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Algorithmic Media Content Awareness, Perceived Loss of Control, Reward Sensitivity, and Addictive Social Media Use Among Young Adults

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ABSTRACT

Social media platforms increasingly rely on algorithmic systems to curate the content users see, raising questions about how users' understanding of this curation relates to problematic engagement. Addictive social media use has been consistently linked to difficulties in self-regulation and to heightened sensitivity to reward, yet the unique contribution of algorithmic awareness relative to these more established mechanisms remains poorly understood. This study examined the associations among algorithmic media content awareness, social media self-control failure, reward sensitivity, and addictive social media use among young adults, and tested whether algorithmic awareness predicted addictive use independently of self-control failure and reward sensitivity. A quantitative, cross-sectional, correlational design was used with young adult social media users, who completed validated self-report measures of the study variables, followed by descriptive, correlational, and multiple regression analyses. Algorithmic awareness, self-control failure, and reward sensitivity were each positively associated with addictive social media use. However, self-control failure and reward sensitivity emerged as the stronger and more consistent correlates of addictive use, while algorithmic awareness added little explanatory value once these two factors were considered. Difficulties in self-regulation and heightened reward sensitivity, rather than awareness of algorithmic curation alone, appear to play a more central role in addictive social media engagement among young adults. The findings point toward interventions that strengthen self-regulatory skills and address reward-driven usage patterns, rather than relying solely on algorithmic literacy education. The study contributes to the growing literature on social media addiction, self-regulation, and digital well-being, and highlights the value of future longitudinal and intervention-based research.

Introduction

Social media platforms occupy a central place in the daily lives of young adults, and a substantial body of research has documented that, for a subset of users, engagement with these platforms takes on features that resemble behavioral addiction (Andreassen, 2015; Kuss & Griffiths, 2017). Heavy and compulsive social networking site use has been linked to lower psychological well-being among adolescents and young adults (Twenge et al., 2018) and shares considerable overlap with problematic smartphone use, which has itself been consistently associated with elevated anxiety and depression (Elhai et al., 2017). At the same time, some scholars caution against treating every pattern of excessive use as a clinical addiction, arguing instead for the more conservative label of problematic use pending stronger diagnostic validation (Panova & Carbonell, 2018). This tension between addiction-framed and problematic-use-framed accounts sets the backdrop for the present study.

Griffiths' (2005) components model of addiction proposes that any behavioral addiction, substance-based or otherwise, can be identified through six overlapping features: salience, mood modification, tolerance, withdrawal, conflict, and relapse. This model underlies the two most widely used self-report measures of social media addiction, the Bergen Facebook Addiction Scale (Andreassen et al., 2012) and its platform-general successor, the Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016), and it has since been extended to describe social network site addiction more broadly (Andreassen & Pallesen, 2014). The components model provides a useful diagnostic lens, but it describes what addictive use looks like rather than why some users are more susceptible than others, which is the question the present study addresses.

One candidate explanation concerns the platform environment itself. What a user encounters on a social media feed is no longer a neutral stream of content but the output of a ranking algorithm optimized to sustain engagement. Using a large-scale analysis of Facebook's News Feed, Bakshy et al. (2015) demonstrated that algorithmic ranking measurably narrows the diversity of content users are exposed to, even though users' own choices narrow it further still. Building on this concern, Zarouali et al. (2021) proposed algorithmic media content awareness as a distinct user competence, defined as the degree to which users recognize and understand that platform content is filtered, ranked, and personalized, and developed the AMCA-scale to measure it across four dimensions: content filtering, automated decision-making, human-algorithm interplay, and ethical considerations. Two competing accounts of this construct are plausible: awareness may function as a literacy-like resource that helps users recognize and resist engagement-driving design, or it may simply reflect knowledge that does not, on its own, supply the self-regulatory capacity required to act on it.

A second, more proximal explanation concerns self-regulation. Baumeister et al.'s (2007) strength model of self-control describes self-regulatory capacity as a limited resource that becomes temporarily depleted with exertion, an account that has been widely used to explain lapses in behavior under repeated temptation. Extending this logic to social media specifically, Du et al. (2018) developed a brief three-item measure of social media self-control failure (SMSCF), capturing the everyday experience of intending to limit one's use and being unable to do so, and treated this as conceptually distinct from generalized trait self-control.

A third explanation concerns individual differences in reward sensitivity. Gray's reinforcement sensitivity theory, as formalized and reviewed by Corr (2004), proposes a Behavioral Activation System (BAS) that governs approach toward appetitive stimuli. Carver and White (1994) operationalized this system in the widely used BIS/BAS scales, including a Reward Responsiveness subscale that indexes positive reactivity to the occurrence or anticipation of reward. Because social media platforms deliver rewards such as likes, replies, and novel content on an unpredictable, variable schedule, users higher in reward responsiveness may be particularly prone to habitual checking behavior. Consistent with this reasoning, Xiang et al. (2021) found that BAS-related reward sensitivity was associated with internet gaming disorder among students, although whether this pattern extends to social media specifically has not been widely tested.

Brand et al.'s (2016) Interaction of Person-Affect-Cognition-Execution (I-PACE) model offers a framework for integrating these three strands, describing specific internet-use disorders as emerging from the interaction of person-level predispositions (e.g., reward sensitivity), cognitive and affective responses to the online environment (e.g., algorithmic awareness), and reduced executive control (e.g., self-control failure). The model, however, does not specify how much explanatory weight each component carries once the others are taken into account, and this is particularly unclear for algorithmic awareness, a construct introduced only recently relative to self-control failure and reward sensitivity.

Taken together, the literature offers reasonably strong, independent support for self-control failure (Du et al., 2018) and reward sensitivity (Carver & White, 1994; Xiang et al., 2021) as correlates of addictive social media use, and more tentative support for algorithmic awareness (Zarouali et al., 2021). What remains unexamined is whether algorithmic awareness contributes anything

to the prediction of addictive use once these two more established self-regulatory and motivational variables are modeled simultaneously. This is not a minor omission: if awareness effects are substantially absorbed by self-control failure and reward sensitivity, policy and intervention efforts built primarily around improving algorithmic literacy may be targeting a lever with limited independent leverage, given how strongly algorithmic ranking already shapes exposure regardless of what users understand about it (Bakshy et al., 2015).

The present study had two objectives: (a) to examine the bivariate associations among algorithmic media content awareness, social media self-control failure, reward responsiveness, and addictive social media use in a sample of young adults, and (b) to test whether algorithmic awareness predicts addictive social media use independently of self-control failure and reward responsiveness in a simultaneous multiple regression model. Based on the reviewed literature, the following hypotheses were formulated:

- H1: Algorithmic media content awareness will be positively associated with addictive social media use.
- H2: Social media self-control failure will be positively associated with addictive social media use.
- H3: Reward responsiveness will be positively associated with addictive social media use.
- H4: Given their more proximal role in self-regulation and motivation, self-control failure and reward responsiveness will explain significant unique variance in addictive social media use beyond algorithmic awareness when all three predictors are entered simultaneously.

Method

Design

The study used a quantitative, cross-sectional, correlational design. All variables were measured once through self-report, without manipulation or random assignment. The design permits estimation of association but not of temporal order or causation.

Participants

The sample comprised 300 young adults aged 18 to 30 years (M = 24.22, SD = 3.79). There were 148 males (49.3%) and 152 females (50.7%). Regarding education, 45 participants (15.0%) held or were pursuing a Bachelor's degree, 150 (50.0%) a Master's degree, and 105 (35.0%) an MPhil/PhD. Participants reported using social media for an average of 4.31 hours per day (SD = 1.70, range 1–10).

Measures

Algorithmic media content awareness. Awareness of algorithmic curation was measured with the 13-item Algorithmic Media Content Awareness Scale (AMCA-scale; Zarouali et al., 2021), which covers content filtering, automated decision-making, human–algorithm interplay, and ethical considerations. Items were answered on a 5-point scale (1–5) and averaged; higher scores indicate greater awareness. Cronbach's α in this sample was .957.

Perceived loss of control. Social media self-control failure was measured with the 3-item Social Media Self-Control Failure scale (SMSCF; Du et al., 2018). Items were answered on a 5-point scale (1–5) and averaged; higher scores indicate more frequent self-control failure. Cronbach's α was .854.

Reward sensitivity. Reward sensitivity was measured with the 5-item Reward Responsiveness subscale of the BIS/BAS scales (BAS-RR; Carver & White, 1994). The original scale uses a 4-point response format, whereas responses here were recorded on a 5-point scale (1–5); the implications of this difference are addressed in the Limitations section. Items were averaged, with higher scores indicating greater reward responsiveness. Cronbach's α was .907.

Addictive social media use. Addictive use was measured with the 6-item Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016), which covers salience, mood modification, tolerance, withdrawal, conflict, and relapse. Items are rated from 1 (very rarely) to 5 (very often) and were averaged; higher scores indicate greater addictive use. Cronbach's α was .910.

Procedure

Participants completed the study measures via a self-report survey. Standard procedures for survey-based psychological research were followed, including participant instructions and a consistent order of presentation of the measures.

Ethical Considerations

The authors followed all relevant ethical considerations in the conduct of this research.

Data Analysis

Data were analyzed in Python using pandas, SciPy, pingouin, and statsmodels. The data were screened for missing values, out-of-range item responses (expected range 1–5), duplicate identifiers, and consistency between item-level responses and scale scores. Descriptive statistics, skewness, kurtosis, and Shapiro–Wilk tests were computed for each scale score, and Cronbach's alpha was computed from item-level responses. Associations were examined with two-tailed Pearson correlations. A simultaneous multiple linear regression predicted BSMAS from AMCA, SMSCF, and BAS-RR. Linearity (Ramsey RESET test), normality of residuals (Shapiro–Wilk), homoscedasticity (Breusch–Pagan test), independence of errors (Durbin–Watson statistic), multicollinearity (tolerance and variance inflation factors), and influence (studentized residuals, leverage, and Cook's distance) were evaluated. Standardized coefficients were obtained by re-estimating the model on z-scored variables. The significance level was set at $\alpha = .05$. No mediation or moderation models were tested because the study questions did not specify a mechanism or moderator.

Results

Data Screening

The dataset contained 300 cases with no missing values, no duplicate identifiers, and no out-of-range responses on any of the 27 scale items. Scale scores recomputed from the items matched the scores in the file exactly (maximum absolute difference $< 1 \times 10^{-15}$). Ages were spread approximately evenly across the 18–30 range (skewness = -.06), and daily social media use was mildly positively skewed (skewness = .22). Demographic characteristics are shown in Table 1. Skewness and kurtosis of all four scale scores fell between -0.34 and 0.06 (Table 2). Shapiro–Wilk tests were non-significant for AMCA and BAS-RR but significant for SMSCF ($W = .979$, $p < .001$) and BSMAS ($W = .988$, $p = .018$); given the sample size and near-zero skewness and kurtosis, these departures were judged too small to matter for the analyses.

Table 1 Demographic Characteristics of the Sample (N = 300)

Variable	n	%	M (SD)
Age (years)	300	—	24.22 (3.79)
Gender			
Male	148	49.3	
Female	152	50.7	
Education			
Bachelor	45	15.0	
Master	150	50.0	
MPhil/PhD	105	35.0	
Daily social media use (hours)	300	—	4.31 (1.70)

Note. Age range = 18–30 years; daily social media use range = 1–10 hours.

Descriptive Statistics and Reliability

Table 2 shows descriptive statistics and internal consistency. All four scales showed good to excellent reliability (α = .854–.957). The alpha for the AMCA-scale (.957, 95% CI [.949, .964]) is very high, which can indicate item redundancy in addition to a coherent construct.

Table 2 Descriptive Statistics and Internal Consistency of Study Variables (N = 300)

Scale	k	M	SD	Min	Max	Skew	Kurt	α
AMCA	13	3.03	0.76	1.08	5.00	0.06	-0.34	.957
SMSCF	3	2.97	0.77	1.00	5.00	-0.07	-0.32	.854
BAS-RR	5	3.08	0.79	1.00	5.00	0.00	-0.19	.907
BSMAS	6	2.90	0.77	1.00	5.00	-0.17	-0.08	.910

Note. k = number of items. All scale scores are item means on a 1–5 metric. Kurt = excess kurtosis. AMCA = Algorithmic Media Content Awareness; SMSCF = Social Media Self-Control Failure; BAS-RR = Behavioral Activation System Reward Responsiveness; BSMAS = Bergen Social Media Addiction Scale.

Bivariate Correlations

Table 3 presents the correlations (N = 300 for every pair). All were positive and significant ($p < .001$). Addictive social media use was most strongly related to self-control failure ($r = .52$), followed by reward responsiveness ($r = .32$) and algorithmic awareness ($r = .28$). Algorithmic awareness was also related to self-control failure ($r = .35$) and to reward responsiveness ($r = .22$). These bivariate results are consistent with Hypotheses 1 through 3.

Table 3 Pearson Correlations Among Study Variables (N = 300)

Variable	1	2	3	4
1. AMCA	—			
2. SMSCF	.35*	—		
3. BAS-RR	.22*	.24*	—	
4. BSMAS	.28*	.52*	.32*	—

Note. * $p < .001$ (two-tailed).

Multiple Regression

Assumptions were satisfied. Tolerance ranged from .85 to .92 and VIF from 1.09 to 1.18, indicating no multicollinearity. The RESET test gave no evidence of nonlinearity, $F = 0.04$, $p = .841$. Residuals were approximately normal ($W = .996$, $p = .689$) and homoscedastic (Breusch–Pagan LM = 1.00, $p = .802$), and the Durbin–Watson statistic was 1.77. One case had a studentized residual slightly above 3 (3.25), but no case was influential (maximum Cook's D = .039; maximum leverage = .036), so all cases were retained.

The model was significant, $R = .56$, $R^2 = .31$, adjusted $R^2 = .30$, $F(3, 296) = 44.56$, $p < .001$ (Table 4). Self-control failure was the strongest unique predictor ($\beta = .44$, $p < .001$), followed by reward responsiveness ($\beta = .19$, $p < .001$). Algorithmic awareness was not a significant unique predictor ($\beta = .08$, $p = .116$), although it correlated significantly with addictive use at the bivariate level.

These results support Hypothesis 4: self-control failure and reward responsiveness, but not algorithmic awareness, explained unique variance once all three predictors were considered together. These results describe associations in cross-sectional data and do not indicate causal effects.

Table 4 Multiple Regression Predicting Addictive Social Media Use (BSMAS)

Predictor	B	SE	β	t	p	95% CI	Tolerance	VIF
Constant	0.78	0.21	—	3.79	< .001	[0.37, 1.18]	—	—
AMCA	0.08	0.05	.08	1.58	.116	[-0.02, 0.19]	.86	1.16
SMSCF	0.44	0.05	.44	8.45	< .001	[0.34, 0.54]	.85	1.18
BAS-RR	0.18	0.05	.19	3.77	< .001	[0.09, 0.28]	.92	1.09

Note. N = 300. R = .56, R^2 = .31, adjusted R^2 = .30, F(3, 296) = 44.56, p < .001. CI = confidence interval for B. β = standardized coefficient.

Discussion

This study examined how algorithmic media content awareness, social media self-control failure, and reward responsiveness relate to addictive social media use among 300 young adults, guided by the components model of addiction (Griffiths, 2005), the strength model of self-control (Baumeister et al., 2007), reinforcement sensitivity theory (Corr, 2004; Carver & White, 1994), and the I-PACE model (Brand et al., 2016). Consistent with Hypotheses 1 through 3, all three predictors were positively and significantly associated with addictive use at the bivariate level, echoing prior evidence linking self-regulatory failure, reward-driven motivation, and heavy platform engagement to problematic outcomes (Elhai et al., 2017; Twenge et al., 2018; Xiang et al., 2021). However, in the simultaneous regression only self-control failure and reward responsiveness retained unique, significant effects, supporting Hypothesis 4 and suggesting that algorithmic awareness's bivariate association with addictive use is largely absorbed by its overlap with these more proximal self-regulatory and motivational variables rather than reflecting an independent pathway; this pattern qualifies the common assumption in the algorithmic-literacy literature that awareness of curation (Zarouali et al., 2021; Bakshy et al., 2015) functions on its own as a protective factor, and it is broadly consistent with the I-PACE model's emphasis on executive and affective mechanisms as more proximal drivers of specific internet-use disorders than cognitive appraisals of the platform environment (Brand et al., 2016). The strength of self-control failure as a predictor also fits Baumeister et al.'s (2007) account of self-regulation as a depletable resource and parallels the conceptual overlap already noted between the SMSCF (Du et al., 2018) and BSMAS (Andreassen et al., 2016) instruments, while the smaller but significant contribution of reward responsiveness extends Xiang et al.'s (2021) gaming-based findings on behavioral activation to the domain of social media, consistent with the broader components model view that addictive engagement with technology reflects the same underlying salience, mood-modification, and relapse dynamics documented across social networking site addiction generally (Andreassen, 2015; Andreassen & Pallesen, 2014; Kuss & Griffiths, 2017); because the design was cross-sectional and entirely self-report, however, these findings describe association rather than causal or temporal sequence, and should be interpreted as a basis for further, more rigorous testing rather than as confirmation of a causal mechanism.

Limitations

- The design was cross-sectional and relied on self-report for all variables, so the regression describes simultaneous association rather than prediction over time, and common-method variance may inflate the observed correlations.
- The BAS-RR items were answered on a 5-point scale, whereas the original scale uses four points (Carver & White, 1994); scores are therefore not strictly comparable with published norms based on the original format.
- The very high internal consistency of the AMCA-scale in this sample raises the possibility of item redundancy or response patterning that a single reliability coefficient cannot resolve.

- Gender, education, and age were not entered as covariates, so the reported estimates are unadjusted for these demographic variables.
- The SMSCF has only three items, which limits its content coverage relative to longer self-control measures.
- Conceptual overlap between the SMSCF and BSMAS instruments may have inflated their observed association beyond what two fully independent constructs would show.

Conclusion

Among 300 young adults, self-control failure and reward responsiveness, but not algorithmic media content awareness, were unique correlates of addictive social media use when all three were modeled together, jointly explaining 31.1% of its variance. These findings support Hypotheses 1 through 4 and suggest that awareness of algorithmic curation overlaps with self-regulatory and motivational variables rather than adding independent explanatory value, in line with the I-PACE model's emphasis on proximal executive and affective mechanisms (Brand et al., 2016). Replication with longitudinal designs, broader demographic coverage, and fully documented sampling procedures is needed before these conclusions can inform intervention design with confidence.

References

1. Andreassen, C. S. (2015). Online social network site addiction: A comprehensive review. Current Addiction Reports, 2(2), 175–184. https://doi.org/10.1007/s40429-015-0056-9
2. Andreassen, C. S., & Pallesen, S. (2014). Social network site addiction: An overview. Current Pharmaceutical Design, 20(25), 4053–4061. https://doi.org/10.2174/13816128113199990616
3. Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. (2016). The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. Psychology of Addictive Behaviors, 30(2), 252–262. https://doi.org/10.1037/adb0000160
4. Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. Psychological Reports, 110(2), 501–517. https://doi.org/10.2466/02.09.18.PR0.110.2.501-517
5. Bakshy, E., Messing, S., & Adamic, L. A. (2015). Exposure to ideologically diverse news and opinion on Facebook. Science, 348(6239), 1130–1132. https://doi.org/10.1126/science.aaa1160
6. Baumeister, R. F., Vohs, K. D., & Tice, D. M. (2007). The strength model of self-control. Current Directions in Psychological Science, 16(6), 351–355. https://doi.org/10.1111/j.1467-8721.2007.00534.x
7. Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific Internet-use disorders: An Interaction of Person-Affect-Cognition-Execution (I-PACE) model. Neuroscience & Biobehavioral Reviews, 71, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033
8. Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS scales. Journal of Personality and Social Psychology, 67(2), 319–333. https://doi.org/10.1037/0022-3514.67.2.319
9. Corr, P. J. (2004). Reinforcement sensitivity theory and personality. Neuroscience & Biobehavioral Reviews, 28(3), 317–332. https://doi.org/10.1016/j.neubiorev.2004.01.005
10. Du, J., van Koningsbruggen, G. M., & Kerkhof, P. (2018). A brief measure of social media self-control failure. Computers in Human Behavior, 84, 68–75. https://doi.org/10.1016/j.chb.2018.02.002
11. Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. Journal of Affective Disorders, 207, 251–259. https://doi.org/10.1016/j.jad.2016.08.030
12. Griffiths, M. D. (2005). A 'components' model of addiction within a biopsychosocial framework. Journal of Substance Use, 10(4), 191–197. https://doi.org/10.1080/14659890500114359

13. Kuss, D. J., & Griffiths, M. D. (2017). Social networking sites and addiction: Ten lessons learned. International Journal of Environmental Research and Public Health, 14(3), Article 311. https://doi.org/10.3390/ijerph14030311

14. Panova, T., & Carbonell, X. (2018). Is smartphone addiction really an addiction? Journal of Behavioral Addictions, 7(2), 252–259. https://doi.org/10.1556/2006.7.2018.49

15. Twenge, J. M., Martin, G. N., & Campbell, W. K. (2018). Decreases in psychological well-being among American adolescents after 2012 and links to screen time during the rise of smartphone technology. Emotion, 18(6), 765–780. https://doi.org/10.1037/emo0000403

16. Xiang, H., Tian, X., Zhou, Y., Chen, J., Potenza, M. N., & Zhang, Q. (2021). The relationship between behavioral inhibition and behavioral activation systems, impulsiveness, and internet gaming disorder among students of different ages. Frontiers in Psychiatry, 11, Article 560142. https://doi.org/10.3389/fpsyt.2020.560142

17. Zarouali, B., Boerman, S. C., & de Vreese, C. H. (2021). Is this recommended by an algorithm? The development and validation of the algorithmic media content awareness scale (AMCA-scale). Telematics and Informatics, 62, Article 101607. https://doi.org/10.1016/j.tele.2021.101607



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