.0 percent (.22) | 14.4 percent (.17) | 12.2 percent (.14) |
| **Controls, Main & Interaction Effects** | Age | -.03 (.763) | -.05 (.587) | -.04 (.495) |
| | Gender (0 = Female, 1 = Male) | .05 (.561) | .13 (.155) | .10 (.103) |
| | Social Media Hours/Day | .17 (.089) | .06 (.552) | .12 (.086) |
| | Privacy Beliefs | -.16 (.217) | .08 (.480) | -.03 (.697) |
| | Risk Beliefs | .17 (.169) | -.24 (.055) | -.01 (.885) |
| | Risk Propensity | .15 (.114) | -.04 (.702) | .10 (.133) |
| | Upward Social Comparison | .18 (.063) | .04 (.685) | .12 (.064) |
| | Downward Social Comparison | **.20 (.036)** | .03 (.766) | .12 (.063) |
| | Undesirable Deviation | **.24 (.015)** | **.48 (<.001)** | **.36 (<.001)** |
| | Reaction Type [0 = Likes, 1 = Dislikes] | | | **.15 (.020)** |
| | Undesirable Deviation x Reaction Type | | | **.13 (.033)** |
| | $R^2$ ($f^2$ in parentheses) | 22.7 percent (.29) | 35.6 percent (.55) | 25.4 percent (.34) |
| | $\Delta R^2$ (*p-value* in parentheses) | **4.8 percent (.015)** | **21.2 percent (<.001)** | **14.9 percent (<.001)** |

[a]Numbers represent standardized coefficients, and p-values (in parentheses). p < .05 values are in bold. TMDB, technology-mediated dangerous behavior.

## General Discussion

RST has been extended from animal foraging behavior [67] to human financial decision-making [48, 49, 55] and IS users engaging in social comparison with others through "like" counts [70]. In this paper, via five studies, we extend these findings in three important ways. First, given recent attempts of social media platforms (e.g., Instagram) to allow hiding others' "like" counts, and by so doing eliminating a key driver of social comparison mechanism, there is a need to know if this suffices for eliminating the toxicity of "likes." As the quotes we provide in the Introduction section suggest, restricting these drivers of social comparisons did not matter much. In this paper, we provide a credible explanation for why this might have happened. Particularly, we showed that there is an additional comparison process, specifically an internal comparison process, namely hemostatic state gauging, that operates beyond social comparisons. This mechanism drives TMDBs even when common social comparison affordances, such as others' reaction counters, are eliminated. People, consciously or unconsciously compare expected and actual states and act to alleviate undesirable deviations.

**Table 12.** Descriptive statistics and between-condition differences for Study 5.[a]

| | | Factor: Undesirable Deviation | | | Factor: Reaction Type | | |
|---|---|---|---|---|---|---|---|
| Pre-task Survey | Overall (n = 200) | No Undesirable Deviation (n = 100) | Undesirable Deviation (n = 100) | *p*-Value | "Likes" (n = 100) | "Dislikes" (n = 100) | *p*-Value |
| Age | 38.40 (11.90) | 37.37 (11.56) | 39.43 (12.21) | .222 | 39.07 (11.59) | 37.73 (12.23) | .427 |
| Gender (F = Female, M = Male) | 110 F 90 M | 51 F 49 M | 59 F 41 M | .258 | 57 F 43 M | 53 F 47 M | .572 |
| Social Media Hours/Day | 3.78 (1.59) | 3.99 (1.62) | 3.57 (1.54) | .062 | 3.84 (1.66) | 3.72 (1.53) | .595 |
| Privacy Beliefs[b] | -.05 (1.02) | -.10 (1.05) | .00 (.99) | .481 | -.11 (1.05) | .01 (.99) | .441 |
| Risk Beliefs[b] | .03 (1.00) | -.01 (1.01) | .05 (1.01) | .681 | .04 (.96) | .01 (1.06) | .875 |
| Risk Propensity | 2.59 (1.04) α = .89 | 2.69 (1.03) | 2.48 (1.05) | .147 | 2.60 (1.09) | 2.57 (1.01) | .877 |
| Post-task Survey | | | | | | | |
| Upward Social Comparison | 2.60 (1.63) α = .93 | 2.44 (1.49) | 2.75 (1.74) | .174 | 2.34 (1.50) | 2.85 (1.72) | **.027** |
| Downward Social Comparison | 4.05 (1.35) α = .93 | 4.49 (1.18) | 3.61 (1.38) | **<.001** | 4.16 (1.35) | 3.94 (1.35) | .244 |
| Perceived Deprivation | 2.65 (1.54) α = .92 | 2.02 (1.23) | 3.28 (1.57) | **<.001** | 2.12 (1.30) | 3.18 (1.59) | **<.001** |
| TMDB 3: Disclosing Private Information | No: 124 Yes: 76 | No: 61 Yes: 39 | No: 63 Yes: 37 | .772 | No: 59 Yes: 41 | No: 65 Yes: 35 | .385 |

[a]Numbers represent mean, and SD (in parentheses). [b]Principal components due to formative specification based on z-score scales. p < .05 values for difference between conditions are in bold. TMDB, technology-mediated dangerous behavior.

Second, recent contemplation and decisions of social media platforms to include "dislike" buttons [62, 63] leaves users in uncharted territories in terms of the effects of these changes on them and highlights the need to study them. In this paper, we show that receiving more "dislikes" than expected can increase TMDBs. Third, there is a need to see which reaction (i.e., "likes" or "dislikes") is more toxic, and why. This is because it is possible that the benefits of removing others' "like" counts are outweighed by adding a "dislike" functionality.

We tested these hypotheses in five randomized controlled experiments using an integrative RST and prospect theory perspective. The results are summarized in Table 14 and discussed in the following section.

Study 1's findings support H1a and show that direct manipulation of one's "likes" while eliminating social comparisons can strongly motivate intention to engage in (TMDB 1) and preference for (TMDB 2) TMDBs. Studies 2 and 4 further corroborated H1a, which focused on "likes" (gain zone), and also supported H2a, which focused on "dislikes" (losses zone). Studies 3 and 5 supported H2b by showing the same effect for an actual TMDB (TMDB 3) in the "dislikes" condition. This is an important extension, as prospect theory points to possible psychological and behavioral differences between being in the losses zone or the gains zone [28]. Moreover, consistent with prospect theory, Studies 2-5 support H3a and H3b. They show that the undesirable deviation effects are stronger in the case of "dislikes" than in the case of "likes." H1b was the only unsupported hypothesis, consistently in Studies 3 and 5. This may suggest that unmet "likes" expectations potentiate intentions and preferences for high-risk/reward choices, but their potential is not strong enough to drive actual behaviors. In contrast, excess

**Table 13.** Tests of H1b-H3b on TMDB 3: Disclosing private information on profile (Study 5).[a]

| | | Test H1b: "Likes" (Gains Zone) (n = 100) | Test H2b: "Dislikes" (Losses Zone) (n = 100) | Test H3b: All Data (n = 200) |
|---|---|---|---|---|
| Controls Only | Constant | -2.66 (.162) [.07] | -.94 (.601) [.39] | -1.90 (.136) [.15] |
| | Age | .01 (.723) [1.01] | -.01 (.537) [.99] | .00 (.945) [1.00] |
| | Gender (F = Female, M = Male) | **.94 (.038) [2.56]** | **1.21 (.013) [3.36]** | **.99 (.002) [2.70]** |
| | Social Media Hours/Day | .29 (.047) [1.34] | .08 (.643) [1.09] | .20 (.065) [1.22] |
| | Privacy Beliefs | -.15 (.683) [.86] | -.53 (.110) [.59] | -.36 (.123) [.70] |
| | Risk Beliefs | -.23 (.542) [.79] | .20 (.529) [1.22] | .03 (.899) [1.03] |
| | Risk Propensity | .09 (.662) [.91] | .17 (.445) [.84] | .10 (.494) [.90] |
| | Upward Social Comparison | .05 (.744) [1.05] | .04 (.813) [1.04] | .01 (.898) [1.01] |
| | Downward Social Comparison | .19 (.262) [1.21] | .16 (.369) [1.18] | .17 (.161) [1.19] |
| | | 13.5 percent (.16) | 13.3 percent (.15) | 12.4 percent (.14) |
| Controls, Main & Interaction Effects | Constant | -2.45 (.205) [.09] | -2.13 (.265) [.12] | -2.24 (.096) [.11] |
| | Age | .01 (.640) [1.01] | -.01 (.515) [.99] | .00 (.952) [1.00] |
| | Gender (F = Female, M = Male) | **.90 (.048) [2.47]** | **1.34 (.008) [3.82]** | **1.03 (.002) [2.79]** |
| | Social Media Hours/Day | .28 (.056) [1.33] | .13 (.483) [1.14] | .20 (.065) [1.22] |
| | Privacy Beliefs | -.19 (.612) [.83] | -.58 (.089) [.56] | -.37 (.121) [.69] |
| | Risk Beliefs | -.19 (.618) [.82] | .26 (.412) [1.30] | .04 (.881) [1.04] |
| | Risk Propensity | .07 (.731) [.93] | .21 (.362) [.81] | .11 (.477) [.90] |
| | Upward Social Comparison | .11 (.486) [1.12] | .02 (.890) [1.02] | .06 (.568) [1.06] |
| | Downward Social Comparison | .14 (.450) [1.15] | .31 (.120) [1.37] | .20 (.128) [1.22] |
| | Undesirable Deviation | -.59 (.233) [.55] | **1.23 (.017) [3.42]** | .30 (.383) [1.35] |
| | Reaction Type [1 = Dislikes, 0 = likes] | | | -.27 (.410) [.76] |
| | Undesirable Deviation x Reaction Type | | | **.40 (.016) [1.48]** |
| | Cox & Snell $R^2$ ($f^2$ in parentheses) | 14.7 percent (.17) | 18.4 percent (.23) | 15.6 percent (.19) |
| | Δ Cox & Snell $R^2$ | 1.2 percent | 5.1 percent | 3.2 percent |

[a]†Numbers represent unstandardized coefficients, p-values (in parentheses), and exp(B) in square brackets. p < .05 are in bold. TMDB, technology-mediated dangerous behavior.

"dislikes" are sufficiently potent to drive actual TMDBs, in addition to intentions and preferences.

These findings extend insights about TMDBs from the "gains" zone to the "losses" zone. They further show that TMDBs are motivated through not only social comparison processes [70], but also internal homeostasis checks. They also present an integrative RST-prospect theory perspective that helps to understand biases in users' behaviors in future research. The integrated perspective suggests that "dislikes" have a significantly higher harm potential than "likes" when users experience undesirable homeostatic deviations.

These findings are important even beyond the social media context because many IS studies have been assuming a rational utilitarian view that is reflected in linear effects and equal weights for gains and losses. For example, information security behaviors have often been studied in this manner, considering the costs versus gains of the behavior [17, 42]. Behavioral economics research suggests that this view needs to be reconsidered in light of the fact that people respond differentially to gains versus losses [38], and that the risk preferences of people are influenced by undesirable deviations from desired states [55]. Such findings, as also supported in our research, highlight the need to consider our integrative perspective for studying, for instance, differences between information security

**Table 14.** Summary of hypothesis test results.[a]

| Hypothesis | TMDB | Result | Study |
|---|---|---|---|
| H1a: Insufficient “likes”→ TMDB 1 (intention) ↑ | Intention to post a risky selfie (TMDB 1) | Support | 1, 2, & 4 |
| H1a: Insufficient “likes”→ TMDB 2 (preference) ↑ | Preference for high-risk/reward selfies (TMDB 2) | Support | 1, 2, & 4 |
| H1b: Insufficient “likes”→ TMDB 3 (behavior) ↑ | Disclosing private information (TMDB 3) | Not Supported | 3 & 5 |
| H2a: Excess “dislikes”→ TMDB 1 (intention) ↑ | Intention to post a risky selfie (TMDB 1) | Support | 2 & 4 |
| H2a: Excess “dislikes”→TMDB 2 (preference) ↑ | Preference for high-risk/reward selfies (TMDB 2) | Support | 2 & 4 |
| H2b: Excess “dislikes”→ TMDB 3 (behavior) ↑ | Disclosing private information (TMDB 3) | Support | 3 & 5 |
| H3a: Excess “dislikes” > insufficient “likes”→ TMDB 1 (intention) ↑ | Intention to post a risky selfie (TMDB 1) | Support | 2 & 4 |
| H3a: Excess “dislikes” > insufficient “likes”→ TMDB 2 (preference) ↑ | Preference for high-risk/reward selfies (TMDB 2) | Support | 2 & 4 |
| H3b: Excess “dislikes” > insufficient “likes”→ TMDB 3 (behavior) ↑ | Disclosing private information (TMDB 3) | Support | 3 & 5 |

[a]“→” indicates expected association; “↑” indicated expected increase or a larger association. TMDB, technology-mediated dangerous behavior.

policy compliance and rewards (gain zone) and violations and punishments (loss zone) [17]. The current paper lays the groundwork for such theoretical advancements. For example, future research can investigate users’ risk sensitivity toward artificial intelligence (AI)-generated recommendations and the role of their framings in this matter.[83]

From a practical standpoint, our findings suggest that both social media platforms and users should be mindful of (a) potential TMDBs in response to social media reactions, and (b) the potentially more toxic effects of “dislikes.” Prior research has shown that negative consequences of TMDBs can lead to users’ permanent or temporary abandonment or reduced use of IS, including social media platforms. One way to alleviate these issues is by acknowledging the toxicity of social media reactions and creating awareness among users about their potentially negative consequences. As such, identifying interventions and design considerations, such as digital nudges, that can increase users’ awareness of the potential toxicity of these reactions is an important area for future research[84]. Furthermore, social media platforms can follow Instagram’s lead and consider making the reaction functionality optional, for example via opt-in or opt-out processes. This might allow users who seek reactions to deploy this functionality and those who suffer from reactions to avoid it. Nevertheless, the efficacy of such policies requires further research.[85,86,87]

Despite its contributions, this paper has several limitations that present important avenues for future research. First, longitudinal tests can extend our findings from immediate outcomes of one-time homeostatic violation due to an undesirable deviation to long-term effects of ongoing repeated homeostatic violations. Second, this paper strived to focus on the effects of internal comparison mechanisms on TMDBs beyond the effects of social comparison mechanisms. Nevertheless, internal expectations may be informed, in part, through social learning processes and social and internal comparisons can work in tandem. As such, future research can focus on the possible relations between the internal and social comparison mechanisms and their collective effects on TMDBs.

Lastly, future research can investigate the desirable side of deviation from expectations, that is, receiving more “likes” or fewer “dislikes” than expected, on user behaviors. An open question worth investigating is whether desirable deviations from expectations of “likes” and “dislikes” reduce TMDBs or exacerbate them. On the one hand, from the RST perspective, desirable deviations should increase risk sensitivity and reduce users’ likelihood of engaging in TMDBs. On the other hand, desirable deviations from the expected number of “likes” and “dislikes” can result in joy and satisfaction which, based on dual system theory [58, 71], might, at least over time, create temptations for further engagement with TMDBs that might reproduce these pleasant feelings. Similarly, expectancy violations theory [12, 13] argues that positive violations of expectations increase the attraction of the violator. This may result in a higher likability of the violator, which as shown in a previous study [58], may increase the susceptibility to TMDBs involving the violator, such as disclosing private information with the violator. Future research should address this conundrum.

## Conclusion

Social media reactions are important for social media platforms to generate engagement and a key mechanism for users to satisfy social-hedonic needs. As such, they keep on evolving. In this paper, we extend our understanding of how users are influenced by such reactions (or lack thereof). We specifically demonstrate that there is an internal comparison mechanism, beyond the oft-studied social comparison mechanisms, that informs people’s homeostasis (or homeostatic violation) and can drive TMDBs that make such reactions toxic. We also point to the higher risk potency of the “dislike” functionality compared to the “like” functionality. Given that such features influence the behaviors of billions of users worldwide, we call for more research on the mechanisms of their effects on users’ behaviors.

## Notes

1. https://aisnet.org/general/custom.asp?page=seniorscholarbasket
2. We borrow the terms “gains zone” and “losses zone” from prospect theory. In our case, “likes” represent the gains (or appetitive) zone as people want more of them, and “dislikes” represent the losses (or aversive) zone as people want fewer of them.
3. We repeated all analyses in studies 1 and 2 with a reflective specification of these constructs and used their means in the analyses. The patterns of results in terms of statistical significance and support for hypotheses remained unchanged.
4. Similar to Studies 1 and 2, we repeated all analyses in Study 3 with a reflective specification of these factors and used their means in the analyses. The patterns of results remained unchanged.
5. Given the significant relation between upward and downward social comparisons and social comparison orientation, the latter was dropped from our analyses to avoid potential multi-collinearity concerns.
6. Similar to Study 4, social comparison orientation was dropped from our analyses to avoid potential multicollinearity problems.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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