

A Need-Satisfaction Paradox: Self-Like Behavior and Young Adults' Mental Health

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Abstract Every social media platform lets users like their own posts, yet this self-directed gesture—visible, countable, and trivially easy—has never been studied as a behavioral variable. Drawing on self-determination theory, cognitive dissonance theory, and social comparison theory, this study surveyed 527 young adult social media users (aged 18–45) and tested a newly developed five-item measure of self-like frequency in an integrated model of mediation and moderation. Self-like frequency positively predicted depressive and anxiety symptoms, weakly predicted lower life satisfaction, and left self-esteem untouched. Social comparison orientation carried roughly one third of the association with emotional symptoms; perceived social support carried none. The pathway was strongest among users high in social interaction anxiety and, more modestly, among those attuned to algorithmic curation. Liking one's own posts thus emerges as an easily observable behavioral marker—relevant to mental health screening, media literacy education, and the question of what self-likers are waiting for.

Keywords self-like behavior; social media; mental health; social comparison orientation; social anxiety; algorithm perception

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1. Introduction

More than one billion people in China are now online, and no age group is more immersed in social media than young adults [1]. Whether that immersion is damaging young people's mental health has become one of the most visible public health debates of the past decade [2,3]. Advisory bodies in the United States have responded with formal health advisories calling for closer study of how, not merely how much, adolescents and young adults use these platforms [4,5]. The case for that shift is straightforward. Meta-analytic associations between total time on social media and depressive symptoms are small [6], whereas problematic patterns of use show considerably stronger links with depression and anxiety [7,8]. Umbrella reviews reach much the same conclusion: average effects are weak, heterogeneous, and person-specific, so researchers stand to learn more from specific behaviors than from total exposure

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[9,10].

The like button is arguably the most consequential of those behaviors. A single click can signal attention, agreement, or simple politeness; its meaning comes from context rather than content, which is why it has been described as a paralinguistic digital affordance [11]. The behavior also has genuine psychological pull. Receiving likes engages reward circuitry in the adolescent brain [12], and a computational analysis of more than one million interactions found that users' browsing and posting conform to a reward-learning model in which likes function as reinforcing social rewards [13]. Studies of liking, however, have concentrated on the two directions the button was designed for: receiving likes from others and giving likes to others. The third direction—clicking like on one's own posts—has gone largely unexamined.

We use the term self-like behavior for that third direction: a user liking the original content they have published, such as status updates, photos, or short videos. The act is technically possible on all major platforms and, anecdotally, is common, yet it has never been treated as an independent variable. The gap matters for two reasons. First, self-liking is a behavior rather than a trait: it is observable, countable, and context-bound, and is therefore conceptually distinct from the trait-like self-appreciation studied in personality research. Second, its probable functions are not trivial. Liking one's own post can serve as emotional self-soothing when expected feedback fails to arrive; as a low-cost confirmation that what one posted was worth posting; as impression management, since a first like tells later viewers that the content merits engagement; and, on algorithmically curated feeds, as a signal deliberately sent to the recommender system in pursuit of visibility [14]. To our knowledge, no published study has developed a measure of self-like behavior or tested its associations with mental health.

The present study was designed to close that gap in a community sample of young adult social media users. Our contribution is fourfold. First, we define and operationalize self-like behavior and introduce a brief, psychometrically defensible measure of it (the Self-Like Behavior Scale, SLBS). Second, we embed the behavior in a theoretical model that combines self-determination theory [15,16] with cognitive dissonance theory [17] and social comparison theory [18], treating self-liking as a self-supplied route to need satisfaction whose downstream costs may run through social comparison. Third, we extend the analysis from person-to-person interaction to person–algorithm interaction by testing whether users' perception of algorithmic curation moderates the association between self-liking and comparison orientation [19]. Fourth, we frame the exercise in public health terms: if self-liking is reliably associated with emotional symptoms, it offers an easily observable behavioral marker for screening and a concrete target for digital literacy education.

2. Background

2.1. Social Media Use and Mental Health Among Young Adults

Concern about social media and mental health rests on converging but uneven evidence. On one side, depressive symptoms and suicide-related outcomes among U.S. adolescents rose after 2010, in parallel with the spread of smartphone-based media [2], and specification-curve analyses indicate that heavier use predicts poorer mental health, particularly among girls [20]. A quasi-experiment exploiting the staggered introduction

of Facebook across U.S. colleges found negative effects on mental well-being that grew with platform penetration [21]. Meta-analytically, time spent on social media correlates only weakly with depressive symptoms [6], but problematic social media use — the loss of control over use — shows moderate associations with depression ($r = .27$) and anxiety ($r = .35$) in adolescents and young adults [7]. Further harms accumulate around the edges of heavy use: perceived social isolation [22], degraded sleep quality [23,24], and early trajectories of problematic use that persist over time [25]. Recent work also suggests that usage patterns differ measurably between adolescents with and without mental health conditions [26], and the broader social and psychological costs of heavy use have been documented in university samples [27].

The other side of the ledger tempers these findings. Associations between digital technology engagement and mental health problems have not strengthened over successive cohorts [28]; developmental sensitivity to social media appears confined to specific age-by-gender windows [29]; and umbrella reviews judge the average effect to be small and dwarfed by between-person heterogeneity [9]. Distinctions between types of use help resolve part of the contradiction: passive scrolling, which exposes users to curated portrayals of other lives, is more consistently linked to worse affect than active interaction [10]. Our own reading of this literature, which the study adopts, is that global measures of exposure are too coarse to carry the causal story, and that the field needs to descend to the level of specific, psychologically loaded behaviors [8]. Liking one's own posts is precisely such a behavior.

2.2. The Like Button: From Social Feedback to Reward Learning

The like is the lightest feedback gesture available on social media, and its ambiguity is part of its power: one click can convey recognition, agreement, obligation, or very little [11]. Sherman et al. [12] showed that viewing likes on one's own photographs engages the nucleus accumbens and other reward-sensitive regions in adolescents, with the response scaled to peer context. Lindström et al. [13] went further, modeling more than one million interactions from an online community and demonstrating that usage conforms to a computational reward-learning account: likes act as social rewards whose prediction errors shape subsequent engagement. In short, the like has become a quantified currency of social approval. Longitudinal evidence complicates the picture in an instructive way — interactive behaviors such as liking relate to adolescent well-being in person-specific directions, helping some users and hurting others [30]. What all of these studies share is an exclusive focus on the interpersonally directed like. None of them considered the self-directed variant.

2.3. Self-Like Behavior: Definition and Research Gap

We define self-like behavior as the act of liking one's own published original content on a social media platform, and we measure it as the self-reported frequency of that act over the previous month. Four functional motives seem plausible from the literature and from our formative interviews: emotional regulation (self-soothing when feedback is absent), self-confirmation (reaffirming the worth of what one posted, consistent with dissonance-reduction logic; [17]), social impression (shaping how later viewers evaluate the content), and algorithm adaptation (using the like as a visibility

signal; [14]). The nearest neighbors in the existing literature are studies of online self-presentation and feedback-seeking, but that work measures posting behavior or profile curation, not the self-directed like. The distinction we draw between behavior and trait is deliberate: self-liking one's posts is an overt, situationally triggered act that can wax and wane with platform, mood, and posting goals, whereas trait self-appreciation is a stable disposition. Conflating the two would obscure the very mechanisms — operant learning, dissonance reduction, strategic signaling — that make the behavior worth studying. What has been missing is a validated measure and a systematic test of its correlates; both are provided here.

2.4. Social Comparison Orientation and Algorithm Perception

Social comparison theory holds that people evaluate their opinions and abilities against those of others when objective standards are unavailable [18]. The Iowa – Netherlands Comparison Orientation Measure (INCOM) captures stable individual differences in this tendency [31]. On social media, comparison is rarely symmetric: feeds assemble other people's edited highlight reels, and repeated exposure to upward comparison predicts lower self-esteem and more depressive symptoms [32]. Social comparison has emerged as one of the more credible mechanisms linking problematic use to depression [33], and a recent meta-analysis confirms a moderate association between problematic social media use and comparison behavior [34]. If self-liking intensifies self-focused feedback monitoring, comparison orientation is the natural conduit for its downstream costs.

The second relevant construct is users' awareness of the algorithms that curate their feeds. Users hold incomplete, folk models of how ranking works [35], and visibility on a platform is allocated by algorithmic power that users learn either to court or to resist [14]. Systematic misconceptions about algorithms are common in the general population and are associated with media-use decisions [19]. Users who understand that interactions feed the recommender system should, in principle, be more inclined to deploy the like strategically on their own content. Self-like behavior, therefore, sits at the intersection of two feedback systems—interpersonal and algorithmic—and both need to be modeled to understand its mental health correlates.

3. Theoretical Framework and Hypotheses

3.1. Self-Determination Theory: Self-Supplied Feedback and the Human–Algorithm Extension

Self-determination theory (SDT) identifies autonomy, competence, and relatedness as basic psychological needs whose satisfaction supports well-being [15]. Applications of SDT to technology argue that the same needs govern digital behavior [16]. On social media, the like is the cheapest carrier of social approval: being liked means being seen and accepted, which speaks directly to relatedness and competence [12,13]. From this vantage point, self-liking can be read as self-supplied need satisfaction: when external feedback is absent or slow, the user generates it. Two features of algorithmic platforms sharpen the account. First, the like doubles as a signal to the recommender system, so the self-liker is also negotiating with an algorithm for visibility—hence our description of the behavior as an instance of human – algorithm interaction. Second, feedback supplied by oneself is not equivalent to feedback from others; it substitutes for

relatedness without delivering it. On balance, we expected self-liking to travel with need-related distress rather than need satisfaction.

3.2. Cognitive Dissonance Theory: Resolving Post-Publication Uncertainty

Publishing content creates a small commitment: the act implies the belief that the post is worth viewing. In the interval before feedback arrives, that belief coexists with uncertainty about its accuracy — a nascent conflict of the kind dissonance theory describes [17]. Liking one's own post resolves the conflict cheaply, by asserting the worth of the post from the one vantage point the user fully controls. Dissonance logic thus predicts short-term relief. It also predicts a trap: if self-liking becomes the habitual answer to feedback uncertainty, the user bypasses the genuine social verification that dissonance reduction is meant to seek [16], and the behavior may entrench itself precisely because it works immediately.

3.3. Social Comparison Theory: Self-Focused Feedback Monitoring

The third account runs in the opposite direction. Liking one's own post is rarely an isolated click; it typically accompanies monitoring of how the post performs — views, likes, comments. Such self-focused monitoring increases exposure to, and sensitivity toward, information about how others are performing, which is the raw material of upward social comparison [18,32]. Comparison orientation, in turn, is reliably associated with lower self-esteem and with higher depression and anxiety [32,33,34]. The theoretical tension is deliberate: one account predicts short-term affective benefits, another predicts durable costs, and the net association with mental health is an empirical question.

3.4. Hypotheses

Figure 1 summarizes the model. We hypothesized that self-like frequency would positively predict depressive symptoms (H1a) and anxiety symptoms (H1b), and negatively predict self-esteem (H1c) and life satisfaction (H1d); that social comparison orientation would mediate these associations (H2); that perceived social support would mediate them in a protective direction (H3); that frequent self-likers would report more depression, anxiety, and comparison orientation than infrequent self-likers (H4); that social interaction anxiety would moderate the path from self-like behavior to comparison orientation (H5a) and the second-stage path from comparison orientation to the outcomes (H5b); and that algorithm perception would moderate the first-stage path (H6).

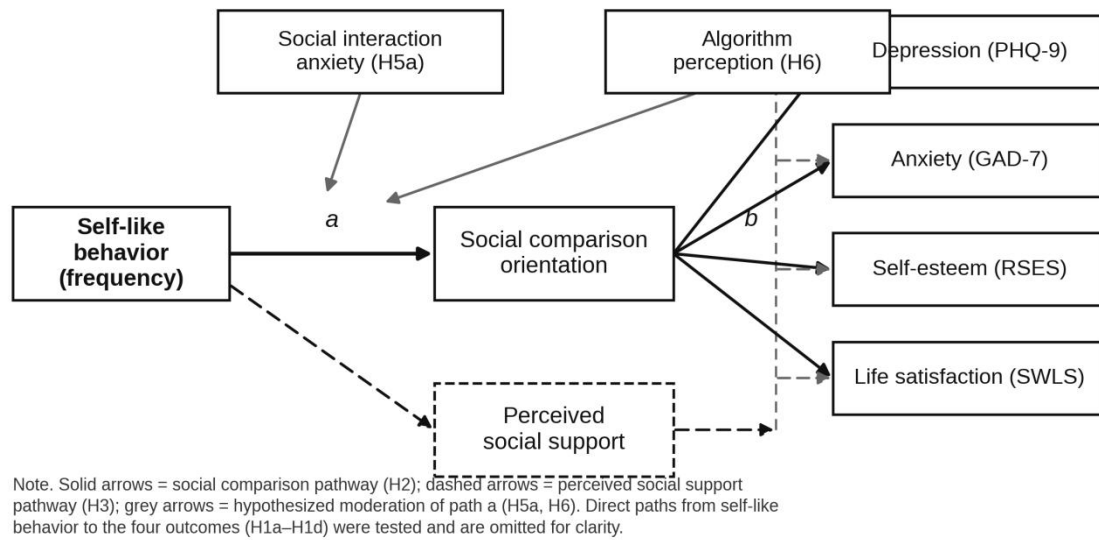


Figure 1. Hypothesized conceptual model.

Solid arrows indicate the social comparison mediation pathway (H2); dashed arrows indicate the perceived social support pathway (H3); grey arrows indicate the hypothesized moderation of the first-stage path by social interaction anxiety (H5a) and algorithm perception (H6). Direct paths from self-like behavior to the four outcomes (H1a–H1d) were tested but are omitted for clarity.

4. Methods

4.1. Design, Participants, and Ethics

The study used a cross-sectional survey design. A sensitivity power analysis in G Power 3.1 (medium-small effect $f^2 = .05$, $\alpha = .05$, $1 - \beta = .95$, 10 predictors) indicated a required minimum of 378 participants; the final sample of 527 exceeded this benchmark. The protocol was approved by the Institutional Review Board of [Institution] (approval no. [number]). Participants gave informed consent online, could withdraw at any point without consequence, and were anonymized in all records.

Participants were recruited between March and May 2025 through the Wenjuanxing survey platform and advertisements placed in social media communities (Weibo, WeChat, Xiaohongshu, and Instagram groups). Eligibility required that respondents be 18–45 years old, use at least one major social media platform actively, publish original content at least once a week, and consent to participate. Of 621 returned questionnaires, 94 were removed for completion times under 180 s, straight-lining, or failure on the embedded attention checks, leaving 527 valid responses (84.8% usable return). Participants were 18–45 years old ($M = 24.74$, $SD = 5.83$) and 54.2% female. The platforms reported as primary were Instagram (38.5%), TikTok/Douyin (27.3%), Weibo (19.2%), or WeChat Moments (15.0%); average daily use was 3.81 h ($SD = 1.92$). Table 1 gives the full demographic profile.

Table 1. Sample characteristics ($N = 527$)

Variable	Category	n	%
Gender	Female	286	54.2
	Male	240	45.5
	Other / undisclosed	1	0.2
Age (years)	18–24	312	59.2
	25–31	138	26.2
	32–38	47	8.9
	39–45	30	5.7
Education	High school or below	55	10.4
	Associate degree	97	18.4
	Bachelor's degree	289	54.8
	Graduate degree	86	16.3
Primary platform	Instagram	203	38.5
	TikTok / Douyin	144	27.3
	Weibo	101	19.2
	WeChat Moments	79	15.0
Platform type	Public	448	85.0
	Private (WeChat Moments)	79	15.0

Note. Age: $M = 24.74$ ($SD = 5.83$) years; daily social media use: $M = 3.81$ ($SD = 1.92$) hours. Percentages may not sum to exactly 100 owing to rounding. Public platforms are those on which content is visible to users outside one's connections (Instagram, TikTok, Weibo); WeChat Moments was classified as private.

4.2. Measures

Self-like behavior (SLBS). The Self-Like Behavior Scale was developed in three steps. First, an item pool was assembled from the affordance and algorithmic-visibility literatures [11,14] and from semi-structured interviews with 12 social media users of varying ages, which supplied typical behavioral situations. Second, the pool was consolidated into an eight-item preliminary scale. Third, in an independent pilot sample ($n = 68$), three items were dropped for factor loadings below .40 or corrected item-total correlations below .30, leaving five items. Respondents rated how often, over the past month, they performed each behavior on a scale from 1 (never) to 5 (always). In the main sample, Cronbach's α was .87, and a single-factor structure showed loadings of .72–.84 ($CR = .89$, $AVE = .61$). Items appear in Appendix A.

Self-like motives. A 12-item measure of self-like motives was constructed alongside the SLBS, covering four subscales (emotional regulation, self-confirmation, social impression, and algorithm adaptation; three items each) on a 5-point scale. Motive scores were used for descriptive purposes and validity checks; hypothesis tests relied on the

SLBS frequency score.

Depression (PHQ-9). The Patient Health Questionnaire-9 [36] comprises nine items rated 0–3; higher scores indicate more depressive symptoms ($\alpha = .89$).

Anxiety (GAD-7). The Generalized Anxiety Disorder-7 [37] comprises seven items rated 0–3 ($\alpha = .91$).

Self-esteem (RSES). The Rosenberg Self-Esteem Scale [38] comprises 10 items rated 1–4 ($\alpha = .86$).

Life satisfaction (SWLS). The Satisfaction With Life Scale [39] comprises five items rated 1–7 ($\alpha = .88$).

Social comparison orientation (INCOM). The Iowa – Netherlands Comparison Orientation Measure [31] comprises 11 items rated on a 5-point agreement scale ($\alpha = .84$). Items appear in Appendix B.

Perceived social support (MSPSS). The Multidimensional Scale of Perceived Social Support [40] comprises 12 items rated 1–7, covering support from family, friends, and significant others ($\alpha = .88$).

Social interaction anxiety (SIAS-6). The six-item short form of the Social Interaction Anxiety Scale [41] was rated on a 5-point scale ($\alpha = .81$). Wording of the short form was established through forward and back translation.

Algorithm perception (APS). The Algorithm Perception Scale was developed for this study from the algorithmic-visibility literature [14,35,19]; six preliminary items were reduced to four after the pilot ($n = 68$). Items are rated on a 5-point agreement scale ($\alpha = .78$; loadings .65–.79; CR = .80, AVE = .51). Items appear in Appendix C.

Covariates. Gender (female = 1, male = 0), age, education (1 = high school or below to 4 = graduate degree), daily social media use in hours, and platform type (public = 1 for platforms on which content is visible to non-connections, i.e., Instagram, TikTok, and Weibo; private = 0 for WeChat Moments).

4.3. Procedure

All instruments appeared in a fixed order in a single online questionnaire: demographics and use characteristics, SLBS, motive items, INCOM, MSPSS, SIAS-6, APS, PHQ-9, GAD-7, RSES, and SWLS, with two attention checks embedded. English-language scales were translated into Chinese by two independent bilingual translators, back-translated, and reconciled through discussion. Median completion time was 12 min.

4.4. Statistical Analysis

Analyses were run in SPSS 26.0, Mplus 8.3, and the PROCESS macro (version 4.1) for SPSS [42]. Confirmatory factor analysis with robust maximum likelihood evaluated the measurement model; common method bias was examined with Harman's single-factor test. Hierarchical regressions entered covariates first, self-like frequency second, and the two mediators third. Parallel mediation was tested with PROCESS Model 4 and moderation with Models 7 and 14, using bias-corrected bootstrap confidence intervals based on 5,000 resamples; an indirect effect or index was judged significant when its 95% CI excluded zero. Group comparisons used independent-samples *t* tests. Two-tailed α was set at .05. Effect sizes are reported as

standardized coefficients, f^2 , and Cohen's d .

5. Results

5.1. Common Method Bias and the Measurement Model

Harman's single-factor test extracted a first factor accounting for 23.4% of the variance, below the 40% criterion, indicating that common method bias was not a serious concern. A nine-factor confirmatory factor analysis of the 69 items from the core scales fit the data adequately: $\chi^2(2,198) = 5,231.60$, $p < .001$, $\chi^2/df = 2.38$, CFI = .943, TLI = .931, RMSEA = .051 (90% CI [.046, .057]), SRMR = .045. The two new instruments showed satisfactory construct reliability and convergent validity (SLBS: CR = .89, AVE = .61; APS: CR = .80, AVE = .51). Measurement-model comparisons supported treating self-liking as a distinct construct: the nine-factor model fit better than a single-factor model ($\Delta\chi^2 = 8,214.3$, $\Delta df = 27$, $p < .001$) and better than an eight-factor model in which the SLBS items were folded into social comparison and social anxiety ($\Delta\chi^2 = 412.7$, $\Delta df = 8$, $p < .001$). Scale-level statistics are summarized in Table 2.

Table 2. Descriptive statistics and reliability of the main scales ($N = 527$)

Scale	Items	M	SD	α	Loading range
Self-like behavior (SLBS)	5	2.42	0.86	.87	.72–.84
Social comparison orientation (INCOM)	11	3.38	0.71	.84	.48–.67
Perceived social support (MSPSS)	12	4.92	1.01	.88	.55–.78
Social interaction anxiety (SIAS-6)	6	2.79	0.92	.81	.58–.74
Algorithm perception (APS)	4	3.51	0.83	.78	.65–.79
Depression (PHQ-9)	9	7.84	5.16	.89	.52–.75
Anxiety (GAD-7)	7	6.38	4.72	.91	.58–.80
Self-esteem (RSES)	10	2.86	0.51	.86	.36–.68
Life satisfaction (SWLS)	5	4.28	1.21	.88	.61–.82

Note. SLBS and APS were developed for this study; M and SD refer to scale mean scores. Nine-factor measurement model: $\chi^2(2,198) = 5,231.60$, $\chi^2/df = 2.38$, CFI = .943, TLI = .931, RMSEA = .051 (90% CI [.046, .057]), SRMR = .045. SLBS: CR = .89, AVE = .61; APS: CR = .80, AVE = .51. The 12-item Self-Like Motives Scale (four subscales, $\alpha = .79$ –.86) was used for descriptive purposes only and was not part of the measurement model.

5.2. Descriptive Statistics and Correlations

Table 3 presents the correlation matrix. Self-like frequency correlated positively with depression ($r = .28$, $p < .001$), anxiety ($r = .22$, $p < .001$), and comparison orientation ($r = .31$, $p < .001$); weakly and negatively with life satisfaction ($r = -.12$, $p = .006$); and nonsignificantly with self-esteem ($r = -.08$, $p = .055$) and perceived social support ($r = -.04$,

$p = .335$). Comparison orientation correlated with every outcome in the expected direction, and perceived social support correlated negatively with depression and anxiety and positively with self-esteem and life satisfaction. The pattern provided initial support for H1a and H1b at the bivariate level, and none for H1c.

Table 3. Correlation matrix ($N = 527$)

Variable	1	2	3	4	5	6	7	8	9	10
1. Self-like frequency	(.87)									
2. Social comparison orientation	.31***	(.84)								
3. Perceived social support	-.04	-.28***	(.88)							
4. Social interaction anxiety	.18***	.29***	-.19***	(.81)						
5. Algorithm perception	.33***	.22***	-.02	.16***	(.78)					
6. Daily use time	.26***	.15***	-.09	.13**	.24***	—				
7. Depression (PHQ-9)	.28***	.38***	-.33***	.35***	.21***	.16***	(.89)			
8. Anxiety (GAD-7)	.22***	.34***	-.28***	.37***	.17***	.13**	.62***	(.91)		
9. Self-esteem (RSES)	-.08	-.35***	.42***	-.31***	-.10*	-.05	-.48***	-.41***	(.86)	
10. Life satisfaction (SWLS)	-.12**	-.29***	.41***	-.22***	-.05	-.03	-.45***	-.38***	.52***	(.88)

Note. Cronbach's α on the diagonal (parentheses). Daily use time is in hours. * $p < .05$, ** $p < .01$, *** $p < .001$ (two-tailed).

5.3. Hierarchical Regressions

Each outcome was regressed on the covariates (Step 1), self-like frequency (Step 2), and the two mediators (Step 3); coefficients appear in Table 4. Among the covariates, daily use predicted depression ($\beta = .11$, $p = .008$) and female gender predicted anxiety ($\beta = .14$, $p < .001$). Over and above the covariates, self-like frequency predicted depression ($\beta = .23$, $p < .001$, $f^2 = .069$) and anxiety ($\beta = .18$, $p < .001$, $f^2 = .041$), weakly and negatively predicted life satisfaction ($\beta = -.10$, $p = .021$, $f^2 = .012$), and did not predict self-esteem ($\beta = -.07$, $p = .098$). H1a and H1b were supported, H1d weakly, and H1c was not. At Step 3, comparison orientation predicted depression ($\beta = .27$, $p < .001$) and anxiety ($\beta = .23$, $p < .001$) and, in the negative direction, self-esteem ($\beta = -.31$, $p < .001$) and life satisfaction ($\beta = -.24$, $p < .001$); perceived social support predicted all four outcomes in the protective direction (β s from $-.19$ to $.38$, all $ps < .001$). The coefficient for self-like frequency fell to $.09$ ($p = .032$) for depression and to $.07$ ($p = .112$) for anxiety—attenuation consistent with mediation.

Table 4. Hierarchical regressions predicting mental health outcomes ($N = 527$)

Variable	Depressio (PHQ-9)	n Anxiet (GAD-7)	y Self-estee (RSES)	m Life satisfaction (SWLS)
Panel A. Covariates and self-like frequency (Steps 1–2)				

Variable	Depressio (PHQ-9)	n Anxiet (GAD-7)	y Self-esteem (RSES)	m Life satisfaction (SWLS)
Gender (female = 1)	.10* *	.14* * *	-.06	.02
Age	-.09*	-.07*	.04	.03
Education	-.08*	-.05	.05	.07*
Daily use time	.11* *	.07*	-.05	-.02
Platform type (public = 1)	.06	.08*	-.03	-.01
Self-like frequency (Step 2)	.23* * *	.18* * *	-.07	-.10*
R ²	.118	.093	.052	.041
ΔR^2 (Step 2)	.052* * *	.031* * *	.004	.012*
Panel B. Mediators added (Step 3)				
Social comparison orientation	.27* * *	.23* * *	-.31* * *	-.24* * *
Perceived social support	-.19* * *	-.15* * *	.34* * *	.38* * *
Self-like frequency (Step 3)	.09*	.07	-.01	-.06
R ²	.224	.176	.211	.234
ΔR^2 (Step 3)	.106* * *	.083* * *	.159* * *	.193* * *

Note. Values are standardized coefficients (β). Panel A reports Steps 1–2 (R^2 cumulative at Step 2); Panel B reports Step 3 (R^2 cumulative at Step 3). Gender: female = 1, male = 0; platform type: public = 1, private = 0. All models except the self-esteem model at Step 1 ($F(6, 520) = 2.86, p = .010$) were significant at $p < .01$. * $p < .05$, ** $p < .01$, *** $p < .001$.

5.4. Parallel Mediation

PROCESS Model 4 with 5,000 bootstrap resamples tested the two mediators simultaneously, with covariates included (Table 5, Panel A). Self-like frequency predicted comparison orientation (a path: $\beta = .31, p < .001$) but not perceived social support ($\beta = -.04, p = .371$). The indirect path through comparison orientation was significant for depression (.082, 95% CI [.052, .115]; 34.8% of the total effect) and for anxiety (.067, 95% CI [.041, .097]; 33.5%), significant and negative for life satisfaction (-.041, 95% CI [-.068, -.017]), and significant for self-esteem (-.063, 95% CI [-.091, -.038]) even though the corresponding total effect was not—a classic suppression pattern. The indirect effects through perceived social support were uniformly nonsignificant (e.g., depression: -.006, 95% CI [-.024, .013]). H2 was supported and H3 was not.

5.5. Moderation and Moderated Mediation

Model 7 tested moderation of the first-stage path (Table 5, Panel B). The interaction of self-like frequency and social interaction anxiety predicted comparison orientation ($\beta = .09, p = .014, \Delta R^2 = .008$). Simple slopes, plotted in Figure 2, showed a steeper association at high (+1 SD) social anxiety ($\beta = .38, p < .001$) than at low (-1 SD) social

anxiety ($\beta = .16, p = .002$). The index of moderated mediation was significant (INDEX = .031, 95% CI [.006, .058]); the conditional indirect effect on depression was larger at high social anxiety (.098, 95% CI [.064, .137]) than at low social anxiety (.043, 95% CI [.018, .073]). H5a was supported. Model 14 found no second-stage moderation (comparison orientation $\times$ social anxiety: $\beta = .04, p = .294$), so H5b was not supported. Algorithm perception moderated the first-stage path weakly ($\beta = .09, p = .041, \Delta R^2 = .007$; index = .026, 95% CI [.003, .052]); the conditional indirect effects were .087 (95% CI [.052, .129]) at high algorithm perception and .048 (95% CI [.021, .081]) at low. H6 received weak support.

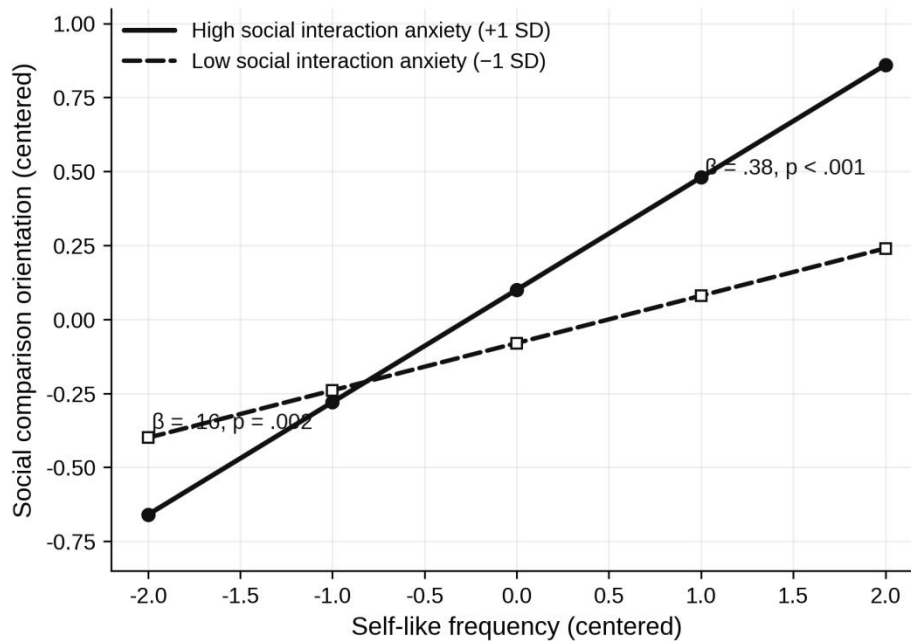


Figure 2 Simple slopes for the interaction of self-like frequency and social interaction anxiety in predicting social comparison orientation (± 1 SD). Slopes: $\beta = .38$ ($p < .001$) at high social interaction anxiety; $\beta = .16$ ($p = .002$) at low social interaction anxiety. Shown for the depression outcome; the pattern was identical for anxiety.

5.6. Group Comparisons

Splitting the sample at the upper and lower 27% of SLBS scores yielded a high-frequency group ($n = 142$) and a low-frequency group ($n = 142$). High-frequency self-likers reported more depressive symptoms (9.72 ± 5.28 vs. 6.43 ± 4.86 ; $t(282) = 5.52, p < .001, d = 0.66$), more anxiety (7.86 ± 4.65 vs. 5.31 ± 4.28 ; $t(282) = 4.93, p < .001, d = 0.57$), and higher comparison orientation (3.61 ± 0.68 vs. 3.13 ± 0.67 ; $t(282) = 6.25, p < .001, d = 0.71$) than low-frequency self-likers. Life satisfaction differed weakly between groups (4.11 ± 1.18 vs. 4.52 ± 1.24 ; $t(282) = 2.95, p = .004, d = 0.34$) and self-esteem did not (2.83 ± 0.52 vs. 2.91 ± 0.50 ; $t(282) = 1.34, p = .181, d = 0.16$). H4 was supported for depression, anxiety, and comparison orientation. As a supplementary check, users whose primary platform was public reported more self-liking (2.51 ± 0.84) than users of private platforms (1.94 ± 0.79 ; $t(525) = 5.63, p < .001, d = 0.70$), consistent with a visibility motive.

6. Discussion

6.1. Principal Findings

In a community sample of young adult social media users, the frequency with which people like their own posts predicted depressive and anxiety symptoms, weakly and inversely predicted life satisfaction, and was unrelated to self-esteem once covariates were held constant. The association with emotional symptoms traveled through social comparison orientation, which accounted for roughly a third of the total effect; perceived social support played no mediating role. Social interaction anxiety amplified the behavioral pathway, and algorithm perception amplified it modestly. To our knowledge, these are the first estimates available for this behavior, and they pattern in a theoretically coherent way.

6.2. A Need-Satisfaction Paradox

Read through self-determination theory, the findings describe what we call a need-satisfaction paradox. Self-liking ought to supply the ingredients of need satisfaction—an instant, costless signal of approval. Instead, it tracked poorer emotional outcomes and left self-esteem untouched. The most plausible reading is that self-supplied feedback substitutes for relatedness without delivering it: the user obtains the form of approval (a like) without the substance (another person’s regard), and repeated substitution may leave the underlying need unmet [16]. This reading converges with the active–passive literature, which shows that not all “active” engagement is beneficial; the function of a behavior matters more than its form [10]. It likewise echoes the person-specific effects found for interactive behaviors such as liking [30], and it cautions against treating engagement metrics as straightforward markers of healthy participation.

6.3. Social Comparison as the Active Mechanism

The mediation results align with a growing body of work placing social comparison between problematic use and depression [33,34] and with evidence that curated feeds invite upward comparison [32]. The suppression pattern for self-esteem deserves comment. The indirect effect through comparison orientation was significant and negative even though the total effect was nil, which implies offsetting components: a positive or null direct component—plausibly the immediate self-confirming function predicted by dissonance theory [17]—cancelled by the negative indirect component running through comparison. Self-esteem, as a relatively stable self-evaluation [38], may buffer direct behavioral effects of this size while remaining sensitive to the comparison-based pathway. For emotional outcomes, the net association was clearly negative, and the mediated proportion was substantial for a single-pathway model.

6.4. Individual Differences: Social Anxiety and Algorithm Perception

The first-stage moderation indicates that self-liking and comparison orientation travel together most strongly among people who fear social evaluation. For socially anxious users, the self-like may function as a safety behavior: a way of pre-empting evaluative uncertainty by supplying the first positive signal oneself (cf. [41]). Safety behaviors relieve anxiety briefly and maintain it over time, which is exactly the pattern

our cross-sectional data cannot yet rule out; the hypothesis is testable in longitudinal or clinical work. Algorithm perception moderated the same pathway, albeit weakly. Users who understand that interactions feed recommender systems appear somewhat more likely to convert that understanding into strategic self-liking, and the supplementary platform contrast — heavier self-liking on public than on private platforms — fits the visibility account [14,19]. Algorithm perception, in other words, shapes the strategy more than the emotional consequence.

6.5. Public Health Implications

Three implications follow for practice. First, screening: a five-item behavior count is cheaper than any diagnostic procedure, and high-frequency self-liking combined with elevated social anxiety may identify young adults worth a closer look. We offer this as a hypothesis for validation rather than a recommendation for deployment, given the cross-sectional design and the modest effect sizes. Second, education: media literacy programs already teach source evaluation, and they could just as easily teach feedback literacy — how like counts are produced, curated, and algorithmically amplified — so that young users can evaluate their own posts against a stable internal standard [5,19]. Third, policy: recent advisories call for interventions aimed at specific digital experiences rather than at screen time in general [4,43]. A behavior that can be observed without instrumentation, and that covaries with emotional symptoms in community samples, is a reasonable candidate for that agenda. Given how contested the overall evidence base remains [3,28], precision about targets matters more than the volume of intervention. Because sleep and related lifestyle factors interlock with social media use [23,24], interventions framed around overall digital well-being are likely to fare better than single-behavior fixes.

6.6. Strengths and Limitations

The study's strengths include a new, psychometrically evaluated measure of a previously unmeasured behavior; a theoretically integrative model tested with bootstrapped mediation and moderated mediation; and a sample with adequate power for small-to-moderate effects. The limitations are equally clear. Causal direction is unresolved in cross-sectional data: depressed or anxious users may self-like more, and bidirectional dynamics are plausible. All variables were self-reported, and self-reports of media use correlate imperfectly with logged behavior [44,45]; future work should pair the SLBS with platform logs (cf. [13]). The sample was an online convenience sample of predominantly Chinese young adults with the platform mix described above, which limits generalizability to other cultures and age groups. The new scales await independent replication, tests of measurement invariance, and retest reliability. Finally, we did not assess within-person fluctuation; experience-sampling designs would show whether self-liking regulates mood in the short run while corroding it in the long run — the very pattern our theoretical account implies.

7. Conclusion

This study introduced self-like behavior — the practice of liking one's own posts on social media — as a measurable, theory-relevant behavior and provided the first systematic evidence on its mental health correlates in young adults. Its frequency was

positively associated with depressive and anxiety symptoms, weakly and negatively with life satisfaction, and not at all with self-esteem. Social comparison orientation carried the association with emotional symptoms; perceived social support did not. Social interaction anxiety strengthened the pathway, marking socially anxious young users as the group for whom self-liking and a comparison mindset are most tightly coupled, and algorithm perception did so to a lesser degree.

Because the behavior is visible, countable, and cheap to ask about, it is a practical candidate marker for mental health screening and a teachable example in digital literacy education. Longitudinal and experimental studies – ideally with behavioral log data – are needed to establish causality before any screening application, and the measure itself requires independent validation. Pending that work, the practical message is modest but usable: when a young client or student habitually likes their own posts, it may be worth asking what they are waiting for.

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Appendices

Appendix A. Self-Like Behavior Scale (SLBS)

Instructions : Thinking about the past month , how often did you do each of the following? (1 = never, 2 = rarely, 3 = sometimes, 4 = often, 5 = always).

1. I click the “like” button on posts that I have published.
2. After posting something, I usually give it a like myself before anyone else does.
3. When likes from others are slow to arrive, I like my own post first.
4. I use self-likes to highlight or draw attention to my own content.
5. After liking my own post, I feel somewhat reassured.

Note. Higher scores indicate higher self-like frequency. Items 4 and 5 were derived from the formative interviews. The scale was developed for this study and requires further validation.

Appendix B. Iowa–Netherlands Comparison Orientation Measure (INCOM; adapted)

Instructions : Please indicate your agreement with each statement (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree).

1. I often compare myself with others.
2. If I want to find out how well I have done something, I compare how I did it with how others have done it.
3. I always like to know what others in a similar situation would do.
4. I never compare my situation with the situations of other people. (reverse-scored)

5. I usually do not look at what others are doing when I make decisions.
(reverse-scored)

6. I never evaluate my situation by how others react to a similar one.
(reverse-scored)

7. I often compare how I am doing socially with how others around me are doing.

8. I usually gauge how well I am coping with difficult tasks by comparing with how others are coping.

9. I usually gauge how well I am handling life problems by comparing with how others handle theirs.

10. When I want to learn more about myself, I compare myself with others.

11. When I want to understand my opinions and thoughts better, I compare them with those of others.

Note. Items 4, 5, and 6 are reverse-scored. Adapted from Gibbons and Buunk (1999).

Appendix C. Algorithm Perception Scale (APS)

Instructions : Please indicate your agreement with each statement (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree).

1. I am aware that platform algorithms affect how visible my posts are.

2. I have a rough idea of how interactions such as likes affect what gets recommended.

3. When I post something, I think about how the algorithm will display it.

4. I have made a point of learning how platforms rank and recommend content (e.g., the feed).

Note. Higher scores indicate higher algorithm perception. The scale was developed for this study and requires further validation.