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Social Motivations' Limited Influence on Habitual Behavior: Tests From Social Media Engagement

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Motivations that drive initial or occasional actions may have less impact as people repeat a behavior and form habits that are automatically cued by contexts. We tested this shifting role of motivation with social media engagement. Specifically, we assessed how the posting rates of habitual and nonhabitual social media users varied with social rewards of others' reactions and comments and with a platform design change in 2007 that increased the salience of one's own and others' posts. In a preliminary study with *Instagram* users and in Study 1's controlled observation of *Facebook* posting, nonhabitual posters increased engagement after receiving social rewards on a prior post, whereas habitual ones were unaffected. In Study 2, occasional *Facebook* posters were motivated by the platform design to increase engagement, but frequent users were not; instead, their posting was disrupted by the new platform features. Finally, suggesting that these effects of reward were not due to waning motivation, habitual posters self-reported being concerned about others' reactions and predicted they would increase engagement following the platform change. Thus, frequent users responded automatically out of habit, showing insensitivity to their own motivations.

Keywords: social media, habit, reward, Facebook, motivation

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Online social interactions have become a significant part of social life, influencing the people who become our friends, our social comparisons and identities, and how we express ourselves (Anderson & Wood, 2021; Bayer et al., 2022). The pervasive adoption of social media, with 70% of Americans having active social media accounts and the majority using them daily (Auxier & Anderson, 2021), provides a unique opportunity to test the role of social motivations across repeated interactions. Understanding the drivers of repeated actions is important given that many everyday actions only benefit our health, well-being, and financial resources when performed regularly.

Social media sites are ideal to test whether the effect of motivation shifts from initiation to continued engagement with others. The discrete, time-stamped metrics on these sites provide an ecologically valid, socially meaningful context to test whether social rewards motivate repeated, habitual interactions in the same way as initial ones. We focus here on posting, given that it is a central means of engagement on social media.

People initially start to use social media for a variety of reasons (Bayer & LaRose, 2018). These include specific goals of relating to others, affiliating, forming relationships, establishing group memberships, reducing loneliness, or creating social networks. Such goals are met as users experience social rewards on a site (e.g., others' likes, comments, social updates, and own self-expressions) that build greater satisfaction, greater enjoyment, and stronger social ties (Zell & Moeller, 2018). These various goals motivate *continuance intentions* and repeated use of a platform (Hsiao et al., 2016). In sum, the present article references broadly based *social motivations* that potentially reflect a number of specific *social goals*. Such goals are met through the *social rewards* that users receive as they interact on social media.

Social media is designed for ease of use, encouraging frequent repetition of a series of component behaviors, including retweeting/reposting, liking others' posts, commenting on/replying to posts, writing posts, looking at others' profiles, and messaging others (Bayer et al., 2022). With enough repetition, users form habits or mental associations between context cues and these responses. Context cues may include the physical location in which one usually posts on social media (e.g., the couch), time of day, emotions (e.g., boredom), the presence of one's smartphone or laptop, the app icon,

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Study 1 and Study 2A data sets are available online (https://osf.io/6ya5d/). The data set for the Preliminary Study is available by request at https://dl.acm.org/doi/10.1145/2631775.2631808 and for Study 2 is available by request at http://socialnetworks.mpi-sws.org/datasets.html. R code for all analyses is available upon request from the authors.

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notifications, the layout of the app itself, and platform features (main scroll feed, your own profile page, others' pages; Anderson & Wood, 2021; Bayer et al., 2022). Once habits have formed, perception of these recurring site cues automatically brings the response to mind (Verplanken & Orbell, 2022; Wood & Rünger, 2016), enabling relatively automatic responding with minimal deliberation (Schnauber-Stockmann & Naab, 2019).

As a result of the habit-learning process, frequent users respond quickly and accurately to stable platform cues indicating where, when, and how to respond (Garaialde et al., 2020). Habitually cued online responding thus is triggered automatically by context cues with limited deliberation (Anderson & Wood, 2021; Schnauber-Stockmann & Naab, 2019). The present research explores whether this repeated, habitual social media posting also proceeds with only limited influence of social motivation.

To test this idea, we compare habitual posters with occasional or infrequent posters. Posting is one of the most ubiquitous, frequently repeated behaviors across social media sites like *Twitter, Facebook*, and *Instagram.* We start by reanalyzing a prior demonstration that social rewards in the form of *likes* motivate posting on *Instagram* (see Lindström et al., 2021). Specifically, we test whether this reward effect holds for repeated as well as beginning and occasional posters. Our first study then directly assesses habit strength and clarifies the sequential relation between the social rewards on a prior post and subsequent *Facebook* posting. Our second study evaluates a 2007 change in *Facebook's* platform that was designed to increase the salience of social rewards and spur increased user engagement. We test whether the design change motivated posting of repeated, habitual posters as well as initial and occasional ones.

When possible, we directly assess participants' self-reported motivation to respond to social rewards in order to ensure that habitual posters possess similar levels of motivation as initial or occasional ones. Our research measures this motivation broadly from users' reports of how much others' feedback matters to them (Study 1). Participants might report that feedback matters because of any of the specific goals mentioned above (e.g., affiliation, social group membership, loneliness). As an indirect indicator of motivation, we also assess self-predictions of how users would respond to the platform design change intended to encourage them to post (Study 2a).

Motivational Influences on Repeated Behavior

Many current theories of motivation in human social behavior do not specify a change in motivation as people repeat an action (e.g., Fishbein & Ajzen, 2011; Inzlicht et al., 2021). A notable exception is goal systems theory, in which repeated pairings of an activity (means) and a goal (ends) increase intrinsic motivation by promoting a fusion between means and ends (Kruglanski et al., 2018). Also worth noting is Hull's (1932) research on goal gradients, which demonstrated that motivated responding increases as animals' repeated actions reduce their distance to a desired end state. Although these important contributions recognize shifts in the content or intensity of goals with repeated pursuit, they assume that well-practiced actions as well as occasional or novel ones are motivated by goal attainment (e.g., Kruglanski & Szumowska, 2020).

Yet, several classic theories in social psychology recognized that the basic role of motivation shifts as people repeat behavior and develop habits. For example, in Triandi's (1977) theory of interpersonal behavior, occasional or novel behaviors are guided by intentions, whereas overlearned, frequently performed responses are guided by habit, so that they become tied to cues within the performance context. In support, behavior prediction research showed that the impact of behavioral intentions lessens with increasing habit strength (Gardner, 2015; Ouellette & Wood, 1998; Webb & Sheeran, 2006). In the study of close relationships, Berscheid and Regan (2005) proposed that repeated interactions with a partner become *meshed interaction sequences,* or joint interaction habits, that run off automatically as each partner's behavior cues the other's. One consequence is that, for partners in successful relationships, partner absence or other disruptions in habitual actions are required for partners to respond to positive features of the relationship.

In predicting that motivation has limited influence on repeated, habitual responding, the above theories are consistent with recent laboratory research in cognitive psychology and behavioral neuroscience. Although initial performance at simple tasks is guided by goal pursuit, once habits form, perception of context cues automatically brings practiced responses to mind without requiring goal activation (Amodio, 2019; Knowlton & Diedrichsen, 2018). This shift has neural correlates; a meta-analytic review of fMRI studies revealed that, with task repetition, neural activation increased in the *sensorimotor system*, especially the *putamen*, which is not directly modulated by reward expectancy (Patterson & Knowlton, 2018).

A shift in the role of motivations has been demonstrated in animal learning research through insensitivity of habit performance to changes in rewards (Perez & Dickinson, 2020). That is, animals persist in acting habitually even when they no longer value the reward. However, insensitivity to reward as behavior becomes habitual and triggered by cues has not been obtained in some research on human performance (de Wit et al., 2018). This failure has raised questions about the nature of human habits (Kruglanski & Szumowska, 2020). One explanation is that human laboratory paradigms create demand characteristics to act on current goals and not habits. Yet cognitive drains may decrease people's capacity to respond to such demands. Thus, people continue to act on habit despite their current goals when goal pursuit is impeded by time pressure (Hardwick et al., 2019), stress (Schwabe & Wolf, 2009), and fatigue (Neal et al., 2013). It is not surprising, then, that the strongest evidence for habit insensitivity to goals comes from studies of everyday behavior, especially social media use. For example, more frequent users of *Facebook* were more likely to respond automatically and accept phishing scams, even when highly motivated to protect their privacy (Vishwanath, 2015, 2017). Nonetheless, failures to find habit insensitivity raise questions about whether motivation does or does not guide habitual responding.

Social media sites' time-stamped metrics of social rewards and subsequent engagement enable fine-grained tests of habit insensitivity to rewards in an everyday setting. These enabled us to test how habitual posting is influenced by two different forms of social rewards: (a) the numbers of spontaneous likes and comments from other users across two social platforms (*Instagram* in a preliminary study and *Facebook* in Study 1) and (b) a *Facebook* platform change that heightened social rewards by increasing the salience of friends' posts and soliciting user posts and self-disclosure (an intrinsic reward, Tamir & Mitchell, 2012). In so doing, we broadly captured the kinds of rewards that motivate posting on social media platforms.

When interpreting these results, please note that, for simplicity, we describe users as having strong or weak posting habits. In actuality, habit strength is a continuum, and our analyses are all conducted on a continuous measure. Furthermore, our research uses multiple measures of habit strength, recognizing that *frequent past performance* is a determinant of habit formation and *automaticity* in response to cues is a consequence of it. In addition, although we refer to habitual posting, in actuality, habit memories guide online responding in combination with more deliberative processes. That is, some posts just spread others' comments with limited deliberation (direct shares on *Facebook*), whereas others require original, self-generated thought about content and phrasing (including shares with commentary). Nonetheless, the basic set of responses are similar each time users post on social media (e.g., clicking open the app, clicking the text box, clicking the post button; Bayer et al., 2022). In other words, the procedural processes become habitual. Habits may automate especially the instigation of responding (Gardner, 2022) so that, once habits have formed, the learning infrastructure promotes rapid, relatively mindless responses to cues on the site and establishes a framework that enables additional decision-making when required. In fact, social media use is higher in automaticity and requires less behavioral control than other potentially habitual behaviors (Gardner, 2022).

Preliminary Study: Rewards Motivate Initial/Occasional *Instagram* Posting

In an initial, exploratory test of habit insensitivity in social media posting, we reanalyzed an existing data set that had shown that social rewards in the form of likes from others influenced social engagement on *Instagram* (Lindström et al., 2021). Likes on social media are experienced as a form of social endorsement that produces neural signatures of reward processing (Sherman et al., 2016). Further suggesting that these rewards are motivating, posts that get more likes and comments from others are perceived as more positive and important and are associated with posters' greater happiness, self-esteem, and satisfaction with others' reactions (Zell & Moeller, 2018). Accordingly, Lindström et al. (2021) found that social media users were motivated to engage with others by posting more rapidly when they had accrued more likes on the site. Users posted more slowly when they received fewer such rewards.

We adapted these data to provide a preliminary test of the effects of user habits. Our prediction was that social rewards would motivate greater engagement with others, as reflected in lesser latency between posts, primarily for initial or occasional *Instagram* posters. Posters with stronger habits should continue posting at their usual rate regardless of others' reactions, given that their behavior is largely controlled by context cues. This pattern should be evident in a significant interaction between the number of rewards users received on a post and the strength of users' posting habits in analyses predicting latency to post again.

The data set consisted of a random sample of 2,100 *Instagram* users who participated in one of a series of 72 weekly photography competitions between July 30, 2010, and February 17, 2017, yielding a total of 1,705,451 posts (taken from Ferrara et al., 2014). Because it was an analysis of historical data, this study was not registered with any institutional review board (IRB). To ensure that users were operating their own accounts (not social media teams or consultants) and were not purchasing likes (a common practice on *Instagram* at that time), we did not include the 264 users who received more than a mean of 1,000 likes on each post. This left 1,836 users and 1,430,360 posts.

In the analyses, posting rate, our primary indicator of social engagement, was represented by the log difference in seconds between posts. Magnitude of rewards was represented by the number of likes received by each post. As a proxy for users' habit strength, we relied on posting frequency, given that frequent use promotes the formation of habits to use sites automatically with minimal thought (Anderson & Wood, 2021; Schnauber-Stockmann & Naab, 2019). Because this data set included people who started to use *Instagram* at different points in time, the frequency measure might be inflated for earlier adopters. Thus, we also conducted a supplemental analysis that reduced the impact of early joiners (i.e., beginning observation on June 17, 2012; Unix timestamp 1.34×10^9). This alternative analysis yielded comparable results to those reported below. Means and bivariate correlations are in Table S1-1 in the online supplemental materials.

Multilevel models predicted latency to post again from the interaction between posting frequency and the number of likes received on the immediately prior post. Importantly, the anticipated interaction was significant, indicating that the number of likes had stronger influence on less frequent posters—motivating them to post again more rapidly, but had only limited influence on more frequent ones, $B = 0.01$, 95% CI [0.0002, 0.01], $p < .001$, $df = 1{,}429{,}000$, Cohen's $f^2 = 0.005$. The only other significant predictor was an uninformative main effect for past posting frequency, reflecting simply that more frequent posters also posted more rapidly, $B = -0.01$, 95% CI, $p < .001$, $df = 1{,}795$ (see Table S1-2 in the online supplemental materials).

In summary, the preliminary study replicated Lindström et al.'s (2021) finding that social rewards on *Instagram* motivated greater engagement with others, but showed additionally that this effect held primarily for infrequent posters. With repetition, posting apparently became more habitual, and social rewards had less impact on engagement. Nonetheless, these results are only suggestive. We treat this evidence as preliminary because the frequency measure of habit strength available in these data necessarily overlaps with the measure of post latency, given that more frequent, strongly habitual posters by definition posted faster. To avoid this limitation in Study 1 and Study 2, we estimated users' past posting frequency, a measure that is sequentially prior to our primary dependent variable, time until a subsequent post. Another limitation of the preliminary study is that timestamps were not available for receipt of rewards. Thus, we cannot be certain that the cumulative number of rewards on any one post were actually received prior to the next post, and thus were able to motivate future engagement. To address these issues, we conducted a live observational study with another social media platform, *Facebook*. As in the preliminary study, social rewards were defined here as numbers of others' reactions to a post. Habit strength was measured through both a self-report assessment of automaticity as well as frequency of posting prior to the study's observation period. Furthermore, the temporal order of posts and rewards was documented in real time. It is worth noting that the platform cues that activate users' posting habits were stable during the observational period of Study 1, as *Facebook* did not update the platform's design during this time.

Study 1: Rewards Motivate Occasional *Facebook* Posting

As in the preliminary study, we predicted that weakly habitual posters would increasingly engage with others and speed their posting rate after receiving positive reactions, but strongly habitual ones would maintain their level of engagement regardless of others' reactions. This pattern would be reflected in an interaction between the number of rewards on a post and habit strength in analyses predicting latency to post again. The full study plan and predictions were preregistered (#19360). All study procedures were approved by the IRB at The University of Southern California, under the name Social Media Habit Study (UP-18-00767).

In addition, we assessed the level of social motivation among our participants. Contrary to our prediction that people act on habit with limited input from motivation, it could be that users' motivation itself changes so that concern about others' reactions wanes or alters after repeatedly using a site. For example, members' motivation in a group can shift with the transition from newcomers to established participants (Yao et al., 2021). We tested this alternative account with participants' ratings of how much feedback from others mattered to them—a broad motivational measure that encompasses a variety of social goals (e.g., social comparison, recognition, support seeking). As another indicator, participants self-predicted whether their posting rates would increase given greater rewards from others. In prior research, self-predictions of future behavior were highly dependent on current motivations (Koehler & Poon, 2006). Support for the altered motivation alternative would be obtained if more frequent, habitual posters reported less social concern and predicted less impact of reward on their own future responding.

Method

Design

For a week, we observed participants' *Facebook* posts and recorded the timestamps on each one in order to measure the exact latency between each post. In order to assess the temporal sequence of social rewards and responses, coders tracked in real time others' reactions and comments as they were made. To our knowledge, this is one of the few live-monitoring observational studies of social media use (see also Deters & Mehl, 2013; Lindström et al., 2021).

Participants

Our sample of 121 participants was recruited through two sources: A snowball sampling method identified 80 active *Facebook* posters from the psychology student pool at a large California university, their family and friends, and posted advertisements placed around campus; in addition, a paid online sample (*Prolific*) provided 42 *Facebook* users. From these participants, we observed 1,907 Facebook posts. Although all participants were required to post at least twice per week, 57 additional participants were excluded because they did not post on *Facebook* during the study period.

To determine the sample size sufficient to detect an estimated small-sized cross-level interaction effect in a multilevel model (Cohen's $f^2 = 0.02$), we used a power simulation tool, *simr* (Version 1.04; Green et al., 2016). A minimum sample size of 50 participants, with an assumed mean of 15 posts collected per participant and $\beta = .2$ CLI term, was estimated necessary to obtain 0.80 power. A description of these simulations and the R code for the power analyses for all studies can be found in the supplement.

Procedure

During the initial session, participants provided background information, indicated habit strength (see below), and added as a "friend" a blank *Facebook* profile (procedure adapted from Deters & Mehl, 2013). Participants' posts were observed for the following week via the observer profile. Participant privacy was ensured by categorizing the observer profile's *friends* list as private.

To monitor comments and reactions to posts, two independent coders tallied *Facebook* activity between 8 am and 11 pm daily. All tallies were recorded into shared, password-protected spreadsheet documents (a main sheet and backup, enabling the collected data to be triple-checked for accuracy by both on-duty research assistants as well as the lead author). Assistants monitored accounts roughly every 15 min, and the lead author checked for consistency between the main and backup sheets 4 times daily. During the final session, participants were shown the list of comments on their own posts, and they coded these for valence (negative, positive, neutral). Finally, participants completed an exit survey including habit and prediction measures and were debriefed.

Measures

Self-Reported Habit Strength (SRHI, Verplanken & Orbell, 2003). On this 12-item scale ranging from 1 (*agree*) to 7 (*disagree*), participants rated the habit strength of *Facebook* posting. Items included, "when I post on *Facebook*, I do so"…."automatically," "without thinking," and "before I realize I am doing so" ($\alpha = .93$).

Past Posting Frequency. After opening their *Facebook* page and reviewing their own posting history, participants reported their average number of weekly posts over the past month on a sliding scale ranging from 0 to 100.

Social Motivation. Participants rated whether feedback (reactions, comments) on their *Facebook* posts mattered to them on a scale ranging from 1 (*strongly disagree*) to 9 (*strongly agree*), as well as how important this feedback was on a scale ranging from 1 (*not at all important*) to 9 (*extremely important*). Responses to these items were highly correlated, $r(113) = .91$, $p < .001$, and were averaged into an index reflecting reward motivation. Seven participants failed to respond to this measure.

Self-Predicted Response to Social Rewards. Using a scale ranging from 1 (*never*) to 9 (*always*), participants rated how often they increased their *Facebook* posting rate after receiving positive feedback (reactions or comments) on a post. Seven participants failed to respond to this measure.

Reactions and Comments. Coders tallied the number of emoji reactions to each post as positive (like, love) or negative (anger, sad). Surprise (wow) and laugh (haha) emojis were not coded, as their valence is unclear. The counts of positive reactions received on posts were standardized. Results comparable to those reported in the text were obtained in analyses with raw, unstandardized numbers of rewards, analyses calculating rewards centered around each participant's mean reactions per post (see Figures S2-2 and S2-3 and Tables S2-1–S2-5 in the online supplemental materials), as well as ratios of positive to negative reactions and comments (see Tables S2-6 and S2-7 in the online supplemental materials). Perhaps due to the low numbers, preliminary analyses revealed no effect of negatively-valenced emoji reactions ($M = 0.15$, $SD = 0.83$; see Tables S2-8 and S2-9 in the online supplemental materials).

At the end of the study, comments on each post were tallied and coded as positive or negative by the participants who received them. Given the small numbers of comments and the assumption that even negative comments reflect social recognition, we combined them into the sum of all comments received on each post. This comment measure was then centered around the sample mean in the same way as described above for emoji reactions.

Latency to Post Again. Our primary dependent variable is the elapsed time in hours between postings. Given that high-frequency posters had shorter latencies because they posted more often, the data were skewed by greater numbers of short-latency posts. Thus, analyses were conducted on log-transformed latencies, with 5 s added to all latencies in order to prevent ln(0) from returning undefined entries.

Results

Correlations, means, and standard deviations are shown in Table 1. As predicted, past posting frequency, an antecedent of habit strength, was strongly correlated with the SRHI (self-report habit index), a consequence of habit strength. Thus, we use both measures in the analysis. Between-post latency was negatively correlated with both past posting frequency and self-report habit (SRHI) measures, reflecting just that users who posted more often in the past also posted more rapidly during the week-long study. Also, perhaps due to the structure of our sample, which necessarily included many posts from habitual posters and relatively few posts from occasional ones, shorter latency between posts during the study week was not associated with more positive reactions and comments from others.

Suggestive support for our hypothesis comes from the negative correlations between the two measures of habit strength (past post frequency and SRHI) and the numbers of positive reactions and comments per post during the study week. Thus, users with stronger posting habits generally received fewer positive reactions and comments per post than users with weaker posting habits, consistent with high use levels not being driven by social motivation. In addition, the motivation rating was linked to the speed of posting and receipt of reward. As would be expected, participants who reported being more motivated by others' reactions received more positive reactions per post during the study week. However, motivation was unrelated to comments, perhaps due to the low numbers of comments given. It is interesting to note that participants' self-predictions were strongly associated with motivation ratings, suggesting that predictions were based on experienced motivation.

Model

Analyses were conducted with multilevel (hierarchical) models in which the Level 1 equation models the relationship between individual *j*'s standardized numbers of positive reactions to the immediately prior post $(i-1)$ and the log-normalized latency until the subsequent post (i), as well as the intercept term, β_{0j} (see below). The variance in posting latency unexplained by the model parameters is represented in Equation 1 by ε_{ji}. These within-participant parameters are constrained by the between-participant components of the model represented in the Level 2 equations (see below). Equation 2a models the participant-level intercept term β_{0j}, which reflects latency to post again, from the intercept, y_{00}, and the fixed effect (y_{01}) of PostHabit_j which is habit strength (continuous, at the participant level), as well as u_{0j}, the Level 2 random intercept, which is the deviation of the actual from the predicted participant intercept. Equation 2b models the cross-level interaction, showing how the participant-level reactions coefficient, β_{1j}, is predicted from (y_{10}), the fixed effect of reactions, and (y_{11}), which represents the fixed effect of the cross-level interaction term, as well as the Level 2 random slope (u_{1j}) which is the deviation of the actual from the predicted participant slope.

$$\text{Latency}_{ij} = \beta_{0j} +_j \beta_{1j}\text{Reactions}_{i-1j} + \varepsilon_{ji} \quad (1)$$

$$\beta_{0j} = y_{00} + y_{01}\text{PostHabit}_j + u_{0j} \quad (2a)$$

$$\beta_{1j} = y_{10} + y_{11}\text{PostHabit}_j + u_{1j} \quad (2b)$$

Influence of Positive Reactions

The above model was computed using the self-report habit index (SRHI) and revealed the predicted interaction between more positive reactions on the prior post and habit strength, $B = 0.31$, 95% CI [0.17, 0.45], $p < .001$, $df = 1{,}727.08$, Cohen's $f^2 = 0.018$ (see Table 2). To graph the interaction, we plotted lines at meaningful points, reflecting the sample minimum of posting two times per week versus daily posters, or seven times per week. As can be seen in Figure 1, greater numbers of positive reactions to the prior post decreased latency to post again among weaker habit participants, $B = -0.34$, 95% CI [−0.58, −0.10], $p = .005$, but had no effect for stronger habit ones, $B = 0.13$, 95% CI [−0.01, 0.27], $p = .103$. Also as expected, a higher SRHI score significantly predicted lower latencies between posts (i.e., more rapid posting).

Table 1
Means, Standard Deviations, and Correlations: Study 1

Variables	*N*	*M*	*SD*	1	2	3	4	5	6
1. Latency between posts	1,907	20.27	166.87	—					
2. Mean positive reactions/post	1,907	2.95	7.66	.13**	—				
3. Mean comments/post	1,907	0.31	1.93	.06**	.50**	—			
4. SRHI	122	3.17	1.39	−.31**	−.25**	−.21**	—		
5. Past posting frequency	122	15.85	19.19	−.52**	−.28**	−.19**	.61**	—	
6. Social motivation	117	4.37	2.19	.33**	.09**	−.03	.25**	.04	—
7. Self-predicted response to social rewards	117	4.30	2.54	.26**	.11**	−.04	.31**	.03	.65**

Note. All means are unstandardized values. Correlations were calculated using standardized values of each measure. SRHI = self-report habit index.
*$p < .05$. **$p < .01$.

Table 2
Multilevel Model Predicting Latency to Post Again From SRHI and Positive Reactions: Study 1

Independent variables	*df*	*B*	*p*	95% CI
Intercept	126.78	0.66	<.001	[0.32, 0.99]
Positive reactions	1,260.08	0.13	.098	[−0.02, 0.28]
SRHI	88.08	−0.41	.008	[−0.72, −0.11]
Positive Reactions × SRHI	1,727.08	0.31	<.001	[0.17, 0.45]

Note. Estimates are unstandardized coefficients (*B*). Degrees of freedom (*df*) are calculated using the Satterthwaite method. CI = confidence interval; SRHI = self-report habit index.

Table 3
Multilevel Model Predicting Latency to Post Again From Past Posting Frequency and Positive Reactions: Study 1

Independent variables	*df*	*B*	*p*	95% CI
Intercept	135.86	0.74	<.001	[0.44, 1.04]
Positive reactions	1,359.52	0.08	.290	[−0.07, 0.23]
Past posting frequency	58.14	−0.68	<.001	[−0.90, −0.46]
Positive Reactions × Past Posting Frequency	1,840.73	0.26	.001	[0.10, 0.43]

Note. Estimates are unstandardized coefficients (*B*). Degrees of freedom (*df*) are calculated using the Satterthwaite method. CI = confidence interval.

The above model was also estimated using past post frequency for habit strength. Again, the predicted interaction emerged between the number of positive reactions on the prior post and past posting frequency, $B = 0.26$, 95% CI [0.10, 0.43], $p = .001$, $df = 1{,}840.73$, Cohen's $f^2 = .016$ (see Table 3). Simple slope analyses revealed that, among users who posted infrequently (2×/week), greater numbers of positive reactions to their immediately prior post slightly reduced latency until the next post, $B = -0.18$, 95% CI [−0.37, 0.01], $p = .067$ (see Figure 2). In contrast, users who posted daily or more often did not increase their posting rates when they received greater numbers of positive reactions, $B = -0.05$, 95% CI [−0.19, 0.09], $p = .513$. The overall model also revealed a main effect for past frequency, reflecting that greater frequency of past posting predicted lower latencies during the study week. No other effects were significant.

Influence of Comments

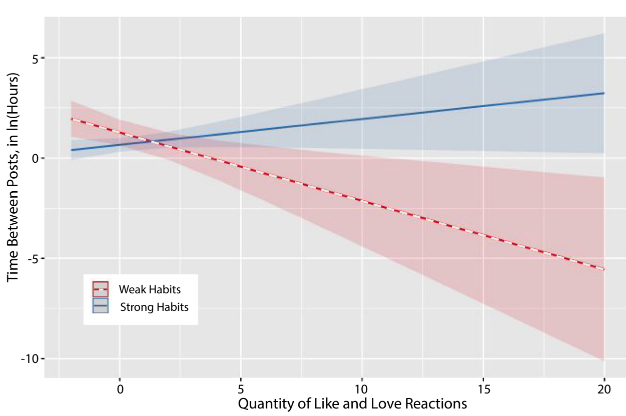
As another measure of social rewards, the above models were computed using the raw number of comments on the prior post as a predictor of posting latency. Echoing the results with emoji rewards, the predicted interaction was significant between habit strength (SRHI) and number of comments on the prior post, $B = 0.28$, 95% CI [0.11, 0.44], $p = .001$, $df = 1{,}558.56$ (see Table 4).

We conducted comparable analyses with habit strength in terms of past posting frequency. Analyses predicted posting latency from the raw number of comments on the prior post, habit strength, and their interaction. However, the predicted interaction did not reach significance in this model, $B = 0.26$, 95% CI [−0.04, 0.29], $p = .128$, $df = 1{,}901.09$. Greater habit strength was again a significant predictor of shorter between-post latency, $B = -0.69$, [−0.91, −0.46], $p < .001$, $df = 57.92$ (see Table S2-10 in the online supplemental materials). It is possible that the predicted interaction failed to emerge due to the low reliability of the comments measure, given the few comments received on posts.

Social Motivation: Concern About Others' Reactions

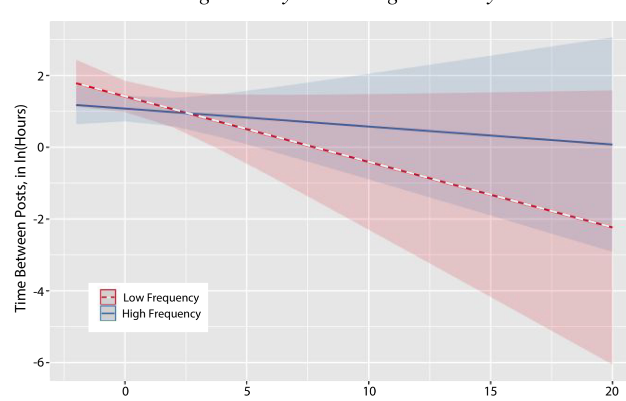
To assess the relation between habit strength and our broad measure of motivation as reflected in concern about others' feedback, we first computed separate regression analyses predicting this

Figure 1
Plot of the Interaction Between SRHI and Positive Reactions Predicting Latency to Post Again: Study 1



Note. Latency (log hours) between posts as a function of habit strength (SRHI) and number of positive reactions to the immediately prior post. For the plot, habit strength was dichotomized with weak habits corresponding to standardized SRHI scores for users posting 2× per week and strong habits corresponding to scores for users posting 7× per week. Error bars represent 95% CIs. CI = confidence interval; SRHI = self-report habit index. See the online article for the color version of this figure.

Figure 2
Plot of the Interaction Between Past Posting Frequency and Social Reactions Predicting Latency to Post Again: Study 1



Note. Latency (log hours) between posts as a function of past frequency of weekly posts and number of positive reactions to the immediately prior post. For the plot, habit strength was dichotomized with low-frequency users posting 2× weekly and high-frequency ones posting daily. Error bars represent 95% CIs. CI = confidence interval. See the online article for the color version of this figure.

Table 4
Multilevel Model Predicting Latency to Post Again From Habit Strength (SRHI) and Comments on Immediately Prior Post: Study 1

Independent variables	*df*	*B*	*p*	95% CI
Intercept	132.53	0.65	<.001	[0.32, 0.99]
Comments	1,305.66	0.12	.136	[−0.04, 0.27]
SRHI	92.86	−0.37	.017	[−0.68, −0.07]
Comments × SRHI	1,558.56	0.28	.001	[0.11, 0.44]

Note. Estimates are unstandardized coefficients (*B*). Degrees of freedom (*df*) are calculated using the Satterthwaite method. CI = confidence interval; SRHI = self-report habit index.

motivation from the two measures of habit strength. SRHI proved to be positively related to concern about others' feedback, $B = 0.03$, 95% CI [0.01, 0.05], $p = .007$, $df = 113$, indicating that strongly habitual participants self-reported greater motivation than weak habit participants. However, in analyses using the past posting frequency measure of habit strength, habit was unrelated to concern about others, $B = 0.01$, 95% CI [−0.01, 0.03], $p = .628$, $df = 113$. Thus, habitual posters' lesser sensitivity to rewards does not appear to be due to waning social motivations. If anything, habitual posters reported being more concerned about others' reactions than less habitual posters.

In analyses directly testing whether habit insensitivity to social rewards was due to waning concern about others, we recomputed the primary multilevel (hierarchical) models reported above with habit strength in terms of SRHI and including concern as a covariate. As anticipated, the interaction between habit strength (SRHI) and positive reactions on the prior post was still significant, $B = 0.31$, 95% CI [0.17, 0.46], $p < .001$, $df = 1{,}613.25$. Whether feedback mattered to users also predicted behavior, although in this model, greater concern was unexpectedly associated with longer latency (slower posting rates), $B = 0.24$, 95% CI [0.08, 0.39], $p = .003$, $df = 92.35$ (see Table S2-11 in the online supplemental materials).

We also recomputed the primary multilevel (hierarchical) models using past posting frequency as the measure of habit strength and including concern as a covariate. As anticipated, the interaction between habit strength remained significant, $B = 0.32$, 95% CI [0.15, 0.50], $p < .001$, $df = 1{,}724.98$. Again, users reporting greater concern with others' feedback also had longer latencies between posts, $B = 0.21$, 95% CI [0.08, 0.34], $p = .002$, $df = 88.19$ (see Table S2-12 in the online supplemental materials).

Lay Theories: Self-Predicted Responses to Rewards

In regression analyses testing the relation between habit strength (SRHI) and self-predictions, greater self-reported habit was associated with self-predictions of posting more rapidly after getting social rewards, $B = 0.05$, 95% CI [0.2, 0.08], $p = .005$, $df = 113$. Habit strength in terms of frequency of prior posting was unrelated to self-predicted response to social rewards, $B = 0.00$, 95% CI [−0.02, 0.02], $p = .746$, $df = 113$. Thus, habitual posters were unaware of their limited sensitivity to rewards. Instead, more habitual posters self-predicted equal or greater responsiveness to others' reactions compared with less habitual posters. For completeness, we computed multilevel models including self-predictions as alternatives to social motivation, and continued to find that habitual posters were insensitive to social rewards (see Tables S2-13 and S2-14 in the online supplemental materials).

Single and Multiple Lag Results

Because each new post latency is driven by reactions that occurred before that post, our reaction counts could be calculated by tallying the number of reactions on the prior 1, 2, or 5 post (s) during the week of the study. We calculated three different models to reflect each of these tallies. Based on simple temporal proximity, the single-post lag model (reflecting the number of reactions received on the immediately prior post) that we presented above should provide the strongest evidence of any causal effect of rewards, and this effect might dissipate at longer delays. Alternatively, if the greater experience of more habitual posters leads them to construe social rewards more abstractly, then their posting might be more sensitive to rewards at longer time scales (Hubbard et al., 2021).

To test these accounts of reward influence across time frames, we computed a 2-post lag model using the same predictors as the single lag model, but aggregating rewards across the prior two posts. Effects were similar to the ones we reported for the single-lag posts (see Table S2-15 in the online supplemental materials). However, the 5-post lag model did not yield the predicted interaction, and the effects were largely uninterpretable, with posting latency increasing for everyone after receipt of more positive feedback from others (see Table S2-16 in the online supplemental materials). This is likely due to limited data to test this model, given that few participants provided five posts during the week-long observational period of our study. Thus, the results do not clearly reveal any systematic effects of time frame, and we will not discuss these further.

Discussion

The findings of Study 1 confirmed our prediction that others' positive responses on *Facebook* motivated infrequent posters and those with weak posting habits to engage again by posting more rapidly. In contrast, high-frequency and strongly habitual posters displayed the predicted reward insensitivity, and their posting rates were little influenced by others' reactions. They persisted in posting again quickly regardless of whether they received high or low levels of social recognition from others on their immediately prior post.

Thus, social media's quantified metrics of repeated sequences of posting and rewards yielded unique insight into the motivation behind habitual social interaction. Prior experimental research in lab contexts has not consistently shown this habit insensitivity to motivation (e.g., de Wit et al., 2018). Our demonstration required an observational design to isolate the temporal order of responses and their outcomes as these were repeated across a week in an everyday social setting, replete with the distractions, stresses, and fatigues of daily life.

It is important to note that our two measures of habit, past posting frequency and self-report habit index (SRHI), were highly correlated. Users who self-reported strong posting habits were also those who posted more frequently. This replicates prior research in social media contexts (Anderson & Wood, 2021) and others (Galla & Duckworth, 2015; Neal et al., 2013) and supports the use of posting frequency as a measure of habit in our next study.

This first study also ruled out several alternative accounts for the pattern of habit insensitivity. First, we assessed whether frequent, habitual posters experienced different levels of motivation or were less concerned about others' reactions than occasional posters. Neither proved to be the case. On average, all participants reported being concerned about others' reactions. In additional tests, we showed that habit insensitivity was maintained even after controlling for the effects of users' concern for others. Thus, occasional posters acted on their concerns about social feedback and their expectations that it would influence their engagement on *Facebook*. Habitual posters reported similar motivations, but their behavior was unaffected by others' reactions. Given that habitual posters have had extensive experience performing a behavior, they should be especially certain about their goals (Ji & Wood, 2007). Thus, goal clarity is not likely to explain these effects.

Finally, one may argue that other types of user goals—which were not measured here—affected the posting rates of habitual and nonhabitual posters. As noted in our introduction, some researchers assume that well-practiced actions as well as occasional or novel ones are motivated by goal attainment (e.g., Kruglanski & Szumowska, 2020). We devised a broad motivational measure assessing concern for others' reactions—the social reward tested in this study. This was designed to encompass a variety of personal, idiosyncratic goals participants might have for using social media (e.g., affiliation, group membership, loneliness), and habitual posters reported that the social motivation activated by rewards was especially important. They reported caring about others' reactions and predicted that they would be motivated by them. The similar patterns for motivation and prediction are understandable given that self-predictions appear to be highly dependent on current intentions (Koehler & Poon, 2006). Thus, habitual participants reported being motivated by others' responses but these responses did not impact their posting behavior. This pattern rules out many alternative, goal-based explanations for the present results.

Finally, we note that the obtained pattern of habit insensitivity cannot be attributed to a ceiling effect, in which social engagement was already maximized among strongly habitual participants. In fact, the habitual posters in our study ranged from those who posted 7 times weekly up to those who posted about 7 times per day. This suggests that all but the most habitual posters could easily have increased their engagement on *Facebook* and posted more often when rewarded by others.

Study 2: Changes to Platform Cues Motivate Some Users, Disrupt Others

The second study took a novel approach to testing whether frequent *Facebook* use shifts the influence of motivation and increases reliance on cues. Specifically, we evaluated a heretofore-untested change in the 2007 posting design of the platform. At that time, users interacted with others primarily by posting content onto others' pages (or "walls"), and thus had to navigate to another part of the site, away from their own page. In this way, social engagement on *Facebook* has taken different forms over time.

These different platforms have been strategically designed and tested to encourage users' engagement (Hagey & Horwitz, 2021). Social media sites are especially likely to make modifications that increase repeated, consistent use, given that their business model depends on creating a deep set of heavy users (Anderson & Wood, 2021). In particular, the 2007 design change altered the way that users posted on the site. It increased the salience of cues to post by adding a blank on the profile page to provide one's "current status." Viewing one's own profile on *Facebook* is highly rewarding and increases self-esteem (Gonzales & Hancock, 2011). The design change also increased the prominence of friends' posts in the scroll feed, thereby heightening the salience of socially rewarding content. Communicating with others on social media has the additional rewarding effect of increasing feelings of social support (Zhang et al., 2021). Thus, this platform change plausibly motivated increased user engagement in a number of ways.

Although the increased salience of social rewards should increase the posting rates of occasional or new posters, more frequent, habitual posters should not be affected in this way. In fact, the platform changes might have deleterious effects on habitual posters. Given that habit performance is activated by recurring cues, changes in site design can slow responding and increase user errors (Garaialde et al., 2020). Prior research found just these effects in an analysis of an earlier *Facebook* platform change (Anderson & Wood, 2021). The disruptive impact of context changes on habit performance have been labeled *habit discontinuity* (Verplanken et al., 2008; Verplanken & Orbell, 2022). Such disruptions remove triggering cues and increase deliberation about what to do next (Wood et al., 2005). Although we were unable to identify the changes in specific cues that could impact users, our study focuses on the full complement of cues within the social media platform itself that influence responding.

Study 2 thus consists of a quasiexperiment testing whether posting rates increased or decreased after the 2007 platform change. Specifically, we anticipated an interaction between the timing of the platform change and past posting frequency. That is, being more motivated to engage with others following the change, occasional and new posters should post more rapidly. However, the posting of more frequent posters should be relatively unaffected by site features that increase motivation. Instead, for them, the change might disrupt the cue-based automaticity with which they post on the site and increase their deliberation about whether and how to post again. Thus, frequent posters may fail to become more engaged and instead the change in platform cues may make them slower to interact with others online.

Method

Design

The study used an existing data set to evaluate a previously untested *Facebook* platform change that occurred on April 20, 2007 (Vishwanath et al., 2009). This change encouraged posts by presenting a greater amount of friends' content at the top of the newsfeed along with the addition of the phrase, "USERNAME is…," next to the status update bar, with the user's name provided and blank space to indicate how they are feeling and/or what they are doing. At that time, users were posting directly within the *Facebook* platform rather than sharing posts from outside the platform, and thus all posters encountered this phrase. Because this was an analysis of historical data, this study was not registered with any IRB.

From this prior data set, we included 5,319 *Facebook* users who had posted at least once during the 6-month period (September 20, 2006 to March 20, 2007) prior to our target assessment period (March 20–May 20, 2007), and also posted at least once during the assessment period. This ensured that our sample included users with a range of posting frequency, our indicator of habit strength. Specifically, we tested wall-posting rates the month before (March 20–April 19, 2007) versus the month after the platform change (April 20–May 20, 2007). Participants made a total of 41,199 wall posts during this period.

Measures

Latency of *Facebook* Wall Posts. Posting rate was measured as the log latency of seconds between posts during the month before the platform change (March 20, 2007–April 19, 2007) as well as latency during the month after the change (April 20, 2007–May 20, 2007). As in Study 1, this measure was transformed to a natural log scale to mitigate the strong skew in observed posting behavior, as more rapid posts are by definition also more frequent posts.

Past Posting Frequency. We estimated habit strength as past posting frequency, using the posting behavior of each user (number of posts) during the 6 months prior to the start of assessment of the impact of the change (i.e., September 20, 2006–March 20, 2007). In so doing, we build on Study 1's findings that past posting frequency was substantially correlated with perceived habit strength (SRHI).

Platform Change Indicator. Timing of the platform change is a group-level variable measuring whether posts were made before or after the platform change (0 = *before April 20, 2007 at 12 am*, 1 = *after this date*).

Self-Post Versus Other-Post. In an exploratory analysis, we examined whether the platform change had differential effects on posts to a user's own page/wall as opposed to others' walls. We speculated that the changes might especially motivate posting on others' walls, given the increased visibility of friends' posts. Consistent with this possibility, the predicted interaction held in the analysis on posts to others' walls but not the analysis on posts to one's own wall. However, this failure to find an effect with self-posts could also be due to low power, given the small sample size of self-posts (N = 294). Thus, we do not present these results in further detail here (see Tables S3-4 and S3-5 in the online supplemental materials), and the reported analyses include self posts with posts to others' walls.

Results

In the data set, participants had posted an average of 14.66 (SD = 19.76) times in the past 6 months, and the mean latency between posts was 21.58 hr or 77,679.34 s (SD = 1,792,592.02). Correlational analyses revealed that the past frequency of posting during the 6 months prior to our assessment of the platform change was negatively associated with the latency between posts during the 2 months of the study, $r(5,317) = -.33$, $p < .001$.

Model

Analyses were conducted with multilevel (hierarchical) models in which the Level 1 equation models the relationship between the timing (*PlatformChangeIndicator*) of a user's (j) post (i) and the log-normalized latency until the subsequent post ($i + 1$), as well as the intercept term, β_{0j} (see below). The variance in posting latency unexplained by the model parameters is represented in Equation 3 by ε_{ji}. These within-participant parameters are constrained by the between-participant components of the model represented in the Level 2 equations below. Equation 4a models the participant-level intercept term β_{0j}, which reflects latency to post again, from the intercept, y_{00}, and the fixed effect (y_{01}) of PostHabit$_j$ which is habit strength (continuous, at the participant level), as well as u_{0j}, the Level 2 random intercept, which is the deviation of the actual from the predicted participant intercept. Equation 4b models the cross-level interaction, in which the participant-level reactions coefficient, β_{1j}, is predicted from (y_{10}), the fixed effect of the platform change indicator, and y_{11} PostHabit$_j$, which represents the fixed effect of the cross-level interaction term, as well as the Level 2 random slope (u_{1j}) which is the deviation of the actual from the predicted participant slope.

$$\mathrm{Latency}_{(i+1)j} = \beta_{0j} +_j \beta_{1j}\mathrm{PlatformChangeIndicator}_{ij} + \varepsilon_{ji} \tag{3}$$

$$\beta_{0j} = y_{00} + y_{01}\mathrm{PostHabit}_j + u_{0j} \tag{4a}$$

$$\beta_{1j} = y_{10} + y_{11}\mathrm{PostHabit}_j + u_{1j} \tag{4b}$$

Posting Latency Before Versus After Change in Platform Cues

As would be expected, the analysis revealed that latency was negatively associated with the platform change, indicating that the change overall increased user engagement as reflected in shorter latency between posts (see Table 5). In addition, the main effect of habit strength reflected the expected shorter latency between posts among more frequent posters. Most importantly, the interaction between habit strength and the change in platform design was significant, $B = 0.003$, $df = 40{,}230$, $p < .001$, Cohen's $f^2 = 0.0003$.

To illustrate the interaction, we performed a spotlight analysis on infrequent, once-per-week posters (i.e., 26 posts over the 6 study months) and more frequent, daily posters (i.e., 180 posts over 6 months). Consistent with our predictions, the between-post latency decreased for infrequent, weak habit posters, $B = -0.10$, CI [−0.15, −0.05], $p < .001$, whereas it increased for more frequent, strong habit posters, $B = 0.36$, CI [0.14, 0.58], $p < .001$ (see Figure 3).

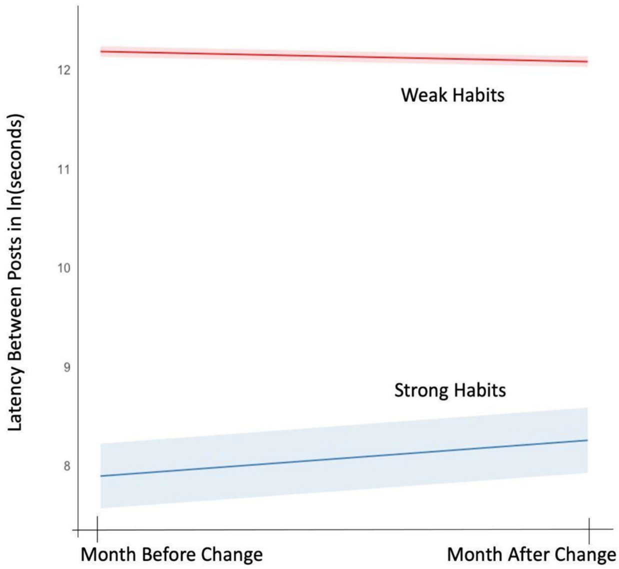
Table 5

Multilevel Regression Predicting Latency Between Posts as a Function of the Platform Change and Past Posting Frequency: Study 2

Independent variables	*Df*	*B*	*p*	95% CI
Intercept	8,959	12.91	<.001	[12.84, 12.98]
Past posting frequency (habit strength)	3,705	−0.028	<.001	[−0.03, −0.025]
Timing of change (0 = before, 1 = after)	41,040	−0.181	<.001	[−0.25, −0.11]
Past Posting Frequency × Timing of Change	40,230	0.003	<.001	[0.001, 0.004]

Note. Estimates are the nonstandardized coefficients (B) of the terms in the multilevel model predicting latency between posts (log seconds). Past posting frequency is a participant-level variable reflecting the number of posts a participant made in the 6 months prior to the analysis period. Degrees of freedom were calculated using the Satterthwaite method.

Figure 3
Plot of Latency Between Facebook Posts as a Function of the Platform Change and Past Posting Frequency: Study 2



Note. Posting latency (log seconds), with higher numbers reflecting greater latency between *Facebook* posts, is depicted as a function of the timing of the *Facebook* design change (1 month before vs. after) and past posting frequency (dichotomized only for presentation-analyzed as a continuous variable), with strong habits defined as 180 posts during the 6 months prior to the assessment, and weak habits as 26 posts. Error bars represent 95% CIs. An alternative plot using habit strength as a continuous variable is available in Figure S3-1 in the online supplemental materials. CI = confidence interval. See the online article for the color version of this figure.

Testing Artifacts: Comparing Engagement Before Versus After Randomly Chosen Dates

To test whether our findings are due to artifacts such as regression to the mean, we selected an arbitrary date of 1 month after our assessment, May 20, 2007, and evaluated posting latency before and after that date. Suggesting that the above effect is not spurious, no significant interaction emerged between users' past posting frequency and the month before versus after this date, $B = 0.001$, $df = 41{,}530$, $p = .16$. When we extended this analysis to include the day after this arbitrary date (May 21, 2007) or the day before (May 19, 2007), again no significant interactions emerged, $B = 0.001$, $df = 41{,}500$, $p = .12$, and $B = 0.001$, $df = 41{,}550$, $p = .14$, respectively (see Tables S3-1–S3-3 in the online supplemental materials).

Finally, we tested whether users' posting rates returned to their initial levels after the platform change. Such a pattern would be consistent with our explanation of the posting rate slowdown among frequent, habitual posters as due to cue disruption. That is, they should regain their automaticity with continued posting. In line with this possibility, habitual posting rates increased to prior levels during the months after the change (see the regression discontinuity analysis and Figure S3-1 in the online supplemental materials). Although their posting was initially disrupted by the platform change, habitual posters apparently recovered as they gained familiarity with the new platform.

Given that habitual and nonhabitual posters reacted differently to the design change, it is also possible that the platform change activated different goals for habitual and nonhabitual posters. We could not ask the users from the 2007 data set directly about what drove their behavior, but Study 2a below tests our habit-based explanation by examining current users' predictions about a similar design-change disruption.

Study 2a: Effect of the Design Change on Users' Self-Predictions

We used a proxy rating from current users to ascertain what role motivation played in also the platform design change. In an attempt to make the assessment as concrete as possible, we asked participants to self-predict how the change would influence their posting. Given self-predictions' high correlations in Study 1 with motivations, we expected that self-predictions in this study would also largely reflect experienced motivation (also Koehler & Poon, 2006). The study method and plan were pre-registered (#58751).

Participants were 243 *Facebook* users recruited via Amazon's MTurk CloudResearch panels who were U.S.-based English speakers with a *Facebook* account. They completed a survey that assessed: (a) habit strength in terms of past frequency of posting on *Facebook*, (b) habit strength from a subscale of the SRHI (Verplanken & Orbell, 2003; the four items of the Self-Report Behavioral Automaticity Index, SRBAI; Gardner et al., 2012), and (c) self-predicted posting rates given the platform change: "If *Facebook* put your friends' posts closer to the top of your newsfeed and added a prompt to post what you're doing right now, how would this impact your next posts?" (1 = *I wouldn't post again for a long time*; 4 = *it wouldn't change how I posted*; 7 = *I would post again almost immediately*).

A regression analysis revealed that the frequency of past posting influenced anticipated responses to the platform change, such that participants who had posted more frequently in the past also anticipated that they would further speed up posting following the design change, $B = 0.008$, $t(241) = 2.07$, $p = .04$. In a separate regression, stronger self-reported behavioral automaticity (SRBAI) was similarly associated with predictions of posting faster after the design change, $B = 0.08$, $t(241) = 3.08$, $p = .002$. In summary, these findings suggest that frequent, habitual posters expected their engagement to increase given the design change as much or more than less frequent, non-habitual posters. Thus, it is likely that design changes do not decrease posting rates among habitual posters by reducing their motivation to post or by activating different goals, but instead decreased posting rates because they disrupted the context cues that triggered habitual responding.

Discussion

Study 2 provided novel insight into the differing impact of social motivation and reliance on cues among frequent and infrequent *Facebook* posters. The 2007 platform change was broadly effective in motivating greater user engagement, as reflected in the decrease in latency between posts following the implementation of the new design. However, this pattern held among occasional and new posters but not among frequent posters, who presumably had stronger habits. Frequent posters did not respond to the new design prompts with increased engagement. Instead, the new platform cues actually slowed the engagement of highly frequent posters (see the regression discontinuity analysis and Figure S3-1 in the online supplemental materials). As Anderson and Wood (2021) found with an earlier *Facebook* platform change, the altered cues apparently disrupted automated use of the site.

We were able to rule out several alternative explanations for the findings of Study 2. First, we demonstrated that they were not an artifact of regression toward the mean. When we tested changes in posting latencies on three randomly-selected dates without a platform change, users did not change their posting behavior. Also noteworthy are additional analyses showing that the design disruption effect waned over time for frequent posters (see the regression discontinuity analysis and Figure S3-1 in the online supplemental materials). That is, frequent posting rates increased when we examined posting in the month following the 1 month disruption period, as they apparently regained their facility in using the new site design.

Given that we could not assess the actual motives and goals of the 2007 Facebook users, it remains possible that the varying responses to the platform change stemmed from the different goals held by more and less frequent posters. We suspect that this is not the case, given that the survey in Study 2a revealed that current *Facebook* users expected the design change to motivate greater engagement with others on the site. These ratings thus converge with Study 1 in suggesting a disconnect between reported motivation and actual behavior among habitual posters.

General Discussion

Across our preliminary study of *Instagram* use and two studies with *Facebook*, social rewards had less impact on repeated, habitual engagement with others than on occasional or new engagement. Social media sites' time-stamped sequences of posts, social rewards, and platform design changes proved to be well suited to reveal the limited influence of social rewards on habitual actions, which are largely triggered by recurring context cues.

Our preliminary study demonstrated this limited impact using an existing *Instagram* data set that had supported the instrumental learning prediction that greater numbers of social rewards motivate greater engagement (Lindström et al., 2021). Our reanalysis revealed that this was true for occasional and new posters, but not for more frequent ones. Study 1 demonstrated this same pattern in a more controlled design with *Facebook* users. Frequent, habitual posters continued to post again regardless of the positive recognition they received from others on their prior post. Only occasional, weak habit posters were motivated by others' like, love, and comment reactions to post more rapidly. The motivation produced by others' reactions did not impact habitual posters. Finally, Study 2's test of a platform change revealed that strongly habitual posters were not motivated to post faster when prompted by changes in *Facebook's* platform design that increased the salience of social rewards in order to motivate users' increased engagement. Although this change was broadly effective in boosting the speed of wall posting overall, and especially among low-frequency posters, the change in cues apparently impeded automatic responses and slowed the posting of highly frequent posters.

The reduced role of social motivations in driving habitual posting was not due to waning motivation. Study 1's frequent, habitual *Facebook* posters reported being concerned about others' reactions, despite that social recognition actually had no effect on their posting rates. Furthermore, analyses that included social motivation as a covariate revealed that it did not explain the effects of frequent, habitual use on posting rates. In Study 2a, current *Facebook* users with stronger habits predicted that they would react more positively to the design change than less habitual posters. However, the change did not increase the actual engagement of frequent posters in 2007. Overall, these findings suggest that the minimal influence of social rewards among frequent, habitual posters was not traceable to reduced levels of motivation, simply to the reduced influence of motivation on behavior.

It is also worth noting that the limited influence of motives among frequent, habitual posters emerged across four different measures of posting habit strength (actual past posting frequency, self-reported habit, self-reported past posting frequency, and perceived automaticity). This uniformity across measures is not surprising given that frequent posting on social media involves standardized ways of interacting that, with repetition, might easily come to be represented as habit (context-response) associations in memory. Furthermore, habit insensitivity to reward was obtained with three different samples and selection criteria (snowball, MTURK online participants, and archival data), although it is worth nothing that the participants in these samples were all English-speakers and largely drawn from the United States. We suspect that the international popularity of social media sites like *Instagram* and *Facebook* reflects basic, common mechanisms of social learning and engagement that hold across cultures. However, additional research on non-U.S. populations would be required to address the cross-cultural generalizability of our findings.

Although our studies demonstrated the influence of social rewards on social media engagement, we did not evaluate other features of the content of users' posts. Features of content may drive the numbers of social rewards (likes, comments, etc.) received by users by influencing how far and how fast posts spread within social platforms (Vosoughi et al., 2018). Our analysis of social rewards thus might indirectly reflect this influence of content on the reward value of an individual post. Future research would usefully examine the relations between different types of content and rewards for habitual or nonhabitual posters.

In addition, Study 2 demonstrated that cues within the design of social platforms have an impact on the posting rates of habitual posters. Social media likely contains a multitude of general cues (e.g., basic platform layout) and specific ones (e.g., a specific type of post in the news feed) that can drive habitual responses. It is interesting to note that external cues, such as time of day or location, appear to have little impact on the habitual use of online apps and media (Schnauber-Stockmann & Naab, 2019). Future research might profitably identify the particular cues that activate habits of social media use.

In the present research, we were unable to clearly differentiate between beginning and occasional, established users of social media. Prior literature suggests that novice users and experienced users of online social fitness apps differ in their motivations (Stragier et al., 2016), much as newcomers to a group have different social motivations than established group members (Yao et al., 2021). Future studies would profitably examine these differences to further identify the role of motivation on social media platforms.

Finally, we believe that social media sites offer a number of advantages for psychological research, including the high ecological validity along with easily quantified, time-stamped response measures. However, causal inference from these data is not assured, and we imposed a longitudinal design in Study 1 and created a quasiexperiment in Study 2 in order to draw conclusions about the effect of motivating experiences on users' engagement. Our conclusions gain confidence from the common finding across the three study designs that social rewards motivated primarily initial and occasional online social communication and had little impact on frequent, habitual online social communication.

Conclusion

The pattern we documented of reward insensitivity among habitual posters has broad implications for social media use. Habitual posters' lesser sensitivity to social rewards may be reflected also in lesser sensitivity to outcomes of their behavior, including the information they share online. In illustration, Ceylan et al. (2023) found that habitual news sharers shared more misinformation and information that conflicts with their own political views than less habitual news sharers. The result is that habitual news sharers are more likely to be superspreaders of misinformation than less habitual ones. Reward insensitivity also affects other aspects of users' content, including the possibility that personal attacks or even hate speech are more likely to come from habitual posters. These findings could be a gateway for future studies on how habits impact the content of users' posts. For example, Brady et al. (2021) demonstrated that users who frequently post on *Twitter* using language related to moral outrage display some reward insensitivity to others' feedback in their subsequent moral outrage posts, much like the habitual posters in the current research. In these ways, habitual responding is insensitive to information content and social rewards, but dependent on contextual triggers.

We anticipate that similar patterns will emerge whenever habits are formed. Specifically, the behavioral patterns in social media users are likely to characterize repeated responding in other life domains, including consumer purchases, sustainable actions like recycling, transport choices, productivity in school and work, and financial behaviors. Understanding how motivations influence repeated behavior is of practical importance, given that so many life goals can only be reached through repeated action. It is also important theoretically, given the recent debate regarding the degree to which repeated actions are motivated by goals or depend on recurring cues in the performance context (see Kruglanski & Szumowska, 2020; Wood et al., 2022). We hope that the present work spurs research using repeated sequential assessments in other behavioral domains to further test the role of motivation in repeated activities.

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