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The Reinforcement Effect of Social Media Likes in Depression

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IMPORTANCE There is growing concern about the impact of social media on mental health. Understanding the psychological processes underlying social media use could lead to greater insight.

OBJECTIVE To investigate individual differences in the effect of social media likes on posting behavior and their association with and specificity to depressive psychopathology.

DESIGN, SETTING, AND PARTICIPANTS This cross-sectional study used longitudinal Twitter behavior to test the association between depressive and other forms of psychopathology and the tendency to be reinforced by likes. The study involved passively scraped Twitter data (dataset 1) or participants recruited online through Twitter ads (dataset 2) and a recruitment platform (dataset 3). In total, the 3 datasets contained over 17 million posts from 7736 Twitter users. These data were analyzed from March 2023 through January 2026.

MAIN OUTCOMES AND MEASURES Reinforcement tendency was estimated as the association between previous-day likes and current-day posting. The depression measure varied between datasets: self-disclosure in dataset 1, past 4-week depression severity in dataset 2, and a validated questionnaire in dataset 3. Dataset 3 also included other psychiatric measures used to estimate scores on transdiagnostic symptom scores.

RESULTS Dataset 1 comprised 1045 users who reported a depression diagnosis on Twitter, and 5001 randomly sampled users. Dataset 2 comprised 601 users (mean [range] age, 45.2 years [18-78]; 251 [41.7%] women, 333 [55.5%] men, and 17 [2.8%] individuals with other gender identities). Dataset 3 comprised 1089 users (mean [range] age, 30.8 years [18-68]; 703 [64.6%] women, 358 [32.8%] men, and 28 [2.6%] individuals with other gender identities). Individuals with a depression diagnosis or higher symptoms of depression tended more to be reinforced by likes in all datasets (dataset 1: $\beta = .013$; $P = .002$; dataset 2: $\beta = .026$; $P = .03$; dataset 3 [preregistered]: $\beta = .008$, $P = .02$), despite substantial differences between datasets in depression measurement and composition. In dataset 3, greater reinforcement tendency was specifically associated with a transdiagnostic anxious-depression factor, whereas behavioral persistence was linked to a compulsivity and intrusive thought factor.

CONCLUSIONS AND RELEVANCE In this study, depressive psychopathology was associated with a greater tendency to be reinforced by a type of social reward on Twitter, in contrast to typical laboratory-based findings of blunted reinforcement learning in depression. These findings suggest potential mechanisms linking social media use to worse mental health or vice versa, and emphasize the importance of studying real-world behavior.

Editorial

Multimedia

Supplemental content

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Social media plays an increasingly large role in our lives, with over 5 billion users globally as of January 2024.[1] The rapid spread of social media has raised concerns about its impact on mental health. Despite an explosion of research on this topic, findings remain inconclusive.[2] While some reviews and meta-analyses have reported associations between frequent social media use and poor mental health,[3-5] others have highlighted positive effects, such as increased social support, or a mix of the two.[6-9] Notably, many of these effects have been deemed too small to justify widespread societal concerns.[6,10]

The heterogeneity in this literature likely reflects the complexity, variability, and bidirectionality of the findings,[11-13] as well as methodological limitations in prior research.[14] First, most studies have relied on self-reported social media use,[15] which only moderately correlates with actual use.[16] Additionally, social media use is often treated as a monolith, with few distinctions past active use (posting) vs passive use (consuming content). To advance the field, researchers have called for more nuanced studies[17] that incorporate behavioral data[14] and focus on psychological mechanisms that might explain how the design features of social media interact with mental health.[18] Here, we leverage behavioral Twitter data to uncover one promising mechanism—social media reinforcement learning—that we show is robustly associated with depressive psychopathology.

The social rewards that people receive from other users when they post—likes, views, shares, or comments—are a central feature of social media, thought to contribute to its addictive nature.[19] Reinforcement learning, a framework for understanding how behavior is shaped by rewards,[20,21] predicts that social rewards should reinforce posting.[22] A higher rate of rewards (eg, more likes per post, on average) should make posting more valuable (ie, more worth the effort and the opportunity cost of giving up other rewards), leading users to post more frequently in the near future.[23] This prediction has been supported in several social media datasets,[24,25] including through computational modeling.[26-28] Moreover, recent evidence suggests that users tend to replicate posts that were rewarded in the past.[25,29]

However, little attention has been paid to individual differences in the reinforcing effect of likes, which might be particularly relevant to mental health. For example, more habitual social media users have been shown to be less sensitive to likes, in line with theories of habit formation,[24] and adolescents have been shown to learn faster from likes.[28] However, no study that we are aware of has investigated how social media reinforcement learning is modulated by depression or other psychiatric symptoms, despite extensive research in computational psychiatry linking depression to atypical reward processing.[30-32] Compared with controls, individuals with depression learn more from negative outcomes[31,33] and are more sensitive to effort.[34] Notably, depression has been meta-analytically linked to reduced reward sensitivity,[35] though some studies challenge this link.[36] A handful of studies have examined the social domain, finding reduced social learning[37,38] in depression and a link between reduced sensitivity to social rewards and poorer mental health.[39] However, it remains unclear to what extent these findings generalize to rich, real-world social contexts (though see[40,41] who examined how neuroticism and depression modulate reinforcement learning from examination grades). Therefore, the study of reward processing on social media could both uncover psychological mechanisms linking social media use to mental health, and test the generalizability of laboratory-identified links between mental health and reward processing in real-world settings.[42]

To this end, we tested whether depression modulates the tendency to be reinforced by social media likes using behavioral data from Twitter. Building on ideas from reinforcement-learning theory,[23] though not directly applying computational models, we quantified reinforcement tendency as the influence of the mean rate of likes in a day on users' next-day posting behavior, and tested its moderation by depression. To ensure the robustness of our findings, we analyzed 3 datasets with different data-collection approaches and depression measures (**Figure 1**), including a preregistered replication.[45] In the absence of clinician assessment, we use depression broadly to denote depressive psychopathology, self-reported as a clinical diagnosis (dataset 1), recent levels of feeling depressed (dataset 2), or recent depression symptom severity (dataset 3).

Key Points

Question Is depressive psychopathology linked to differential reinforcement by a type of social reward, namely likes on social media?

Findings In this cross-sectional study using Twitter data, depression was significantly associated with an increased tendency for likes to reinforce posting frequency. This association replicated across 3 datasets with differing sample compositions and depression measures, and was robust to a range of controls.

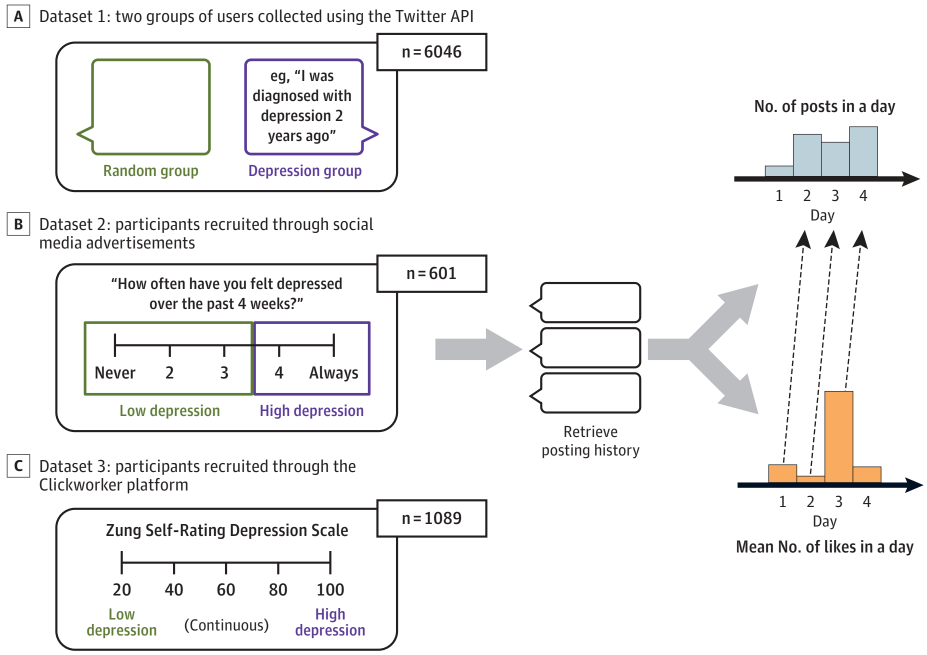
Meaning In this study, depressive psychopathology was associated with a greater tendency to be reinforced by rewards on social media, a behavioral pattern that might link poor mental health to social media use.

Methods

Datasets

We used 3 datasets with different data-collection strategies and measures of depression. Dataset 1 (N = 6046 after filtering) consisted of a group of Twitter users (n = 1045) who self-disclosed a depression diagnosis via tweets and a group of random users (n = 5001). Note that we labeled this group random rather than control or nondepressed, as the users' depression status is unknown. This dataset was collected entirely by scraping existing data using the Twitter API (ie, without participant recruitment), allowing us to reach a much larger sample size than would be feasible otherwise. The procedure and sample size were based on previous recommendations.[46,47] Dataset 2 (N = 601 after filtering) was an existing dataset[48] comprising Twitter users recruited through Twitter ads, who reported their level of depression in the past 4 weeks on a 5-point Likert scale.

Figure 1. Schematic Showing Data Collection and Processing Pipeline



We analyzed 3 Twitter datasets. Dataset 1 (N = 6046) was a fully scraped dataset containing 2 groups of Twitter users: a depression group of users (n = 1045) who disclosed a diagnosis of depression in a tweet and a random group of users (n = 5001). Dataset 2 (N = 601) consisted of participants, recruited through Twitter ads, who self-reported their level of depression in the past 4 weeks on a 5-point Likert scale. Lastly, dataset 3 (N = 1089) consisted of participants recruited mostly through the Clickworker platform, who self-reported their level of depression using a validated and widely used scale (Zung Self-Rating Depression Scale[43]). For each user in each dataset, we retrieved their history of posts, including retweets, replies, and quote tweets. We binned the posts into days and built models in which the number of posts on a given day was regressed against the mean number of likes per post on the previous day. Note that we do not have the precise timing of likes and therefore consider the likes for each post as received on the day of the post. This is in line with empirical data that suggest that the median half-life of engagement with a tweet (including likes) is approximately 80 minutes.[44] See Methods for further details.

Dataset 3 (N = 1089 after filtering) was an existing dataset[49,50] comprising users recruited via crowdsourcing, who completed the Zung Self-Rating Depression Scale[43] (a validated depression questionnaire with a long history of use) as part of a larger questionnaire battery that has been used in previous studies.[51] Across datasets, each user's 3200 most recent tweets were retrieved using the Twitter API. Suspected bots, duplicates, infrequent posters, users who had received no likes and users in datasets 2 and 3 without mental health or demographic information were filtered out, resulting in our final samples (dataset 1: 14 791 435 posts; dataset 2: 1 278 311 posts; dataset 3: 1 341 608 posts). Although the Twitter data are longitudinal in nature, this is a correlational study. Dataset 1 was deemed not human participants research by the Princeton Institutional Review Board (IRB). Datasets 2 and 3 were shared by the teams who collected them according to their institutional guidelines (New York University IRB protocol IRB-FY2022-5783; Trinity College Dublin Department of Psychology Research Ethics Committee, approval ID: SPREC112018-32). All participants in Datasets 2 and 3 provided informed written consent. For more details, see the eMethods and eTable 1 in Supplement 1.

Data Preprocessing

To account for differences in time zones or circadian rhythms between different users, we defined each user's day empirically by identifying their least active hour and binning posts into daily (24-hour) intervals. For each day, we calculated the total number of posts, the mean likes per post, and the like count of the most liked post, applying a log(x + 1) transformation to normalize distributions (eMethods in Supplement 1).

Depression Measures

Depression was measured in different ways across datasets: self-disclosure on Twitter in dataset 1, past 4-week self-reported severity in dataset 2, or the validated Zung Self-Rating Depression Scale in dataset 3, which measures current depression symptom severity.

Factor Analysis

Dataset 3 also included other psychiatric symptom measures (eMethods in Supplement 1), allowing us to test whether our findings generalize beyond depressive symptoms. Following prior methodology,[51] we performed factor analysis with promax rotation using the *factanal* function in R version 4.1.3 (R Project) and specifying a 3-factor solution, in line with previous factor solutions of this questionnaire battery.[51,52] We verified that factor loadings were similar to previous studies (eFigure 1 in Supplement 1) and subsequently used the same labels: anxious-depression (highest loadings: depressive symptoms, trait anxiety, apathy), compulsivity and intrusive thought (highest loadings: obsessive-compulsive, alcohol addiction, eating disorder symptoms), and social withdrawal (highest loading: social anxiety). Factor scores were computed using the regression method.

Statistical Analyses

Linear mixed-effects regression models used the previous-day number of likes per post as an independent variable and the current-day number of posts as the dependent variable. The models included per-user random intercepts and slopes for likes, with the random slopes representing individual reinforcement tendency. Depression was included as an interaction term. In within-participant models, all variables that varied within-participant were mean-centered to isolate within-participant relations. Only random slopes were fit in these models, as centering rendered all intercepts close to 0. Whenever specified, we also controlled for previous-day posts (by adding this variable as a regressor) to account for autocorrelation in posting. In transdiagnostic analyses, the coefficient of the autocorrelation term, which quantifies consistency in posting frequency, was used as a measure of behavioral persistence. All models are listed in the eMethods in Supplement 1.

We use b for unstandardized and β for standardized coefficients. Standardization was performed by z scoring the independent and dependent variables. 95% CIs were computed using the Wald method. In dataset 3, mean-centered analyses and transdiagnostic analyses were exploratory. We report 2-tailed P values for all preregistered analyses in dataset 3 as we found an opposite main effect than expected.

Code Availability

Analysis code in R is available in our OSF repository.[45]

Results

Participant Characteristics

Dataset 1 (N = 6046) comprised 1045 users who reported a depression diagnosis on Twitter, and 5001 randomly sampled users. In dataset 2 (N = 601), 251 (41.7%) were women, 333 (55.4%) were men, 17 (2.8%) were individuals with other gender identities, and the mean (range) age was 45.2 (18-78) years. In dataset 3 (N = 1089), 703 (64.6%) were women, 358 (32.9%) men, 28 (2.6%) were individuals with other gender identities, and the mean (range) age was 30.8 (18-68) years.

Social Media Likes Reinforce Posting Behavior More Strongly in People With Depression

In dataset 1, an association between likes per post on the previous day and posts on the current day was found (b = 0.098; 95% CI, 0.091-0.105; $P < 2 \times 10^{-16}$) (eTable 2 in Supplement 1 for model fits). Importantly, this association was higher in the depression group than in the random group (**Figure 2**A) (likes × group interaction: b = 0.035; 95% CI, 0.019-0.052; $P = 1.73 \times 10^{-5}$) (see the eResults in Supplement 1 for associations between depression and posting frequency or mean number of likes). This group difference was robust to mean-centering (to isolate within-participant variance) and controlling for previous-day posts (Figure 2B) (main effect: β = 0.030; 95% CI, 0.026-0.033; likes × group interaction: β = 0.013; 95% CI, 0.005-0.022; P = .002), and to using only each day's most-liked post in the model (eTable 3 in Supplement 1). Thus, depression was associated with a greater tendency to be reinforced by a type of social media reward. Additionally, in both groups, a subset of users showed a negative association between previous-day likes and current-day posts (Figure 2C).

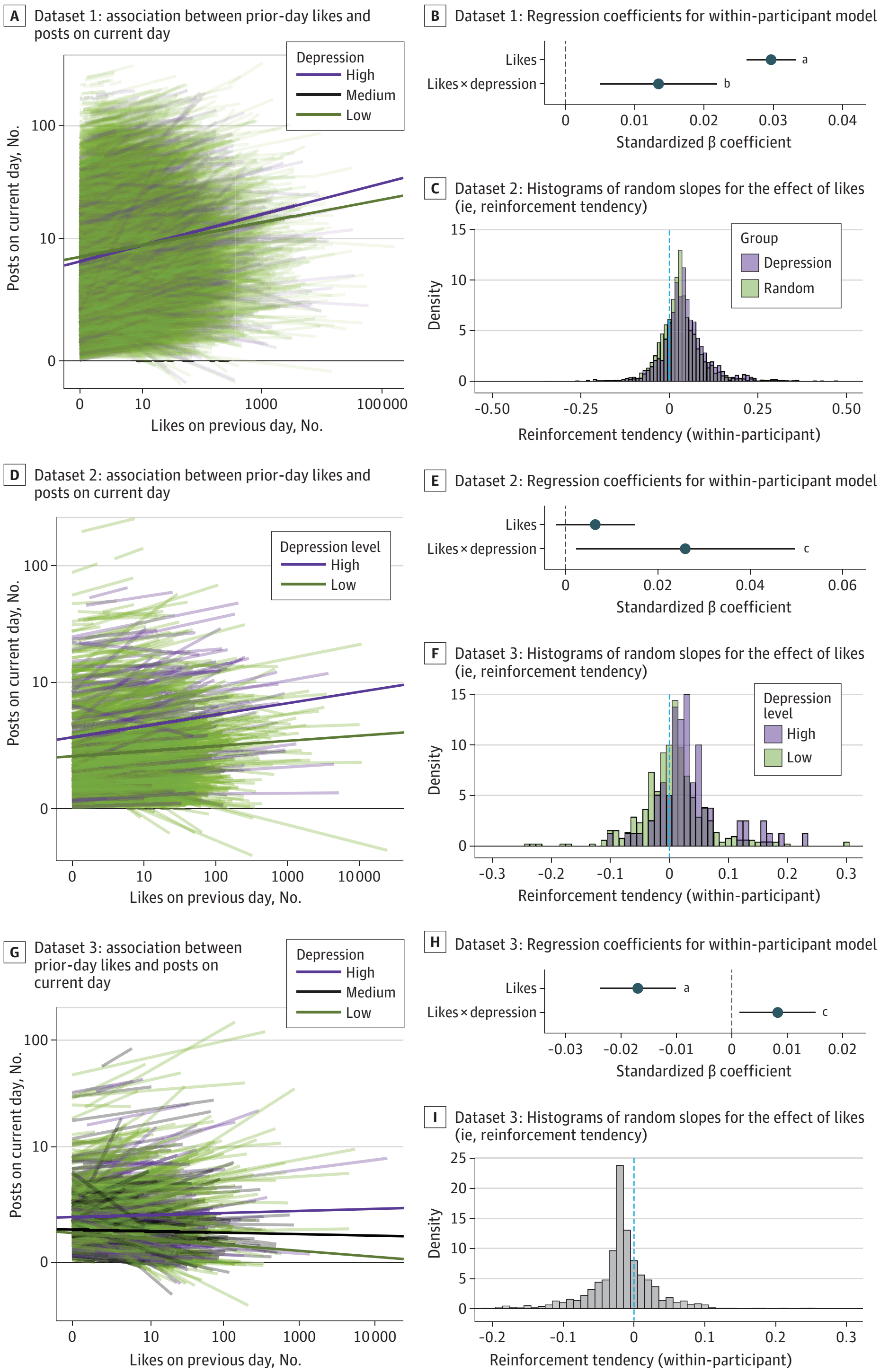
Heightened Reinforcement Tendency in Depression Replicates Across Datasets

Dataset 1 suffered from common method bias (as the dependent and independent variables stem from the same behavioral data), selection bias (as users in the depression group chose to disclose their diagnosis on social media),[46] and the lack of a true control group (as the random group likely contained users with depression). Therefore, the study team sought to replicate the findings in 2 additional datasets. In dataset 2, Twitter users recruited through ads reported their recent depression level.

As in dataset 1, more previous-day likes were associated with more current-day posts (b = 0.042; 95% CI, 0.029-0.056; $P = 2.22 \times 10^{-9}$), with a higher reinforcement tendency in participants with high levels of depression (Figure 2D) (likes × depression level interaction: b = 0.051; 95% CI, 0.014-0.089; P = .008). The depression moderation also held when mean-centering and controlling for previous-day posts (Figure 2E) (β = 0.026; 95% CI, 0.002-0.050; P = .03), though the main association with likes was not significant (β = 0.006; 95% CI, −0.002 to 0.015; P = .14). Once again, individual differences were observed, with some participants showing a negative effect of likes (Figure 2F). Parallel results emerged when considering only the most-liked previous-day post (eTable 3 in Supplement 1). Other mental health constructs (overall mental health and loneliness) did not moderate reinforcement tendency, showing its specificity to depression (eFigure 2 in Supplement 1). However, when treating depression as a continuous variable, the likes × depression interaction was not significant (mean-centered and autocorrelation-controlled analysis: β = 0.004; 95% CI, −0.004 to 0.012; P = .30), possibly due to the item being ordinal, high measurement error when using a single item to assess depression, or insufficient power. To address these concerns, a preregistered replication[45] was conducted using a validated depression measure in dataset 3.

In dataset 3, participants recruited through crowdsourcing completed the Zung Self-Reported Depression Scale.[43] The association between depression and reinforcement tendency was replicated (Figure 2G) (b = 0.0018; 95% CI, 0.0004-0.0032; P = .01). Notably, however, the association between previous-day mean likes and current-day number of posts was negative (β = −0.101; 95% CI, 0.168 to −0.033; P = .003). The results held when mean-centering and controlling for previous-day posts (Figure 2H) (main effect of likes: β = −0.017; 95% CI, −0.024 to −0.010; $P = 1.57 \times 10^{-6}$; likes × depression interaction: β = 0.008; 95% CI, 0.001-0.015; P = .02), and when only the most-liked post was considered (eTable 3 in Supple-

Figure 2. Graphs Showing the Association Between Depression and the Tendency for Likes to Reinforce Posting



A, D, and G, Visualization of associations between the mean number of likes per post obtained on the previous day and the number of posts made on the current day for datasets 1 to 3 (without mean-centering or controlling for previous-day posts to increase interpretability). Thin lines represent individual fits; thick lines represent group-level effects. In D, high depression level represents a response of often or always on a question about the past 4-week level of depression, whereas low is a response of never, rarely, or sometimes. In G, high depression level is 1 SD or more above the mean, low is 1 SD or more below the mean, and medium is within 1 SD above or below the mean. B, E, H, Regression coefficients for within-participant models in all 3 datasets, in which current-day posts are regressed against previous-day likes, moderated by depression. These regression models controlled for the number of posts on the previous day, and all social media variables were mean-centered within participant. In H, depression was *z* scored and thus the main effect of likes represents the mean effect. C, F, and I, Histograms of the random (individual participant) slopes for the effect of likes (the reinforcement tendency) in each of the models in B, E, and H, respectively.

[a] $P < .001$.

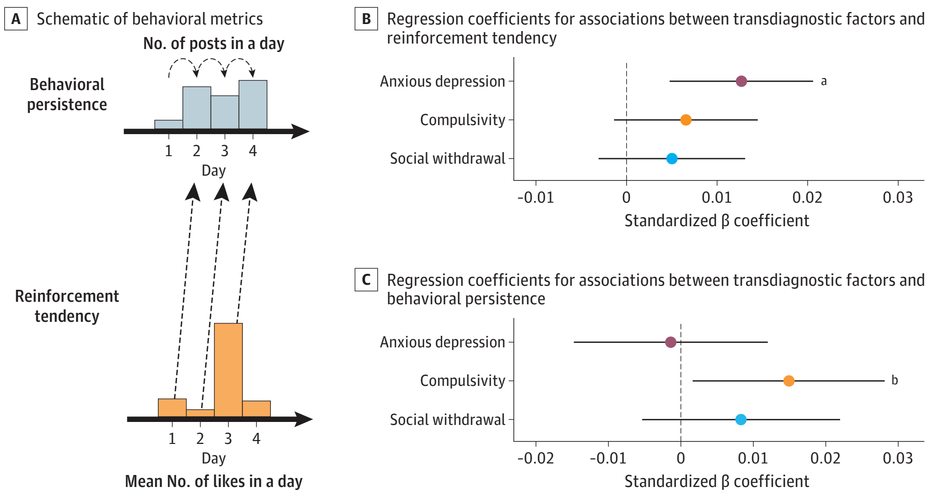
[b] $P < .01$.

[c] $P < .05$.

ment 1). Again, there was substantial heterogeneity (Figure 2I). Participants in this dataset also reported whether they had been diagnosed with depression by a physician. Moderation by this diagnostic measure was directionally consistent but not significant (eTable 4 in Supplement 1), suggesting continuous measures of symptom severity may be more sensitive. In sum, depression was associated with a greater tendency to be reinforced by likes across 3 datasets with substantial differences in data collection and depression measurement methods.

In all 3 datasets, the association between depression and reinforcement tendency was robust to controlling for age and gender, and the data also revealed an association between heightened reinforcement tendency and age. Moreover, mean likes per post positively moderated reinforce-

Figure 3. Schematic and Graphs Showing Associations Between Behavioral Metrics and Transdiagnostic Factors



A, Schematic of the 2 behavioral metrics: reinforcement tendency (ie, the correlation of current-day likes and next-day posts) and behavioral persistence (ie, the autocorrelation between current-day and next-day posts).
B, Standardized regression coefficients for the moderation of 3 transdiagnostic factors on reinforcement tendency. The coefficients were not significantly different from 0 for compulsivity and intrusive thought (β = 0.010; 95% CI, −0.003 to 0.022; *P* = .14) and social withdrawal (β = 0.010; 95% CI, −0.003 to 0.023; *P* = .14). C, Standardized regression coefficients for the moderation of 3 transdiagnostic factors on behavioral persistence. The coefficients were not significantly different from 0 for anxious depression (β = −0.002; 95% CI, −0.015 to 0.012; *P* = .78) and social withdrawal (β = 0.008; 95% CI, −0.006 to 0.022; *P* = .24).

[a] $P < .01$.

[b] $P < .05$.

ment tendency, potentially explaining the mean negative effect of likes in dataset 3 (eResults in Supplement 1). Interestingly, depression was not robustly associated to the tendency to be reinforced by another type of social media reward—retweets—with a significant association observed only in dataset 3 (eResults in Supplement 1).

Reinforcement Tendency and Behavioral Persistence Map onto Different Transdiagnostic Factors

Psychiatric research has been moving toward multidimensional measures that cross diagnostic boundaries.[53,54] To establish the specificity of these results along such transdiagnostic dimensions, in line with prior work,[51,52] 3 transdiagnostic factors (anxious-depression, compulsivity and intrusive thought, and social withdrawal) were derived from the battery of mental health symptom questions in dataset 3. Reinforcement tendency was specifically associated with anxious-depression (likes × anxious-depression interaction: β = 0.013 95% CI, 0.005-0.021; *P* = .002) (**Figure 3**B) and not with the other 2 factors, including when mean-centering and controlling for demographics and other moderators (eFigure 3A in Supplement 1). The anxious-depression factor was associated with 3 scales: depression, apathy, and trait anxiety. Similar to the depression scale, apathy and trait anxiety were significantly associated with reinforcement tendency (apathy: β = 0.012; 95% CI, 0.004-0.017; *P* = .002; trait anxiety: β = 0.008; 95% CI, 0.001-0.014; *P* = .03). By contrast, behavioral persistence (the autocorrelation between current-day and next-day posting) (Figure 3A) was associated with compulsivity and intrusive thought (Figure 3C) (β = 0.015; 95% CI, 0.002-0.028; *P* = .03) and not with the other 2 factors (although this association did not survive mean-centering and additional controls) (eFigure 3B in Supplement 1).

Discussion

We investigated whether people with depression are differentially reinforced by a type of social media reward. Across 3 datasets, we found that depression was associated with a greater tendency to be reinforced by likes. This association was strikingly consistent in all datasets despite differences in sample composition and depression measures, and was largely robust to demographic controls and other moderators, persisting even though likes tended not to reinforce posting in participants who received fewer likes in general (see eDiscussion in Supplement 1). We also showed heightened reinforcement tendency was specific to an anxious-depression factor. Another compulsivity and intrusive thoughts factor was specifically associated with heightened behavioral persistence, although this association was not robust to further controls.

Our findings add nuance to the existing literature, which generally links depression to blunted reinforcement learning.[35,39] However, previous studies mostly relied on laboratory-based cognitive tasks, where small monetary rewards might not have been motivating enough for participants. Our study examined reward-driven behavior in a real-world environment, where users behave out of their own volition. Thus, our results might be more characteristic of general processing of real-world rewards. Similarly, in the field of emotional reactivity, early laboratory-based work supported a link between depression and reduced emotional reactivity to valenced stimuli,[55] but subsequent experience-sampling studies showed heightened emotional reactivity to daily events, life stressors, and peer rejection in depression.[56-58] Thus, our results add to an emerging body of evidence suggesting depression may be associated with heightened, rather than blunted, responses to rewards in the real world. Future studies should integrate both in-laboratory and real-world assessments of reinforcement learning in the same subjects to more directly measure their convergent validity (or divergence) and relationship with depression.[42]

Our findings also identify a behavioral trait that links a feature of social media platforms—quantitative social rewards—to depression. While heightened reinforcement by real-world rewards in depression might be domain-general, its effects could be particularly pronounced on social media due to the social nature of these rewards. For example, depression has been associated with increased sensitivity to social exclusion,[59] which might explain reduced posting in response to fewer likes. In line with interpersonal theories of depression that posit increased feedback-seeking,[60] depression has been linked in self-report studies to higher seeking and monitoring of social feedback on social media.[61-63] These links could also be explained through the social compensation hypothesis,[64,65] which suggests that people receiving fewer offline social rewards, including people with depression,[66] use social media as a compensatory source of accessible reward. Thus, our findings may reflect increased subjective value of social media rewards, driven by feedback-seeking motivations or social compensation needs in people with depression.

Given the correlational nature of our study, we cannot infer causal relations. Rather than depression increasing reinforcement tendency, increased social media reinforcement tendency could worsen depressive symptoms. Indeed, in one study, adolescents reporting using social media for feedback-seeking developed worse symptoms of depression a year later,[61] potentially due to high reward sensitivity intensifying the negative impacts of social media rewards on mental health. Moreover, studies using self-report,[67] simulated social media environments,[68] and Facebook data[69,70] suggest that social media rewards can signal social support, increase happiness, and reduce loneliness. Conversely, paucity of social reward triggers negative emotions and reduces self-esteem and feelings of belongingness.[68,71,72] This could lead to heightened symptoms of depression in social media users that are strongly reinforced by such rewards.

Lastly, dataset 3 revealed that greater reinforcement tendency generalizes across a broader anxious-depression internalizing dimension (and is specific to this dimension), potentially highlighting a shared mechanism of depression and anxiety that is in line with their high comorbidity. We also found a specific association between a compulsivity and intrusive thought dimension and behavioral persistence in posting, a putative indicator of real-world habit tendencies. This finding extends laboratory-based work linking increased habitual behavior to compulsivity,[51,73] and suggests compulsive individuals might be more prone to forming social media habits.

That said, the reported effects are small—unsurprisingly given noisy real-world digital behavioral data.[42] Such effects can however still be meaningful and are considered key to a replicable and cumulative science.[42,74] Notably, our key finding replicated across 3 heterogenous datasets, suggesting it is robust and generalizable. Over 60% of humans use social media and approximately 4% of people experience depression,[75] hence even weak associations between social media reinforcement tendency and mental health may have significant public health consequences.

Limitations

Our study has several limitations. First and foremost, our results apply only to people with depressive psychopathology who choose to post on social media. This population may not be representative of people with clinical depression. Second, despite the longitudinal nature of our data and within-participant behavioral effects, our mental health data were cross-sectional, and we do not know when symptoms began. As such, we cannot resolve the causal relationship between behavior and symptoms, a topic for future research using repeated symptom measures. Third, our findings from Twitter may not generalize to other platforms, such as Instagram or TikTok, which differ in features and usage patterns, including the use of likes, though studies have found similar reinforcement-learning mechanisms on other platforms.[26,28] Fourth, we did not consistently replicate the likes results with retweets, which may reflect a true difference between types of social rewards (likes more directly signaling validation or praise) or statistical limitations (eg, lower variance in retweet effects on posting). Fifth, although our samples were geographically diverse, they consisted mainly of English speakers, and cross-cultural replication is needed. Sixth, all depression measures were self-reported; clinician assessments would provide stronger validation of our findings. Notably, our study cannot distinguish between clinically significant depressive symptoms and constructs such as neuroticism, nor determine whether greater reinforcement tendency reflects a stable trait or a transient state. Moreover, analyses using binary vs continuous measures sometimes yielded different results, suggesting that more work is needed to understand the shape of the relationship between depressive psychopathology and reinforcement tendency. Lastly, our regression models do not fully capture the dynamics of reinforcement learning. For example, people learn from prediction errors (the difference between outcomes and expectations) and may vary in their sensitivity to positive vs negative errors. Fitting reinforcement-learning models to social media data could uncover finer associations between psychopathology and computational parameters,[22] for instance by operationalizing reinforcement tendency as a reward sensitivity parameter scaling the magnitude of reward, or as a learning rate parameter, similarly to previous studies.[28,35,36] However, this approach is challenging due to the noisy nature of posting data.[42] Ultimately, the different operationalizations lead to similar behavioral hypotheses: reward increases will be associated with greater behavioral reinforcement in individuals with greater reinforcement tendency.

Conclusions

In this cross-sectional study, we found that individuals with depressive psychopathology showed a greater tendency to be reinforced by likes on Twitter. Our results underscore the importance of studying real-world behavior in computational psychiatry and highlights a putative psychological mechanism linking social media use to mental health.

ARTICLE INFORMATION

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Concept and design: Mirea, Nook, Niv.
Acquisition, analysis, or interpretation of data: Mirea, Chen, Palacio-Soto, Ding, Mildner, Kelley, Gillan, Niv, Nook.
Drafting of the manuscript: Mirea.
Critical review of the manuscript for important intellectual content: Mirea, Chen, Ding, Mildner, Kelley, Gillan, Nook, Niv.
Statistical analysis: Mirea.
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