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Algorithmic Selves: How AI Recommendation Systems Shape Identity, Belonging and Well-Being among University Students

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ABSTRACT

Addressing the concept of algorithmic selves, this study examines how engagement with AI-curated Instagram and TikTok environments relates to identity-relevant self-evaluation, belonging, and psychological well-being among university-age users. It investigates whether platform engagement and the importance assigned to likes and followers are associated with problematic social-media use, low self-esteem, loneliness, and depressive symptoms. A secondary cross-sectional analysis was conducted using data from 252 respondents. Reliability assessment, hierarchical regression with HC3 robust standard errors, parallel and sequential mediation, exploratory moderation, sensitivity analyses, and external longitudinal triangulation were undertaken. Ordinal confirmatory factor analysis was not estimated because a suitable SEM estimator was unavailable. Platform engagement predicted problematic use, $B=0.923$, $p=.001$, as did likes salience, $B=1.475$, $p=.004$. Problematic use was associated with low self-esteem, $B=0.208$, $p=.004$, and depressive symptoms, $B=0.561$, $p<.001$, but not loneliness. The indirect effect through low self-esteem was significant, $IE=0.233$, 95% CI [0.070, 0.410]. The loneliness pathway was nonsignificant. TikTok-preferring respondents reported higher engagement and depressive symptoms, although platform preference did not moderate the primary relationship. Problematic use and self-evaluation may explain how algorithmically curated engagement relates to well-being, but causal claims require direct longitudinal measures of recommendation exposure.

Keywords:
algorithmic curation; problematic social-media use; depressive symptoms; university students

1. INTRODUCTION

AI-powered recommendation systems are shaping more and more of the daily experiences of university students with social media. Instagram and TikTok, for example, rely on behavioural signals like how long content is watched, how many likes/comments are received, how many times it is shared, how many people search for it, how many people follow it, etc., to prioritize content and improve future recommendations. Algorithms must thus not only be considered as a technical sorting process, but as a sociotechnical system which shapes what users see, what matters and what can be done (Kitchin, 2019). These processes can be used to highlight social comparison, tailor exposure to identity-relevant content, reinforce peer norms, and impact perceptions of popularity and community participation through the use of recommendation systems.

Personalised algorithmically curated platforms expose users to specific lifestyles, bodies, values, interests and social expectations over and over again. User behaviour, platform incentives, and perceived audience response are all factors in the visibility that these systems generate (Cotter, 2019). Users also have expectations and affective interpretations on how algorithms classify and react to them, what Bucher (2019) calls an "algorithmic imaginary." As time passes, users and recommendation systems evolve by interacting with each other: the users' behaviour affects the recommendations, and the recommendations affect the users' behaviour (Siles et al., 2019). The interpretation and reaction to these systems can vary among young people based on their awareness and experiences and how much control they feel they have (Swart, 2021). Algorithmic awareness is thus pertinent as users do not always know when they are being personalised through algorithms to select content (Zarouali et al., 2021).

The importance of university age users is particularly pronounced as this is a time of identity development, social adjustment, independence, peer-group formation, academic pressure and changing relationships. However, previous studies often focus on one of these factors separately, such as screen time, platform preference, problematic use, loneliness or depression. The present study fills this gap by combining algorithmically determined engagement, social-validation salience, problematic social-media use, self-evaluation, belonging and psychological well-being. It specifically investigates if there is a relationship between engagement and the significance of likes and followers and depressive symptoms via problematic use, low self-esteem and loneliness.

The study pursues three objectives:

- To determine whether platform engagement and the importance of likes and followers predict problematic social-media use.
- To test whether problematic use is associated with low self-esteem, loneliness, and depressive symptoms, including parallel and sequential indirect pathways.

- To assess platform differences, robustness across alternative model specifications, and the relevance of external longitudinal social-identification evidence.

2. LITERATURE REVIEW

AI recommendation systems organise social-media visibility by translating behavioural signals—such as viewing time, likes, follows, searches, and shares—into personalised content rankings. This creates a recursive feedback loop in which user behaviour informs algorithmic selection, recommended content shapes subsequent interaction, and new interaction further refines future recommendations. On TikTok, users also develop “folk theories” about how the algorithm reads identity and may attempt to resist or retrain it when its classifications feel inaccurate (Karizat et al., 2021). The “algorithmic crystal” perspective similarly explains how personalised systems can reflect and refract users’ understandings of themselves through repeated content exposure (Lee et al., 2022).

Social-media platforms have long supported identity construction through selective self-presentation and interaction with known audiences (Zhao et al., 2008). Research on MySpace showed that users strategically presented gendered and socially desirable versions of themselves (Manago et al., 2008). Facebook research further demonstrated that emerging adults may present real, ideal, and false selves depending on context and audience (Michikyan et al., 2015). In the present study, this identity-related dimension is operationalised through self-esteem rather than a comprehensive identity-development measure.

Visual and popularity-oriented platforms also intensify social comparison. Exposure to idealised images, influencer lifestyles, curated achievements, and visible metrics may encourage users to evaluate themselves against selectively positive portrayals. Such comparison has been associated with lower self-esteem (Vogel et al., 2014). Instagram browsing may also relate to loneliness when users engage in unfavourable comparison rather than active interaction (Yang, 2016). Envy has similarly been identified as a mechanism linking Facebook use with depressive symptoms among university students (Tandoc et al., 2015).

Social-validation salience refers to the psychological importance attached to likes, followers, and visible engagement. This may be more consequential than time spent alone because it connects platform activity with perceived social worth. Accordingly, problematic social-media use is positioned as the central behavioural mechanism. Greater engagement and stronger validation salience are expected to predict problematic use (H1–H2), which is hypothesised to relate to low self-esteem, loneliness, and depressive symptoms (H3a–H3c). Low self-esteem and loneliness are further expected to mediate this association (H4–H5), while sequential indirect effects are proposed through problematic use and each psychological pathway (H6–H7). Longitudinal evidence among international students also suggests that social-media contact can influence group identification and adaptation over time (Gaitán-Aguilar et al., 2022).

3. METHODOLOGY AND MATHEMATICAL MODEL

3.1 Research Design and Data Sources

This study used a secondary quantitative design based on the participant-level dataset of Limniou and Hendrikse (2023), containing 252 respondents. The dataset includes demographic characteristics, Instagram and TikTok engagement, importance assigned to likes and followers, problematic social-media use, self-esteem, loneliness, and depressive symptoms. A supplementary three-wave study of 233 international university students was used as external longitudinal evidence concerning social-media contact, group identification, and psychological and sociocultural adaptation. Because the supplementary workbook contains published summary statistics and model estimates rather than participant-level records, it was not merged with or independently reanalysed alongside the primary dataset.

The primary data are cross-sectional; consequently, all coefficients and indirect effects are interpreted as associations rather than causal effects.

3.2 Construct Operationalisation

Instagram and TikTok use represented engagement in algorithmically curated platform environments, not direct exposure to specific recommendations. Importance assigned to likes and followers represented social-validation salience. Problematic social-media use was treated as the principal behavioural mechanism, low self-esteem as an identity-related self-evaluation indicator, loneliness as diminished belonging, and depressive symptoms as the well-being outcome. As illustrated in Figure 1, platform engagement and social-validation salience were modelled as antecedents of problematic social-media use, which was subsequently linked to depressive symptoms through low self-esteem and loneliness.

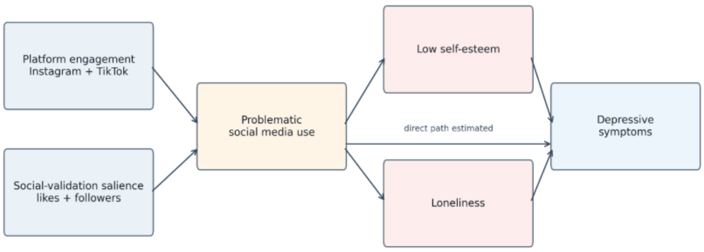

Figure 1. Conceptual model linking platform engagement and social-validation salience with problematic social-media use, low self-esteem, loneliness, and depressive symptoms.

3.3 Measures and Scoring

Platform engagement was calculated as the mean of the ordinal Instagram and TikTok time-use categories:

$$E_i = \frac{IG_i + TT_i}{2}. \qquad (1)$$

Likes and follower variables were reverse-coded so that higher values indicated greater salience. Follower salience was calculated as:

$$F_i = \frac{(5 - Q10_i) + (5 - Q11_i)}{2}. \qquad (2)$$

Low self-esteem, loneliness, depressive symptoms, and problematic social-media use were reconstructed from their respective 10-, 20-, 20-, and 6-item blocks. Higher values represented poorer self-esteem, greater loneliness, more depressive symptoms, and more problematic use. The transformations implemented in the analysis script are documented in the uploaded code.

Age, gender, and preferred platform were included as covariates. Gender and preferred platform were dummy-coded.

3.4 Data Preparation

Literal null values were converted to missing values. Duplicate records, invalid category codes, missingness, scale ranges, straight-line response patterns, skewness, kurtosis, and robust multivariate outliers were examined. Composite scores were recalculated from the original items and compared with the supplied totals. Cases were not removed solely because they were unusual; influential observations were evaluated through sensitivity analyses.

3.5 Reliability and Measurement Assessment

Cronbach's alpha, McDonald's omega, corrected item–total correlations, bootstrap confidence intervals, and one-factor loading proxies were calculated separately for the four psychological scales. Ordinal confirmatory factor analysis was not available in the execution environment; therefore, CFA fit indices were not claimed. A future validation should apply WLSMV and report $\chi 2$, CFI, TLI, RMSEA, SRMR, and standardised loadings.

3.6 Descriptive Analysis

Categorical variables were summarised using frequencies and percentages. Continuous variables were described using means, standard deviations, medians, ranges, confidence intervals, skewness, and kurtosis. Pearson and Spearman correlations were calculated among platform engagement, social-validation salience, problematic use, low self-esteem, loneliness, depressive symptoms, and age.

3.7 Mathematical and Mediation Models

Problematic social-media use was estimated as:

$$M_i = \alpha_0 + \alpha_1 E_i + \alpha_2 L_i + \alpha_3 F_i + \gamma' \mathrm{C}_i + \varepsilon_{Mi}. \qquad (3)$$

The depression model was:

$$Y_i = \theta_0 + \theta_M M_i + \theta_I I_i + \theta_B B_i + \theta \mathrm{C}' \mathrm{C}_i + \varepsilon_{Yi}. \qquad (4)$$

The parallel indirect effects were:

$$IE_I = \beta_M \theta_I, IE_B = \delta_M \theta_B, \qquad (5)$$

with the total indirect effect:

$$IE_{\text{parallel}} = IE_I + IE_B. \qquad (6)$$

Regression models used HC3 heteroscedasticity-robust standard errors. Parallel mediation confidence intervals were estimated using 5,000 bootstrap resamples, while sequential pathways used 3,000 resamples. The estimated parallel mediation structure is presented in Figure 2, which displays the standardised paths from problematic social-media use to depressive symptoms through low self-esteem and loneliness.

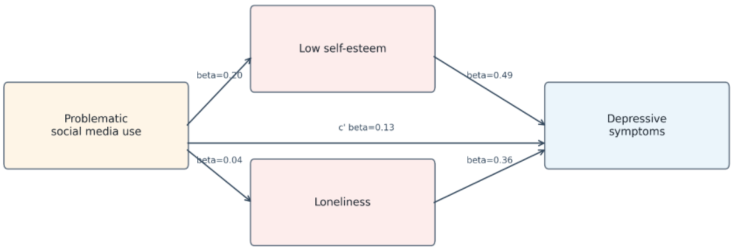

Figure 2. Standardised parallel mediation model linking problematic social-media use with depressive symptoms through low self-esteem and loneliness.

3.8 Diagnostics and Robustness

For checking multicollinearity, heteroscedasticity and influential observations regression diagnostics were performed. All predictors were tested for variance-inflation factors and tolerance statistics and heteroscedasticity was assessed by a Breusch–Pagan test and a look at the residual-versus-fitted patterns. The studentised residuals, leverage values and Cook's distance were examined to see if there were any cases that were more influential on model estimates than the rest. The regression models that were used for the principal results were based on HC3 heteroscedasticity robust standard errors. The analyses were repeated with alternative platform-engagement measures, with age-restricted subsample (age 18-29), with Huber regression, and with models excluding the cases with Cook's distance greater than 4/n to robustly check the results. An alternative-direction model was used to examine the possibility of depressive symptoms, loneliness, low self-esteem predicting problematic social-media use. The exploratory probability values were corrected by the Benjamini–Hochberg false-discovery-rate procedure.

3.9 Ethics and Reproducibility

In this study, secondary analysis of data from anonymous participants was conducted and these data did not involve additional recruitment of participants or direct contact with their data. The manuscript should describe informed consent procedures, and ethical approvals and data-reuse conditions provided by original investigators. The main data set was used as published data and retrieved from Zenodo under its reuse licence; the international-student workbook was not combined with the participant-level data set, but used as published longitudinal supporting evidence. Reproducibility was achieved by having a scripted analytical procedure and fixed random-number seed for the bootstrap procedures. Analytical variables (cleansed), codebook, reliability outputs, regression tables, mediation estimates, diagnostic outputs, robustness checks, and figures for publishability were included in the analysis materials. All the Python script should be shared with the paper or in an available repository to allow other researchers to replicate the construction of variables, estimation of the models, and the plots.

4. RESULTS

4.1 Data Screening

The total of 252 imported cases were all kept. No duplicate records or impossible ages were found, nor was there any invalid gender code nor any invalid platform-preference value. Entries of 'NULL!' were not automatically recoded as missing data, but were treated as such. The reconstructed analytical composites were complete while 250 respondents did not provide all of the raw fields (mostly multiple-response variables). Self-esteem, loneliness, depression, and problematic social-media-use scores were also re-calculated, and matched the scores provided for the composite scores.

Thirty-two cases exceeded the robust multivariate-outlier threshold, while eight respondents showed constant responding on the self-esteem items and 16 on the problematic-use items. These cases were retained because no independent evidence demonstrated invalid responding. Table 1 summarises the screening and sample profile.

Table 1. Data screening and sample characteristics

Indicator	Result
Imported and retained cases	252
Duplicate records	0
Invalid age/category values	0
Robust multivariate outliers	32
Age, mean (SD)	19.93 (4.70)
Age, median [range]	19 [18–55]
Female	217 (86.1%)
Male	35 (13.9%)
TikTok preferred	204 (81.0%)
Instagram preferred	48 (19.0%)

4.2 Sample Characteristics and Distributions

Instagram use was concentrated in the two lowest time categories, accounting for 76.2% of respondents, whereas 71.0% of respondents were classified in TikTok categories 3–7. Most responses concerning likes and follower importance occurred in categories 3 or 4. TikTok-preferring respondents reported higher overall platform engagement than Instagram-preferring respondents, $g=0.47$, $p=.003$. They also reported higher depressive symptoms, $g=0.32$, $p=.041$, although group differences in problematic use and low self-esteem did not reach conventional significance. Figure 3 presents the score distributions. Figure 4 compares the principal outcomes by preferred platform.

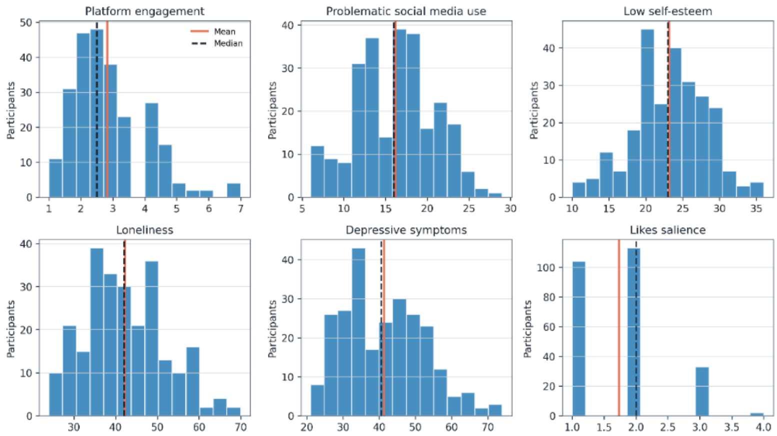

Figure 3. Distributions of platform engagement, problematic social-media use, low self-esteem, loneliness, depressive symptoms, and likes salience.

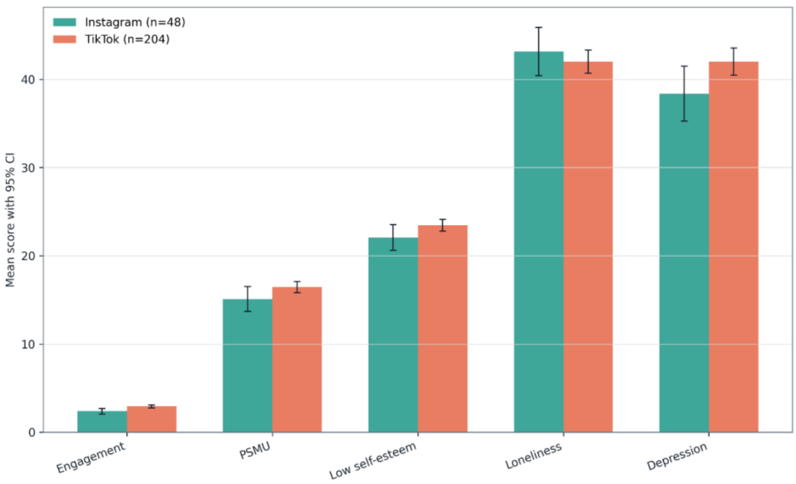

Figure 4. Mean platform engagement and psychological outcomes among Instagram- and TikTok-preferring respondents.

4.3 Reliability and Measurement Results

Internal consistency was acceptable to excellent. However, loneliness item Q14_20 produced a negative corrected item–total correlation (r=−.668), suggesting a probable scoring-direction anomaly. Because ordinal **confirmatory** factor analysis was unavailable in the analytical environment, χ2, CFI, TLI, RMSEA, and SRMR were not estimated. Consequently, the study reports reliability and one-factor loading proxies rather than claiming confirmatory measurement-model validity. Table 2 presents reliability and descriptive results. Figure 5 illustrates the reliability estimates and their bootstrap confidence intervals.

Table 2. Reliability and descriptive statistics

Construct	Mean (SD)	Range	α	ω
Problematic social-media use	16.19 (4.78)	6–29	.793	.853
Low self-esteem	23.19 (4.95)	10–36	.875	.901
Loneliness	42.23 (9.51)	24–70	.889	.911

Depressive symptoms	41.31 (11.26)	21–74	.918	.929

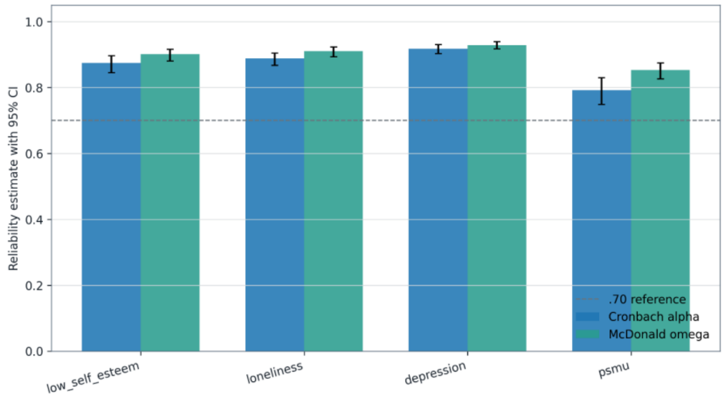

Figure 5. Cronbach's alpha and omega estimates for the four reconstructed psychological scales.

4.4 Correlations and Prediction of Problematic Use

Platform engagement correlated with problematic use, r=.314, p<.001, while likes salience showed a smaller positive association, r=.259, p<.001. Problematic use correlated with low self-esteem, r=.246, and depressive symptoms, r=.288, both p<.001, but not with loneliness, r=.051, p=.417. Low self-esteem and loneliness were strongly related to depression, r=.714and r=.607, respectively. Table 3 combines the principal correlations and hierarchical-model results.

Table 3. Selected correlations and hierarchical prediction of problematic use

Result	Estimate
Engagement–problematic use correlation	.314***
Likes salience–problematic use correlation	.259***
Problematic use–low self-esteem correlation	.246***
Problematic use–loneliness correlation	.051
Problematic use–depression correlation	.288***
Controls: R^2	.099
+ Platform engagement: ΔR^2	.059
+ Social-validation salience: ΔR^2	.044
Final adjusted R^2	.183

In the final HC3 model, platform engagement independently predicted problematic use, B=0.923, β=.225, 95% CI [0.372, 1.474], p=.001. Likes salience was also significant, B=1.475, β=.220, 95% CI [0.471, 2.480], p=.004, whereas follower salience was not significant.

4.5 Psychological Outcomes and Mediation

Problematic use predicted low self-esteem, B=0.208, β=.201, p=.004, but not loneliness, B=0.071, β=.036, p=.605. It initially predicted depression, B=0.561, β=.238, p<.001. After adding both mediators, the model explained 62.8% of depressive-symptom variance. Low self-esteem and loneliness were the strongest predictors, although the direct problematic-use path remained significant. Table 4 presents the outcome and mediation estimates. Figure 6 shows the observed PSMU–outcome relationships. Figure 7 displays the bootstrapped indirect effects.

Table 4. Regression and mediation results

Effect	Estimate	95% CI
Problematic use → depression, direct	0.297	[0.109, 0.485]
Low self-esteem → depression	1.118	[0.883, 1.354]
Loneliness → depression	0.432	[0.318, 0.546]
Indirect through low self-esteem	0.233	[0.070, 0.410]
Indirect through loneliness	0.031	[-0.087, 0.155]
Total indirect effect	0.263	[0.013, 0.507]
Engagement → PSMU → self-esteem → depression	0.278	[0.059, 0.587]
Engagement → PSMU → loneliness → depression	0.018	[-0.172, 0.212]

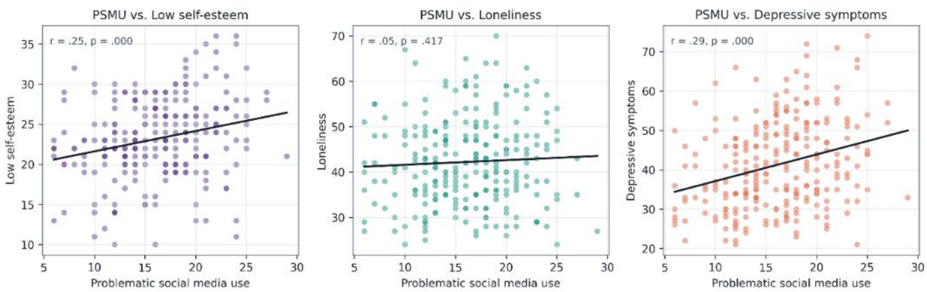

Figure 6. Associations between problematic social-media use, low self-esteem, loneliness, and depressive symptoms.

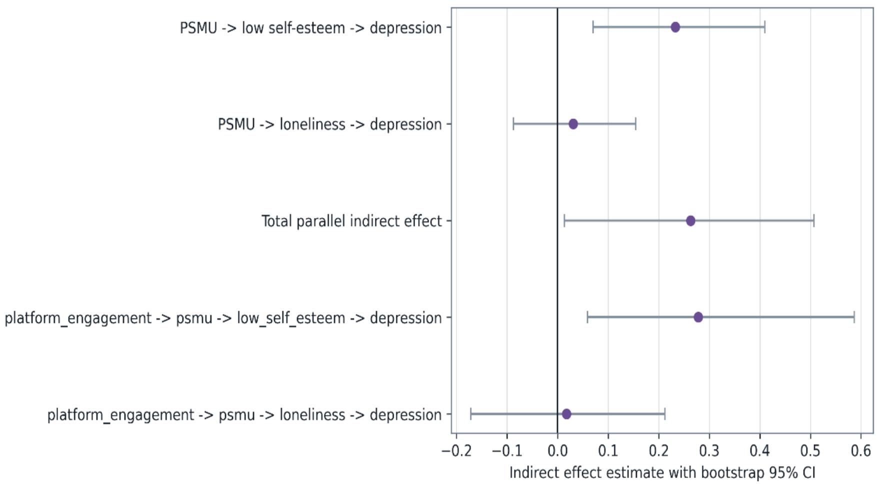

Figure 7. Parallel and sequential indirect effects with percentile-bootstrap 95% confidence intervals.

4.6 Moderation, Diagnostics, and Robustness

Preferred platform did not significantly moderate the engagement–problematic-use association, B=1.010, 95% CI [-0.333, 2.353], p=.140. VIF values ranged from 1.04 to 1.61, and Breusch–Pagan tests did not indicate material heteroscedasticity. Twelve cases exceeded Cook's D>4/nin the final depression model; excluding them did not alter the conclusions.

The engagement coefficient remained significant in respondents aged 18–29 and under alternative engagement codings. Correcting the apparent Q14_20 scoring anomaly increased loneliness reliability to approximately .916, but problematic use remained unrelated to loneliness. Table 5 summarizes hypothesis decisions.

Table 5. Hypothesis summary

Hypothesis	Conclusion	Supported?
H1: Engagement predicts problematic use	Positive association	Yes
H2: Validation salience predicts problematic use	Likes significant; followers nonsignificant	Partial
H3a: PSMU predicts low self-esteem	Positive association	Yes
H3b: PSMU predicts loneliness	Nonsignificant	No
H3c: PSMU predicts depression	Positive association	Yes
H4: Self-esteem mediates PSMU–depression	Significant indirect effect	Yes
H5: Loneliness mediates PSMU–depression	Nonsignificant indirect effect	No
H6: Sequential self-esteem pathway	Significant	Yes
H7: Sequential loneliness pathway	Nonsignificant	No

4.7 Longitudinal External Triangulation

The supporting international-student study was not reanalysed from raw data. Its published three-wave results nevertheless indicate that social-media contact can precede changes in group identification and adaptation, although effects differ according to the contacted group. These findings provide longitudinal context for the identity and belonging interpretation but do not validate the causal ordering of the primary cross-sectional model (Gaitán-Aguilar et al., 2022). The primary results should therefore be interpreted as associations within algorithmically curated environments rather than direct effects of recommendation algorithms (Limniou & Hendrikse, 2023).

5. DISCUSSION

The results indicate a link between engagement in an algorithmically curation social media environment and self-evaluation and psychological well-being in relation to identity. The number of followers wasn't alone significantly predicting problematic social-media use, but platform engagement and the importance given to likes did. The relationship with lower self-esteem and higher depressive symptoms were associated with problematic use, while no relationship was found with loneliness. The relationship between problematic use and depression symptoms was strongly mediated by low self-esteem, with platform engagement being antecedent to problematic use and low self-esteem, which was supported. The loneliness pathways were not significant, however, when compared to this. There were no significant differences between the engagement–problematic-use relationship for respondents who preferred TikTok or Instagram, except at the descriptive level, where both groups had higher scores on engagement and depressive-symptom scales, respectively. The results were consistent when the engagement measures were varied, when the younger-adult subsample was used, when robustness estimation was used, and when influential case sensitivity was used.

These findings indicate that there is a partial lack of fit between engagement intensity and problematic use. The added value of psychological investment in visible approval signals, such as likes, was added to the explanation of the visible signals. This one is significant, as engagement that is curated by algorithms doesn't just mean spending time on the platform; it also means being repeatedly shown features like popularity indicators, opportunities for comparison, and feedback loops that can create a sense of importance around metrics. The use of problematic social media seems to serve as a behavioural mechanism between this use context and the negative self-evaluation and depression symptoms. The direct pathway to depression was still significant after both mediators were introduced, indicating that only a part of the pathway from problematic use to depression was mediated by self-esteem and loneliness.

The results of the self-esteem measures provide some limited evidence of the "algorithmic self." Personalised environments can impact self-evaluation, through the constant barrage of idealised lifestyles, status visuality and socially rewarded appearances, or behaviours. The study, however, assessed evaluative rather than identity exploration, commitment, or identity clarity, and thus did not provide evidence that algorithms changed identity comprehensively during development. As with loneliness, it is important to acknowledge that it is less than fullness of belonging, or perceived lessening of connection. The non-existence of a problematic-use–loneliness association suggests that frequent or dysregulated engagement is not necessarily associated with weaker feelings of belonging and that the quality and social context of engagement is more significant than the level of engagement.

This interpretation is consistent with evidence that image-based social media may reduce loneliness under some conditions, particularly when it provides socially rich communication (Pittman & Reich, 2016). Experimental research has shown that active posting can increase perceived social connection (Deters & Mehl, 2013). The effect of social-media use on well-being also depends on communication type and relationship strength (Burke & Kraut, 2016). Conversely, intensive Facebook use has been associated with subsequent declines in subjective well-being (Kross et al., 2013). Passive consumption has likewise been linked with poorer affective well-being (Verduyn et al., 2015). Evidence that limiting social-media use can reduce loneliness and depression further suggests that behavioural regulation may have practical value (Hunt et al., 2018).

The study contributes theoretically by integrating curated engagement, problematic use, self-evaluation, social connection, and well-being within one model. Methodologically, it combines reconstructed scale assessment, HC3 estimation, parallel and sequential mediation, competing specifications, and external longitudinal triangulation. The supporting international-student evidence indicates that social-media contact may precede changes in group identification and adaptation, although those estimates were not reanalysed from participant-level data.

Universities should therefore combine

digital-well-being education with algorithmic-literacy training, peer-support programmes, counselling pathways, and guidance on validation-seeking and comparison triggers. Platforms could support user well-being through clearer recommendation controls, diversified exposure, greater transparency, and reduced emphasis on popularity metrics. Nevertheless, the cross-sectional design, self-reported use, absence of direct recommendation-exposure measures, proxy operationalisation of identity and belonging, unequal demographic and platform groups, and residual confounding restrict causal interpretation. Future research should employ feed logging, algorithm-awareness measures, self-concept and university-belonging scales, experience sampling, longitudinal panels, recommendation-diversity experiments, qualitative interviews, and cross-cultural subgroup analysis.

6. CONCLUSION

This study examined how engagement within algorithmically curated Instagram and TikTok environments relates to identity-relevant self-evaluation, belonging, and psychological well-being. The findings indicate that platform engagement and the importance attached to likes were associated with greater problematic social-media use, while follower salience showed no independent effect. Problematic use was, in turn, associated with lower self-esteem and greater depressive symptoms, but not with loneliness. Low self-esteem emerged as the principal explanatory pathway: it significantly mediated the relationship between problematic use and depressive symptoms, and the sequential pathway from platform engagement through problematic use and low self-esteem was also supported. By contrast, the loneliness-based indirect pathways were not statistically supported.

The study therefore advances the idea of "algorithmic selves" by moving beyond simple screen-time explanations and integrating engagement, social-validation salience, problematic use, identity-related self-evaluation, social disconnection, and depressive symptoms within a single analytical framework. Its results suggest that the psychological significance of algorithmically curated platforms may depend less on exposure alone than on how users internalise visible popularity cues and develop dysregulated engagement patterns.

Nevertheless, the findings support an association-based rather than causal account. The data did not directly measure recommendation exposure, identity development, or university belonging, and the primary design was cross-sectional. Stronger claims about how AI recommendation systems shape students therefore require longitudinal panels, experimental manipulation, experience sampling, and direct logging of personalised recommendations.

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