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Understanding the Heterogeneity of Problematic Social Media Use Among University Students: A Latent Class Analysis

Abstract

Background:
Problematic social media use among university students is increasingly recognized as a multidimensional phenomenon. However, few studies have examined its heterogeneity based on symptom severity and motivational pathways.

Objectives:
This study aimed to identify distinct latent classes of social media users, assess psychological burden across classes defined by the Bergen Social Media Addiction Scale.

Methods:
A sample of 936 university students from Poland completed the Bergen Social Media Addiction Scale and measures of depression, anxiety, loneliness, self-esteem, daily time spent on social media, and perceived excessive internet use. Latent class analysis was conducted.

Results:
Four classes were identified: No-Risk/Minimal Symptoms (25.1%), Addictive Use/Severe Symptoms (15.0%), Gratification-Driven/Moderate Symptoms (34.4%), and Situational Use/Mild-Moderate Symptoms (25.5%). The two moderate-risk groups differed qualitatively: the Gratification-Driven class was characterized by the pursuit of positive experiences, whereas the Situational Use class reflected context-dependent engagement without strong emotional drivers. High-risk users reported significantly greater depression, anxiety, and lower self-esteem. Loneliness was elevated across all symptomatic classes but did not differentiate between them, suggesting its role as a transdiagnostic vulnerability factor.

Conclusions:
The findings highlight the heterogeneity of problematic social media use among Polish university students and underscore the importance of addressing emotional vulnerabilities and motivational profiles in prevention and intervention efforts.

Keywords: *Problematic social media use; Latent class analysis; Young adults; Psycho-social and behavioral functioning*

INTRODUCTION

Problematic social media use (PSMU) refers to a maladaptive pattern of excessive engagement with social networking platforms, resulting in psychological, social, and functional impairments (Shannon et al., 2022). Research has demonstrated that somatic symptoms of addiction include sleep disturbances, chronic fatigue (Feng et al., 2025; Zhang et al., 2023), poor dietary habits, and a lack of physical activity (Douglas et al., 2008; Lai et al., 2015; Soothram & Prakash, 2024; Waldo, 2014). Numerous meta-analyses have linked excessive social media use to increased levels of anxiety, depression (Abbouyi et al., 2024; Tullett-Prado et al., 2023; Wang et al., 2022; Yigiter et al., 2024), declining interpersonal relationship quality (Feng et al., 2025; Gabrielle et al., 2024; Shi et al., 2023; Wu et al., 2024), and the emergence of Fear of Missing Out (Hurley et al., 2024; Soothram & Prakash, 2024).

Conceptualized as a form of behavioral addiction (Andreassen et al., 2012; Griffiths, 2005), PSMU is characterized by six core symptoms: salience (preoccupation with social media and dominance of online activities in daily life), mood modification (using social media to achieve emotional relief or mood enhancement), tolerance (needing to spend increasing amounts of time on social platforms to achieve the same effect), withdrawal symptoms (experiencing irritability, anxiety, or distress when access to social media is restricted), conflict (social, occupational, or academic problems resulting from excessive use), and relapse (reverting to problematic usage patterns after periods of control or abstinence).

Over the past decade, the prevalence of PSMU has steadily increased in parallel with the global expansion of social media platforms and the growing daily time spent online (Kemp, 2025). This upward trend was significantly intensified during the COVID-19 pandemic, when widespread lockdowns, social distancing measures, and increased psychological stress led individuals to rely even more heavily on digital communication and social networking platforms (Marciano et al., 2022; Wiederhold, 2020).

Adolescents and young adults are consistently identified as particularly vulnerable groups due to their intensive digital engagement, emotional reactivity, and developmental challenges (Meng et al., 2022; Tullett-Prado et al., 2023). Given that this developmental period is marked by identity exploration, emotional instability, and heightened social media engagement, we examine patterns of problematic social media use in a university student sample.

Theoretical framework: The I-PACE model

Among the theoretical frameworks aiming to explain the psychological mechanisms underlying PSMU, one of the most prominent is the Interaction of Person–Affect–Cognition–Execution (I-PACE) model (Brand et al., 2016, 2019). The I-PACE model explains the development and maintenance of problematic social media use. According to the model, PSMU results from the interaction between individual predispositions (e.g., personality traits, psychopathology), affective and cognitive reactions to situational triggers, and executive functions regulating behavior. The model distinguishes two motivational pathways: gratification (pursuing pleasure and social rewards) and compensation (down-regulating negative affect (e.g., anxiety) and alleviating aversive internal states such as loneliness and boredom). These mechanisms can coexist and shift over time. Problematic use may start with gratification motives but later become driven by compensation as emotional or regulatory difficulties grow (Brand et al., 2025).

Person-centered approaches to problematic social media use

The I-PACE model explicitly implies heterogeneity: different configurations of person-related predispositions, affective and cognitive responses, and executive control may lead to distinct patterns of problematic use. In empirical research, this heterogeneity can be examined by classifying individuals into subgroups that share similar symptom patterns and related psychological characteristics. Person-centered methods, including latent class analysis (LCA) and latent profile analysis (LPA), are commonly used for this purpose because they can identify unobserved subgroups based on responses to symptom indicators and associated psychosocial and motivational correlates. In the present study, we use LCA to derive interpretable subgroups of PSMU based on ordinal the Bergen Social Media Addiction Scale (BSMAS) item responses and then examine whether these subgroups differ in psychosocial functioning and motivational mechanisms, as suggested by the I-PACE framework.

Previous findings on latent profiles

Previous studies using latent profile analysis with the Bergen Social Media Addiction Scale usually identify three or more classes of social media users differing in PSMU symptom severity. Research from Hungary (Bányai et al., 2017), Finland (Hylkilä et al., 2025), and the United Kingdom and United States (Cheng et al., 2022) most often found low-risk, moderate-risk, and high-risk groups. Similar results were reported in China (Cui et al., 2023; Luo et al., 2021; Peng & Liao, 2023), suggesting that severity-based heterogeneity is relatively robust across contexts.

Importantly, these subgroups may differ not only in severity but also in psychosocial correlates. Higher-risk profiles tend to co-occur with broader psychosocial burden, such as higher levels of depressive symptoms (Huang, 2022; Yigiter et al., 2024), anxiety (Du et al., 2024; Huang, 2022), loneliness (Huang, 2022; O'Day & Heimberg, 2021), and low self-esteem (Casale et al., 2022; Huang, 2022). Moreover, more severe profiles are often accompanied by stronger behavioral involvement, such as longer daily time spent on social media (Schmelzer et al., 2022) and stronger perceptions of excessive internet use (Kırcaburun, 2016).

Finally, emerging evidence suggests that users with comparable overall symptom levels may nonetheless differ in symptom configuration and, consequently, in the relative prominence of underlying motivational pathways.

For example, Cui et al. (2023) identified two distinct moderate-risk profiles among college students – a "moderate-risk with pleasure" profile and a "moderate-risk with compulsion" profile – despite similar overall severity, indicating that heterogeneity can be expressed not only as a severity gradient but also as differences in symptom patterns at intermediate levels. This pattern maps onto the I-PACE framework's distinction between pathways characterized more by gratification-related features ("feels better") versus more compulsive, control-related features ("must do") and provides an empirical rationale for examining motivational differentiation within the moderate-symptom range.

The present study

Building on gaps identified in previous research and guided by the I-PACE model (Brand et al., 2016, 2019), the present study had two main aims: (1) to identify latent classes of problematic social media use among young adults (university student sample) based on ordinal BSMAS item responses using latent class analysis; and (2) to examine whether these classes differ in psychosocial functioning (depression, anxiety, loneliness, self-esteem), behavioral indicators (daily time spent on social media, perceived excessive internet use), and dominant motivational mechanisms (gratification vs. compensation).

Based on the I-PACE framework and previous person-centered research, we formulated a set of interrelated expectations. First, we expected the emergence of distinct latent classes differing in symptom severity (H1). Second, we expected that the class with the highest symptom severity would also show the greatest psychosocial burden and behavioral involvement (H2a–H2b). Third, among users with moderate symptom levels, we expected qualitative differentiation in dominant motivational pathways (H3).

H1: At least three distinct latent classes will emerge, differing primarily in the severity of PSMU symptoms.

H2a: Individuals in the high-risk class will report higher levels of depression, anxiety, and loneliness, and lower levels of self-esteem compared to individuals in lower-risk classes.

H2b: Individuals in the high-risk class will also report greater daily time spent on social media and stronger subjective perceptions of excessive internet use.

H3: Among users with moderate symptom levels, distinct subgroups reflecting different dominant motivational tendencies (especially gratification-related versus compensation-related mechanisms) were expected.

METHODS

Participants and Procedures

The study included 936 students (78.1% female) from the University of XXX, representing 65 different fields of study (majors). Most were undergraduate students (46.3%), followed by long-cycle master's (38.5%) and postgraduate students (15.2%). The mean age was 21.64 years (SD = 2.08), with a range of 17–29 years. Most participants (66.5%) lived in rural areas, and 93.9% identified as single.

Data were collected through an online survey on the LimeSurvey platform (LimeSurvey GmbH, 2024) at the end of the first semester of the 2024/2025 academic year. Students received an invitation and two reminders over 1.5 weeks via university-registered emails. Participation was voluntary and anonymous. Participants gave informed consent before starting. The study was approved by the Bioethics Committee at the University of XXX.

MEASURES

Problematic Social Media Use: Bergen Social Media Addiction Scale

PSMU was measured with the Bergen Social Media Addiction Scale (Andreassen et al., 2016), a six-item self-report tool assessing behaviors over the past 12 months. The Polish version of the Bergen Social Media Addiction Scale was developed based on the conceptual framework of the original scale and the existing Polish adaptation of the Bergen Facebook Addiction Scale (Charzyńska & Góźdź, 2014). The wording was generalized from "Facebook" to "social media" in line with the original development of the BSMAS (Andreassen et al., 2016), using a translation and back-translation procedure to ensure linguistic and conceptual equivalence. Responses are given on a five-point Likert scale from 1 ("very rarely") to 5 ("very often"), with total scores ranging from 6 to 30. Higher scores indicate more severe symptoms. In this study, the scale showed high internal consistency (Cronbach's alpha = 0.84). Response distributions are shown in Figure S1, item intercorrelations in Table S1, and the density distribution of total scores in Figure S2 (Panel A) in the Supplementary Materials.

Depressive Symptoms: Patient Health Questionnaire-9

Depressive symptoms were measured using the Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001), a nine-item self-report tool based on Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) criteria (APA, 1998). We used the validated Polish version of the PHQ-9 (Ślusarska et al., 2019). The items assess symptoms such as low mood, anhedonia, sleep problems, fatigue, appetite changes, guilt, concentration issues, psychomotor changes, and suicidal thoughts. Respondents rated symptom frequency over the past two weeks on a scale from 0 ("not at all") to 3 ("nearly every day"). Total scores range from 0 to 27, with higher scores indicating greater severity. In this study, the PHQ-9 showed strong internal consistency (Cronbach's alpha = 0.86). The density distribution of PHQ-9 scores is shown in Figure S2 (Panel B) in the Supplementary Materials.

Anxiety Symptoms: Generalized Anxiety Disorder Scale

Anxiety symptoms were measured using the Generalized Anxiety Disorder Scale (GAD-7; Spitzer et al., 2006), using the validated Polish adaptation by Basińska and

Kwissa-Gajewska (Basińska & Kwissa-Gajewska, 2023). Respondents rated how often they experienced symptoms like excessive worry, restlessness, or trouble concentrating over the past two weeks. Responses were given on a four-point scale from 0 (“not at all”) to 3 (“nearly every day”). Total scores range from 0 to 21, with higher scores indicating more severe anxiety. In this study, the GAD-7 showed excellent internal consistency (Cronbach’s alpha = 0.91). The density distribution of GAD-7 scores is shown in Figure S2 (Panel C) in the Supplementary Materials.

Self-Esteem: Rosenberg Self-Esteem Scale

Self-esteem was measured using the Brief Rosenberg Self-Esteem Scale (B-RSES; Monteiro et al., 2022), a five-item version of the original Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965), with Polish wording based on the validated Polish adaptation of the RSES (Dzwonkowska et al., 2008). Respondents rated agreement on a four-point scale from 1 ("Strongly disagree") to 4 ("Strongly agree"). Total scores range from 5 to 20, with higher scores indicating greater self-esteem. In this study, the B-RSES showed high internal consistency (Cronbach’s alpha = 0.86). The density distribution of RSES scores is shown in Figure S2 (Panel D) in the Supplementary Materials.

Loneliness: De Jong Gierveld Loneliness Scale

Loneliness was measured using the validated Polish adaptation of the 11-item De Jong Gierveld Loneliness Scale (Grygiel et al., 2013). Respondents rated each item on a five-point scale from 1 (“Definitely no”) to 5 (“Definitely yes”), giving total scores between 11 and 55. Higher scores indicate greater loneliness. The DJGLS showed strong internal consistency (Cronbach’s alpha = 0.89). The density distribution of DJGLS scores is shown in Figure S2 (Panel E) in the Supplementary Materials.

Time Spent on Social Media

Participants' average daily social media use was measured with a single item: “On average, how much time per day do you spend using social media (e.g., Facebook, Instagram, TikTok)?” Responses ranged from (0) “I do not use social media at all” to (9) “More than 7 hours,” with 30- to 60-minute increments between categories. This format has been used in large-scale studies on digital media use among adolescents and young adults (e.g., Orben & Przybylski, 2019; Twenge et al., 2018). The distribution of time spent on social media (TSM) is shown in Figure S2 (Panel F) in the Supplementary Materials.

Perceived Excessive Internet Use

Perceived overuse of the internet was measured with a single item: “Over the past week, how often did you feel that you were spending too much time online?” Responses were given on a scale from 0 (“not at all”) to 100 (“all the time”). This measure, referred to as Perceived Excessive Internet Use (PEIU), captures feelings of excessive internet use during the past week. The distribution of PEIU scores is shown in Figure S2 (Panel G) in the Supplementary Materials. Descriptive statistics and inter-correlations of study variables are presented in Table S2.

ANALYSIS

Latent Class Analysis

This study used Latent Class Analysis (Collins & Lanza, 2010) to identify subgroups of social media users based on their responses to the six items of the Bergen Social Media Addiction Scale. LCA is a model-based, person-centered method that classifies individuals into mutually exclusive classes based on item-response probabilities. Because BSMAS items are measured on a five-point Likert scale and are therefore ordinal, we used LCA (rather than Latent Profile Analysis) to model categorical response patterns at the item level.

Most prior person-centered studies using the BSMAS applied latent profile analysis, which typically treats indicators as continuous (Flaherty & Kiff, 2012). However, BSMAS items are measured on a five-point Likert scale and are therefore ordinal; in ordinal scales, response options show order but not equal spacing between values (Carifio & Perla, 2008; Jamieson, 2004). Consequently, applying LPA to ordinal item responses may yield different solutions than categorical mixture models (Flaherty & Kiff, 2012). For example, an average item score of “3” may reflect consistently moderate responding (“sometimes”) or alternating between response extremes (“never” and “very often”) — a distinction that can be obscured when ordinal indicators are treated as continuous (Flaherty & Kiff, 2012). We therefore used LCA to model categorical response patterns at the item level, yielding class-specific item-response probabilities and more interpretable class profiles (Nylund-Gibson & Choi, 2018).

To determine the optimal number of latent classes, we estimated models with one to seven classes. Model fit was evaluated using standard LCA indicators (Nylund-Gibson & Choi, 2018), including four information criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (SSA-BIC), and finite sample corrected AIC (AICc), and two likelihood ratio tests: the Vuong–Lo–Mendell–Rubin Likelihood Ratio Test (VLMR-LRT) and the Lo–Mendell–Rubin adjusted LRT (LMR-LRT) (Lo, 2001; Nylund et al., 2007). The likelihood ratio tests were used to compare k-class and (k–1)-class solutions.

Lower values of AIC, BIC, SSA-BIC, and AICc indicate better relative model fit. For the VLMR-LRT and LMR-LRT, a significant p-value ($p < .05$) indicates that the k-class solution provides a statistically better fit than the (k–1)-class solution, whereas a non-significant result suggests that adding another class does not meaningfully improve model fit. Following prior recommendations, greater weight was given to BIC and SSA-BIC in class enumeration, while final model selection also considered parsimony and substantive interpretability.

In LCA, three main indicators of classification quality are: (1) average latent class probabilities, (2) classification probabilities for the most likely class, and (3) entropy index (Nylund-Gibson & Choi, 2018). The first index shows the average probability that individuals belong to their assigned class. High diagonal values (e.g., > .80) suggest that individuals assigned to a class have a high probability of actually belonging to it, indicating good within-class homogeneity. The second index shows the proportion of individuals correctly classified into their true latent class. High diagonal values mean good classification accuracy, with few individuals misclassified. The third index, entropy, summarizes overall classification precision across all classes (Celeux & Soromenho, 1996). Entropy values range from 0 to 1, with higher values (e.g., > .80) indicating high certainty and clear separation between classes.

Comparing latent classes on psychological and behavioral correlates

We compared latent classes on five variables: depressive symptoms (PHQ-9), anxiety symptoms (GAD-7), loneliness (DJGLS), daily time spent on social media (TSM), and perceived excessive internet use (PEIU). Differences between classes were tested using one-way analyses of variance (ANOVAs) with class membership as the independent variable. When the omnibus test was significant, pairwise comparisons were conducted using Tukey's HSD (Honestly Significant Difference) post hoc tests.

RESULTS

Determining the optimal number of latent classes

To determine the optimal number of latent classes, a series of models ranging from one to seven classes was estimated. All four information criteria – AIC, BIC, sample-size adjusted BIC (aBIC), and AICC – decreased systematically with the increasing number of classes, indicating an overall improvement in model fit. Therefore, the primary criteria for model selection were the VLMR-LRT and the LMR-LRT, which compare the fit of a k-class model to that of a (k–1)-class model.

The results indicated significant improvements in model fit from one to four classes, as reflected by significant p-values for the VLMR and LMR tests ($p < .001$ for the 2-, 3-, and 4-class models). In contrast, adding a fifth class did not yield a statistically significant improvement (VLMR-LRT $p = .68$; LMR-LRT $p = .69$). The six- and seven-class solutions were likewise non-significant, suggesting that more complex solutions were not justified.

The four-class model showed high entropy (0.81), indicating strong classification quality. Individuals were assigned to classes with high posterior probabilities. All four classes had satisfactory classification quality based on average latent class probabilities and classification probabilities. Average posterior probabilities ranged from 0.88 (Class 4) to 0.92 (Class 1), and classification probabilities ranged from 0.88 (Class 3) to 0.93 (Class 1), indicating high certainty in class membership. Overall, the results show strong internal consistency within classes and clear differentiation between them (Table 1).

Interpretation of latent class profiles

Based on the six BSMAS symptoms, LCA identified four distinct profiles of social media users (Figure 1). The classes differed primarily in overall symptom severity and in the relative prominence of gratification-related features (e.g., salience, mood modification, tolerance) versus compulsion-related features (e.g., conflict, withdrawal, relapse), which can be interpreted within the I-PACE framework (Brand et al., 2016, 2019).

Class 1 (25.1%) represents a low-symptom, no-risk pattern. Participants in this class most often endorsed the lowest response categories ("very rarely/rarely") across all items, indicating controlled and largely functional social media use with no clear signs of either gratification- or compulsion-driven problematic engagement.

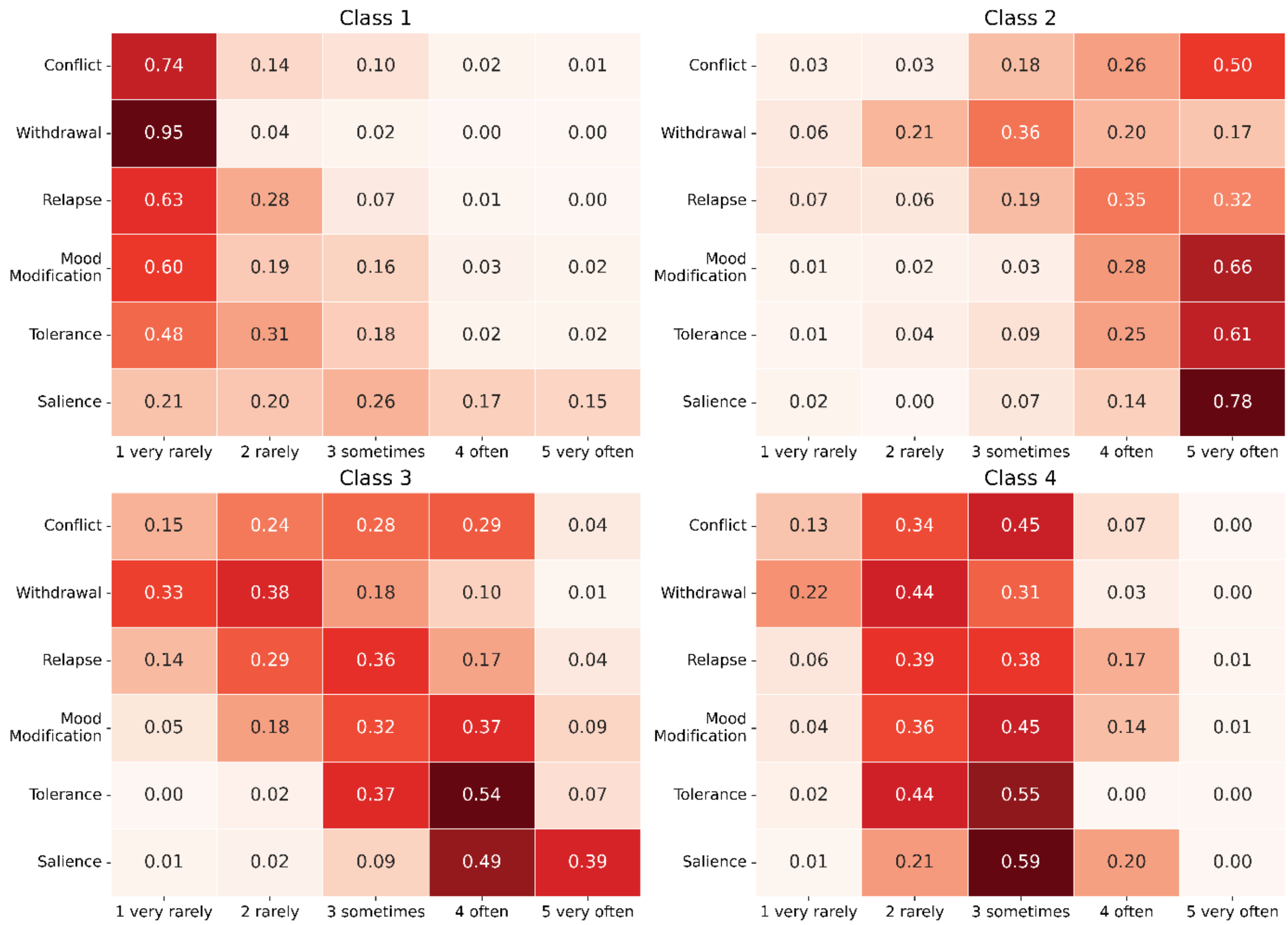
Class 2 (15.0%) shows a high-symptom, high-risk profile. This class was characterized by consistently elevated endorsement across the full set of BSMAS symptoms (Figure 1), suggesting both strong gratification-related involvement (using social media for mood

Table 1. Comparison of Fit Indices and Statistical Tests Across Latent Class Solutions

Class	*Entropy*	*AIC*	*BIC*	*aBIC*	*AICC*	*VLMR.LRT.p*	*LMR.p*
1;	NA	16897.16	17013.35	16937.13	16898.47	NA	NA
2;	0.81	15625.37	15862.61	15706.99	15630.90	0.00	0.00
3;	0.81	15055.07	15413.35	15178.33	15067.96	0.00	0.00
4;	0.81	14879.71	15359.03	15044.61	14903.39	0.00	0.00
5;	0.82	14748.58	15348.94	14955.13	14786.81	0.68	0.69
6;	0.82	14670.12	15391.52	14918.31	14726.99	0.76	0.76
7;	0.81	14621.40	15463.84	14911.23	14701.43	0.84	0.84

Note. Entropy indicates the precision of class assignment, with values closer to 1.00 reflecting better classification quality. AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), aBIC (sample-size adjusted BIC), and AICC (corrected Akaike Information Criterion) are fit indices used to compare model performance; lower values indicate better fit. VLMR-LRT p refers to the p-value from the Vuong-Lo-Mendell-Rubin Likelihood Ratio Test, and LMR p refers to the p-value from the Lo-Mendell-Rubin adjusted LRT. Significant p-values suggest that the model with k classes fits significantly better than the model with k–1 classes.

Figure 1. Patterns of social media addiction symptoms across latent classes.



Note. The figure presents item-level response probabilities on the Bergen Social Media Addiction Scale (BSMAS) across four latent classes identified via Latent Class Analysis (LCA). Each heatmap cell displays the probability of endorsing a given response category (from "very rarely" to "very often") for a specific item within a given class. Darker shades indicate higher probabilities. The four classes reflect distinct patterns of risk for problematic social media use.

modification and high salience) and more advanced compulsive features (relapse/conflict/withdrawal). In I-PACE terms, this pattern is compatible with a more progressed stage of problematic use, where pleasure-seeking and loss-of-control processes co-occur.

Class 3 (34.4%) reflects a moderate-risk profile dominated by gratification-related symptoms. Respondents in this class tended to report high salience and increased tolerance more frequently than conflict or withdrawal, suggesting intensive engagement that is primarily reward-driven, with comparatively weaker indications of persistent negative consequences or marked distress. This profile may reflect an earlier or less advanced form of problematic involvement.

Class 4 (25.5%) represents a low-to-moderate symptom profile with generally non-persistent endorsement, most often around the "rarely/sometimes" range. Compulsive indicators (especially conflict and withdrawal) were comparatively infrequent, and the overall pattern suggests situational or transitional risk rather than sustained problematic use.

Overall, the four-class solution highlights meaningful heterogeneity in PSMU. Importantly, it provides a structured basis for examining how psychosocial functioning, behavioral indicators (e.g., time spent on social media), and motivational mechanisms differ across empirically derived subgroups.

Differences between latent classes in psychological and behavioral indicators

To examine whether the latent classes differed in selected psychological and behavioral variables, a series of one-way analyses of variance (ANOVAs) was conducted, with class membership as the independent variable and the following continuous variables as dependent measures: depressive symptoms (PHQ-9), anxiety symptoms (GAD), loneliness (DJGLS), time spent on social media (TSM), and perceived excessive internet use (PEIU).

The analyses (see Figure 2) revealed significant differences across the classes for all variables examined: PHQ-9, $F(3, 882) = 48.10$, $p < .001$; GAD, $F(3, 882) = 46.67$, $p < .001$; DJGLS, $F(3, 882) = 6.43$, $p < .001$; TSM, $F(3, 882) = 83.52$, $p < .001$; and PEIU, $F(3, 882) = 65.12$, $p < .001$.

Follow-up analyses using Tukey's HSD post hoc test showed that individuals classified into the Addictive Use / Severe Symptoms group (Class 2) scored significantly higher on depressive and anxiety symptoms than individuals in all other classes (p < .001). In terms of loneliness, this class differed significantly from the No-Risk / Minimal Symptoms (Class 1) and Situational Use / Mild-Moderate Symptoms (Class 4) groups, but not from the Gratification-Driven / Moderate Symptoms group (Class 3). Individuals in the Addictive Use / Severe Symptoms class also reported substantially more time spent on social media and a stronger sense of excessive internet use compared to each of the other classes (p < .001). A full summary of all pairwise comparisons between latent classes is provided in Supplementary Materials (Table S3).

These results show that the Addictive Use / Severe Symptoms class had the highest levels of psychological distress and problematic digital media use among the identified subgroups.

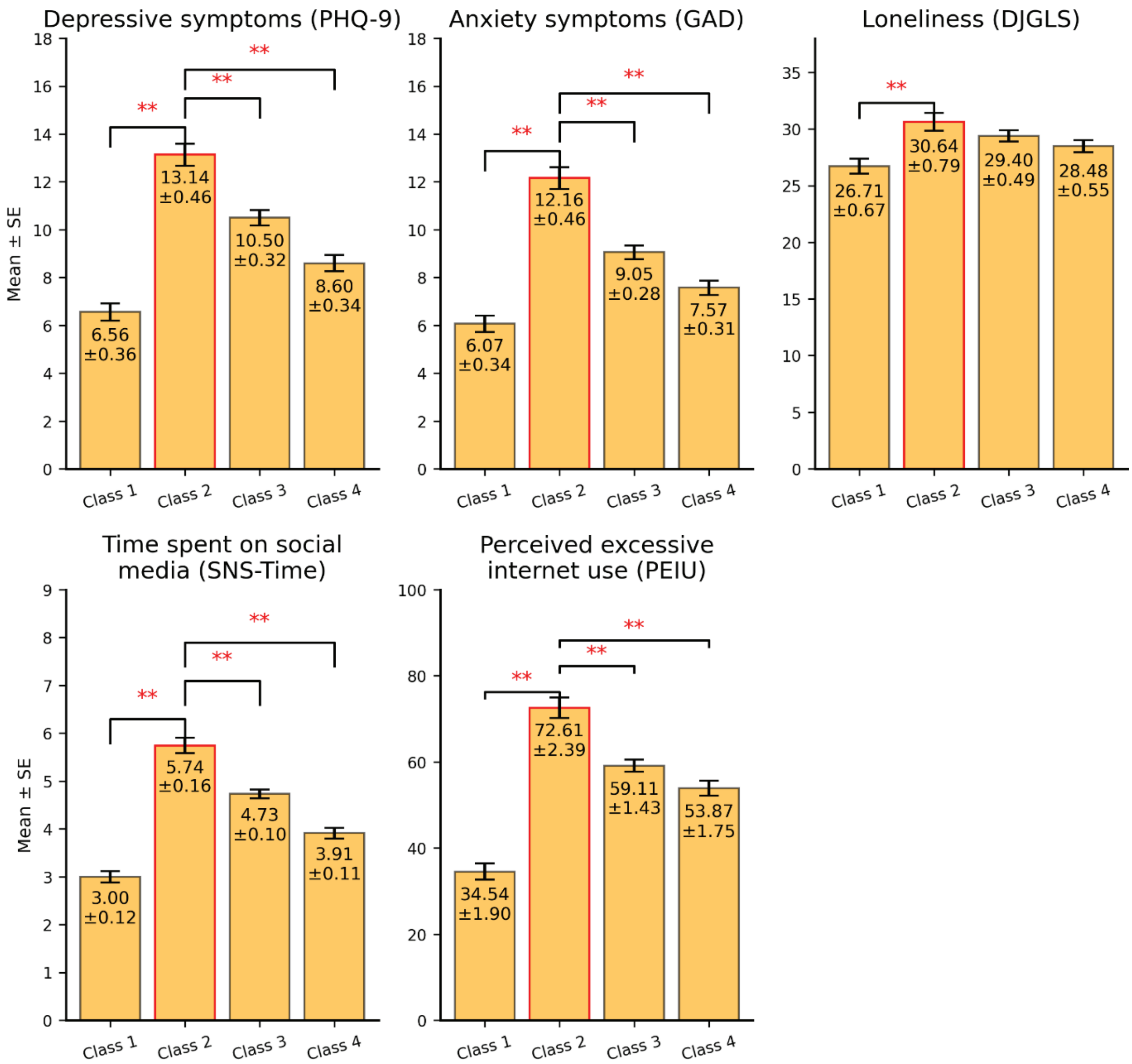
DISCUSSION

This study explored the heterogeneity of problematic social media use among university students and examined psychological burden across latent classes based on the Bergen Social Media Addiction Scale. Guided by the I-PACE model (Brand et al., 2016, 2019, 2025) and prior findings, several hypotheses were tested. The results were broadly consistent with our hypotheses and offer preliminary insights into the motivational and emotional profiles linked to different PSMU patterns.

Latent class structure of problematic social media use (H1)

Consistent with Hypothesis 1, which predicted at least three distinct classes differing in PSMU symptom severity, latent class analysis revealed four groups. This finding is

Figure 2. Latent class differences in mental health and online behavior-related measures



Note. PHQ = depressive symptoms (Patient Health Questionnaire-9); GAD = anxiety symptoms (Generalized Anxiety Disorder Scale); DJGLS = loneliness (De Jong Gierveld Loneliness Scale); SNS-Time = self-reported daily time spent on social media (in hours); PEIU = perceived excessive internet use. Bars represent mean values with standard errors. Significant pairwise differences between Class 2 and other classes are indicated with horizontal lines. Red asterisks denote statistical significance (p < .05, p < .01).

broadly consistent with previous person-centered studies, which most often identified three or more classes differing in symptom severity (e.g., Bányai et al., 2017; Cheng et al., 2022; Cui et al., 2023; Luo et al., 2021), and it reinforces the view of PSMU as a heterogeneous rather than unitary construct. Identifying multiple classes is consistent with varying levels of psychological burden associated with different engagement patterns and is compatible with a person-centered perspective as described in the I-PACE model.

The profiles identified in this study help to characterize potential psychological mechanisms that may underlie PSMU. The "Addictive Use / Severe Symptoms" class (Class 2) showed high frequencies of both gratification- and compulsion-related symptoms, which may be interpreted as compatible with a pattern in which hedonic motives co-occur with more compulsive features, potentially including attempts to regulate negative affect. This trajectory aligns with the I-PACE model's view that gratification-driven motives can evolve into compulsive patterns as emotional or regulatory problems intensify. In contrast, the "Gratification-Driven / Moderate Symptoms" class (Class 3) showed elevated pleasure-seeking without strong compulsive features, which may reflect a less advanced pattern of problematic use.

Psychological burden across classes (H2a)

Hypothesis 2a predicted greater psychological burden in the high-risk class. Consistent with this prediction, participants in the Addictive Use / Severe Symptoms class reported higher depression and anxiety and lower self-esteem than the lower-risk classes. For loneliness, the high-risk and the two intermediate classes (Classes 2–4) reported higher levels than the No-Risk / Minimal Symptoms class (Class 1). However, we did not observe statistically significant differences in loneliness among Classes 2, 3, and 4. These null findings should be interpreted cautiously, as non-significant differences do not constitute evidence of no effect. It is important to note that loneliness differs from objective social isolation and reflects a subjective sense of unmet social needs (Perlman & Peplau, 1981). While transient loneliness can motivate social connection (Cacioppo & Cacioppo, 2018), chronic loneliness is linked to negative outcomes such as depression, anxiety, substance use problems, and behavioral addictions (Alimoradi et al., 2024; Park et al., 2020).

In the context of digital behaviors, social media may be used to cope with emotional discomfort associated with loneliness. Individuals facing relational deficits or offline stress may turn to online environments to reduce negative feelings (Kardefelt-Winther, 2014). In such cases, loneliness may function as a compensatory motive rather than primarily reflecting gratification seeking. However, loneliness alone does not necessarily increase PSMU severity, as its effect may depend on factors like the quality of offline relationships, emotional regulation skills, and alternative coping strategies. Recent research by Schivinski et al. (2020) supports this view. In a large cross-sectional study, intrapersonal motives – using social media to cope with loneliness or stress – were the strongest predictors of PSMU, exceeding interpersonal and entertainment motives. This is consistent with the possibility that individuals who use social media primarily to regulate emotional distress may be at greater risk of developing maladaptive usage patterns.

This interpretation may help explain why loneliness levels did not differ significantly between the Addictive Use/Severe Symptoms, Gratification-Driven, and Situational Use classes. Loneliness may represent a transdiagnostic vulnerability factor that is associated with greater susceptibility to problematic engagement across symptom severity levels. However, the underlying mechanisms may differ: in Class 3 (Gratification-Driven), loneliness may be linked to seeking social rewards, whereas in Class 4 (Situational Use), it may be related to temporary offline restrictions due to lifestyle, academic demands, or pandemic-related disruptions rather than emotional regulation deficits.

This differentiation is broadly consistent with the I-PACE model's view that the same predisposing factor (e.g., loneliness) can lead to different motivational pathways depending on emotional, cognitive, and contextual factors. It is also compatible with the compensatory internet use theory (Kardefelt-Winther, 2014), which suggests that unmet social needs may drive online engagement either toward social gratification or emotional relief, depending on the user's profile.

Behavioral indicators of PSMU severity (H2b)

In line with Hypothesis 2b, high-risk individuals reported spending more daily time on social media and perceiving their internet use as more excessive than lower-risk groups. This pattern indicates that both behavioral and subjective indicators are associated with more severe PSMU.

Motivational differentiation at moderate symptom levels (H3)

Hypothesis 3 proposed that users with moderate symptom levels would form distinct subgroups characterized by different dominant motivational mechanisms (gratification vs. compensation). We identified a gratification-driven subgroup (Class 3). However, we did not identify a clearly separable compensation-driven subgroup at moderate symptom levels in the present data. The comparison between Class 3 and Class 4 adds nuance to this pattern. Both showed moderate symptom severity, but Class 3 was driven by gratification motives, while Class 4 reflected situational and adaptive use without clear dominance of gratification or compensation. This suggests that similar symptom levels can co-occur with different motivational patterns, which may be associated with divergent risk trajectories. Class 4 reflects context-dependent, adaptive engagement rather than systematic affective compensation.

This finding is consistent with the possibility that at moderate symptom levels, stress-related coping motives may not yet be structured into more compulsive patterns.

Users may occasionally use social media to alleviate negative emotions, but this has not yet formed a stable emotional regulation strategy. Moderate severity may reflect a transitional phase in which compensatory mechanisms begin to emerge but may not yet be well consolidated. According to research (Brand et al., 2025), symptom escalation may be necessary for compensatory motives to consolidate into rigid, compulsive use. In other words, moderate symptom levels may be associated with more flexible, situational responses, whereas higher severity may be accompanied by more fixed, compensation-driven patterns. This finding is broadly consistent with the I-PACE model's focus on motivational processes and emphasizes the need to consider emotional drivers when classifying problematic social media use. It also suggests that mechanism-based classifications could potentially inform early identification before maladaptive coping strategies fully develop.

Implications and Directions for Future Research

Although the present study was not designed to test intervention effects, the identified latent classes may help generate hypotheses for future prevention and intervention research on problematic social media use. Any applied implications should therefore be treated cautiously, given the cross-sectional and observational nature of the data.

First, the high-risk class identified in the present study may represent a particularly relevant group for future intervention research. Interventions aimed at improving emotional regulation and reducing maladaptive coping mechanisms could be examined in future studies. For example, mindfulness-based interventions (MBIs; Creswell, 2017), including programs such as mindfulness-based cognitive therapy (MBCT), have been discussed in the literature as potential approaches for reducing problematic digital media use (Meynadier et al., 2024; Xiong et al., 2025). Similarly, cognitive-behavioral approaches (CBT; Kazantzis et al., 2018), which target maladaptive thoughts and behavioral patterns, may provide a useful framework for future research on interventions addressing problematic internet-related behaviors, although current evidence remains limited (Zajac et al., 2017).

Second, moderate symptom severity may represent a potentially important stage for preventive efforts. At this level, users may not yet display entrenched compulsive patterns but may still be vulnerable to escalation. Future research could examine whether preventive strategies focused on adaptive coping, emotional resilience, and mindful, goal-directed social media use are particularly relevant at this stage. Previous studies have discussed interventions combining mindfulness, mood tracking, and self-monitoring as potentially useful approaches for reducing digital distraction and improving emotional regulation (Throuvala et al., 2020; Weaver & Swank, 2019).

Third, although time spent on social media is not sufficient as a diagnostic indicator of PSMU, it may still function as an early behavioral marker worthy of further investigation. Elevated online time, especially when linked to concentration issues, insomnia, fatigue, or psychomotor agitation (Lee et al., 2022; Nurudeen et al., 2023), may signal emerging problems. A recent review shows that limiting screen time alone yields inconsistent effects (Plackett et al., 2023), suggesting that preventive efforts should target both excessive engagement and emotional and cognitive factors before compulsive patterns form.

Future research may also examine whether strategies such as digital self-monitoring (e.g., using screen-time tracking apps with personalized feedback; Stinson & Dallery, 2023) and digital hygiene routines (e.g., limiting evening screen exposure to improve sleep quality; Cajochen et al., 2011; Rao et al., 2024) are differentially relevant across latent profiles of problematic social media use. Short digital detox interventions(e.g., 14-day abstinence from social media; De Hesselle & Montag, 2024) have also shown promise in reducing depressive and anxiety symptoms, suggesting even temporary media reductions can yield psychological benefits.

Beyond behavioral strategies, future research may also examine whether psychoeducational approaches promoting mindful digital engagement are particularly relevant for problematic social media use (Thomas et al., 2024). Such approaches may include helping users recognize emotional triggers, such as boredom or loneliness, and reflect more intentionally on how they engage with social media. Future studies may also explore whether encouraging users to differentiate between passive and active social media use is associated with lower emotional dysregulation and reduced vulnerability to digital overuse (Verduyn et al., 2017).

Fourth, the finding that loneliness acts as a transdiagnostic vulnerability across different motivational profiles – being elevated in the Addictive Use / Severe Symptoms, Gratification-Driven, and Situational Use classes – highlights the need to address not just behavioral symptoms but also emotional and cognitive drivers of PSMU. Loneliness should be understood as a subjective emotional experience – a perceived gap between desired and actual social relationships – rather than objective social isolation (Grygiel et al., 2024).

Given that loneliness may foster both gratification-driven and compensatory social media use, differentiated interventions may be warranted based on users' emotional profiles and motivations. For individuals showing early-stage, gratification-driven patterns (Class 3), interventions should focus on strengthening offline relational skills and social connectedness, using programs like social skills training (SST; De Mooij et al., 2020) or interpersonal therapy (IPT; Lipsitz & Markowitz, 2013).

For individuals with more severe, compensation-driven patterns (Class 2), cognitive-behavioral approaches targeting negative self-perceptions and maladaptive emotional regulation are more appropriate. CBT has shown effectiveness in reducing loneliness and sadness by modifying dysfunctional thoughts about oneself and others and improving coping strategies (Masi et al., 2011; Smith et al., 2021).

LIMITATIONS

Despite its strengths, the present study has several limitations. First, the sample consisted solely of university students, limiting generalizability to other populations. PSMU patterns and psychosocial correlates may differ across age groups and contexts. Moreover, because the latent class structure was derived within a single sample, it should be considered provisional until replicated. Importantly, the most appropriate validation of a latent class solution is replication in independent samples, which we highlight as a key direction for future research. Second, the cross-sectional design prevents causal inferences. Although the I-PACE model suggests directional pathways (e.g., emotional distress leading to compensatory use), longitudinal studies are needed to test these assumptions and clarify temporal dynamics. Third, the study relied on the BSMAS as a self-report measure of PSMU symptoms; self-report data may be influenced by reporting biases and does not capture functional impairment or contextual factors. Future studies should integrate clinical interviews for a more comprehensive understanding. Fourth, perceived excessive internet use was assessed with a single-item indicator. Although such measures may be useful for broad screening purposes, they provide limited psychometric precision and do not capture the potentially multidimensional character of perceived digital overuse. Fifth, motivations were inferred indirectly through symptom patterns rather than measured explicitly. Adding direct measures of user motives (e.g., social, coping, enhancement motives) would offer a more nuanced understanding of psychological processes differentiating the latent classes. Sixth, while the study identified loneliness as a transdiagnostic vulnerability factor, it did not directly assess offline relationship quality or available social support. Future research should include such measures to better understand how relational factors moderate the impact of loneliness on compensatory social media use.

CONCLUSIONS

This study identified four distinct classes of social media users among university students, differing in symptom severity and motivational mechanisms. Specifically, we distinguished a No-Risk / Minimal Symptoms class (Class 1; 25.1%), an Addictive Use / Severe Symptoms class (Class 2; 15.0%), a Gratification-Driven / Moderate Symptoms class (Class 3; 34.4%), and a Situational Use / Mild-Moderate Symptoms class (Class 4; 25.5%).The identification of a high-risk group (Class 2), marked by severe symptoms and emotional vulnerabilities (elevated depression, anxiety, and low self-esteem), is consistent with the I-PACE model's emphasis on emotional dysregulation in PSMU escalation. The emergence of a gratification-driven group (Class 3) without a distinct compensation-driven group is compatible with the interpretation that compensatory patterns may consolidate only at higher symptom levels. Loneliness was elevated across all symptomatic classes (2, 3, and 4) but did not differentiate between them, supporting its role as a transdiagnostic vulnerability factor.

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REFERENCES

Abbouyi, S., Bouazza, S., El Kinany, S., El Rhazi, K., & Zarrouq, B. (2024). Depression and anxiety and its association with problematic social media use in the MENA region: A systematic review. *The Egyptian Journal of Neurology, Psychiatry and Neurosurgery*, *60*(1), 15. https://doi.org/10.1186/s41983-024-00793-0

Alimoradi, Z., Broström, A., Potenza, M. N., Lin, C.-Y., & Pakpour, A. H. (2024). Associations between behavioral addictions and mental health concerns during the COVID-19 pandemic: A systematic review and meta-analysis. *Current Addiction Reports*, *11*(3), 565–587. https://doi.org/10.1007/s40429-024-00555-1

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

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

APA (Ed.). (1998). *Diagnostic and statistical manual of mental disorders: DSM-IV ; includes ICD-9-CM codes effective 1. Oct. 96* (4. ed., 7. print).

Bányai, F., Zsila, Á., Király, O., Maraz, A., Elekes, Z., Griffiths, M. D., Andreassen, C. S., & Demetrovics, Z. (2017). Problematic social media use: Results from a large-scale nationally representative adolescent sample. *PLOS ONE*, *12*(1), e0169839. https://doi.org/10.1371/journal.pone.0169839

Basińska, B. A., & Kwissa-Gajewska, Z. (2023). Psychometric properties of the Polish version of the *Generalized Anxiety Disorder Scale* (GAD-7) in a non-clinical sample of employees during pandemic crisis. *International Journal of Occupational Medicine and Environmental Health*, *36*(4), 493–504. https://doi.org/10.13075/ijomeh.1896.02104

Brand, M., Müller, A., Wegmann, E., Antons, S., Brandtner, A., Müller, S. M., Stark, R., Steins-Loeber, S., & Potenza, M. N. (2025). Current interpretations of the I-PACE model of behavioral addictions. *Journal of Behavioral Addictions*, *14*(1), 1–17. https://doi.org/10.1556/2006.2025.00020

Brand, M., Wegmann, E., Stark, R., Müller, A., Wölfling, K., Robbins, T. W., & Potenza, M. N. (2019). The Interaction of Person-Affect-Cognition-Execution (I-PACE) model for addictive behaviors:

Update, generalization to addictive behaviors beyond internet-use disorders, and specification of the process character of addictive behaviors. *Neuroscience & Biobehavioral Reviews*, *104*, 1–10. https://doi.org/10.1016/j.neubiorev.2019.06.032

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

Cacioppo, J. T., & Cacioppo, S. (2018). Loneliness in the modern age: An evolutionary theory of loneliness. In J. M. Olson (Ed.), *Advances in Experimental Social Psychology* (pp. 127–197). Elsevier. https://doi.org/10.1016/bs.aesp.2018.03.003

Cajochen, C., Frey, S., Anders, D., Späti, J., Bues, M., Pross, A., Mager, R., Wirz-Justice, A., & Stefani, O. (2011). Evening exposure to a light-emitting diodes (LED)-backlit computer screen affects circadian physiology and cognitive performance. *Journal of Applied Physiology*, *110*(5), 1432–1438. https://doi.org/10.1152/japplphysiol.00165.2011

Carifio, J., & Perla, R. (2008). Resolving the 50-year debate around using and misusing Likert scales. *Medical Education*, *42*(12), 1150–1152. https://doi.org/10.1111/j.1365-2923.2008.03172.x

Casale, S., Fioravanti, G., Bocci Benucci, S., Falone, A., Ricca, V., & Rotella, F. (2022). A meta-analysis on the association between self-esteem and problematic smartphone use. *Computers in Human Behavior*, *134*, 107302. https://doi.org/10.1016/j.chb.2022.107302

Celeux, G., & Soromenho, G. (1996). An entropy criterion for assessing the number of clusters in a mixture model. *Journal of Classification*, *13*(2), 195–212. https://doi.org/10.1007/BF01246098

Charzyńska, E., & Góźdź, J. (2014). W sieci uzależnienia. Polska adaptacja Skali Uzależnienia od Facebooka (the Bergen Facebook Addiction Scale) C. S. Andreassen, T. Torsheima, G. S. Brunborga i S. Pallesen. *Chowanna*, *1*(42), Article 42.

Cheng, C., Ebrahimi, O. V., & Luk, J. W. (2022). Heterogeneity of prevalence of social media addiction across multiple classification schemes: Latent Profile Analysis. *Journal of Medical Internet Research*, *24*(1), e27000. https://doi.org/10.2196/27000

Creswell, J. D. (2017). Mindfulness interventions. *Annual Review of Psychology*, *68*(1), 491–516. https://doi.org/10.1146/annurev-psych-042716-051139

Cui, J., Wang, Y., Liu, D., & Yang, H. (2023). Depression and stress are associated with latent profiles of problematic social media use among college students. *Frontiers in Psychiatry*, *14*, 1306152. https://doi.org/10.3389/fpsyt.2023.1306152

De Hesselle, L. C., & Montag, C. (2024). Effects of a 14-day social media abstinence on mental health and well-being: Results from an experimental study. *BMC Psychology*, *12*(1), 141. https://doi.org/10.1186/s40359-024-01611-1

De Mooij, B., Fekkes, M., Scholte, R. H. J., & Overbeek, G. (2020). Effective components of social skills training programs for children and adolescents in nonclinical samples: A multilevel meta-analysis. *Clinical Child and Family Psychology Review*, *23*(2), 250–264. https://doi.org/10.1007/s10567-019-00308-x

Douglas, A. C., Mills, J. E., Niang, M., Stepchenkova, S., Byun, S., Ruffini, C., Lee, S. K., Loutfi, J., Lee, J.-K., Atallah, M., & Blanton, M. (2008). Internet addiction: Meta-synthesis of qualitative research for the decade 1996–2006. *Computers in Human Behavior*, *24*(6), Article 6. https://doi.org/10.1016/j.chb.2008.05.009

Du, M., Zhao, C., Hu, H., Ding, N., He, J., Tian, W., Zhao, W., Lin, X., Liu, G., Chen, W., Wang, S., Wang, P., Xu, D., Shen, X., & Zhang, G. (2024). Association between problematic social networking use and anxiety symptoms: A systematic review and meta-analysis. *BMC Psychology*, *12*(1), 263. https://doi.org/10.1186/s40359-024-01705-w

Dzwonkowska, I., Lachowicz-Tabaczek, K., & Łaguna, M. (2008). *Samoocena i jej pomiar. Polska adaptacja skali SES M. Rosenberga [Self-Esteem and Its Measurement: The Polish Adaptation of M. Rosenberg's SES Scale]*. Pracownia Testów Psychologicznych PTP.

Feng, T., Wang, B., Mi, M., Ren, L., Wu, L., Wang, H., Liu, X., & Wang, X. (2025). The relationships between mental health and social media addiction, and between academic burnout and social media addiction among Chinese college students: A network analysis. *Heliyon*, *11*(3), e41869. https://doi.org/10.1016/j.heliyon.2025.e41869

Flaherty, B. P., & Kiff, C. J. (2012). Latent class and latent profile models. In H. Cooper, P. M. Camic, D. L. Long, A. T. Panter, D. Rindskopf, & K. J. Sher (Eds.), *APA handbook of research methods in psychology, Vol 3: Data analysis and research publication.* (pp. 391–404). American Psychological Association. https://doi.org/10.1037/13621-019

Gabrielle, T., Mathius Sonne, & Niama Nina Indolo. (2024). The Impact of Social Media on Adolescent Mental Health: A Meta-Analysis. *Scientia Psychiatrica*, *5*(3), 551–564. https://doi.org/10.37275/scipsy.v5i3.175

Griffiths, M. (2005). A 'components' model of addiction within a biopsychosocial framework. *Journal of Substance Use*, *10*(4), 191–197. https://doi.org/10.1080/14659890500114359

Grygiel, P., Dolata, R., & Humenny, G. (2024). Perceived quality of peer relationships and position in peer network from late childhood to early adolescence: A three-wave longitudinal study with cross-lagged panel model. *Journal of Social and Personal Relationships*, *41*(9), 2740–2765. https://doi.org/10.1177/02654075241255392

Grygiel, P., Humenny, G., Rębisz, S., Świtaj, P., & Sikorska, J. (2013). Validating the Polish Adaptation of the 11-Item De Jong Gierveld Loneliness Scale. *European Journal of Psychological Assessment*, *29*(2), 129–139. https://doi.org/10.1027/1015-5759/a000130

Huang, C. (2022). A meta-analysis of the problematic social media use and mental health. *International Journal of Social Psychiatry*, *68*(1), 12–33. https://doi.org/10.1177/0020764020978434

Hurley, E. C., Williams, I. R., Tomyn, A. J., & Sanci, L. (2024). Social media use among Australian university students: Understanding links with stress and mental health. *Computers in Human Behavior Reports*, *14*, 100398. https://doi.org/10.1016/j.chbr.2024.100398

Hylkilä, K., Kääriäinen, M., Peltonen, A., Castrén, S., Mustonen, T., Konttila, J., & Männikkö, N. (2025). Young adults' risk profiles and predictive factors of Problematic Social Media Use (PSMU): A cross-sectional study. *Current Psychology*. https://doi.org/10.1007/s12144-025-07662-w

Jamieson, S. (2004). Likert scales: How to (ab)use them. *Medical Education*, *38*(12), 1217–1218. https://doi.org/10.1111/j.1365-2929.2004.02012.x

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior*, *31*, 351–354. https://doi.org/10.1016/j.chb.2013.10.059

Kazantzis, N., Luong, H. K., Usatoff, A. S., Impala, T., Yew, R. Y., & Hofmann, S. G. (2018). The processes of Cognitive Behavioral Therapy: A review of meta-analyses. *Cognitive Therapy and Research*, *42*(4), 349–357. https://doi.org/10.1007/s10608-018-9920-y

Kemp, S. (2025, February 5). *Digital 2025: Global Overview Report.* DATAREPORTAL. https://datareportal.com/reports/digital-2025-global-overview-report

Kırcaburun, K. (2016). Self-esteem, daily internet use and social media addiction as predictors of depression among Turkish adolescents. *Journal of Education and Practice*, *7*(24), 64–72.

Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x

Lai, C. M., Mak, K. K., Watanabe, H., Jeong, J., Kim, D., Bahar, N., Ramos, M., Chen, S. H., & Cheng, C. (2015). The mediating role of Internet addiction in depression, social anxiety, and psychosocial well-being among adolescents in six Asian countries: A structural equation modelling approach. *Public Health*, *129*(9), Article 9. https://doi.org/10.1016/j.puhe.2015.07.031

Lee, D. S., Jiang, T., Crocker, J., & Way, B. M. (2022). Social media use and its link to physical health indicators. *Cyberpsychology, Behavior, and Social Networking*, *25*(2), 87–93. https://doi.org/10.1089/cyber.2021.0188

LimeSurvey GmbH. (2024). *LimeSurvey: An Open Source Survey Tool* [Computer software]. https://www.limesurvey.org

Lipsitz, J. D., & Markowitz, J. C. (2013). Mechanisms of change in interpersonal therapy (IPT). *Clinical Psychology Review*, *33*(8), 1134–1147. https://doi.org/10.1016/j.cpr.2013.09.002

Lo, Y. (2001). Testing the number of components in a normal mixture. *Biometrika*, *88*(3), 767–778. https://doi.org/10.1093/biomet/88.3.767

Luo, T., Qin, L., Cheng, L., Wang, S., Zhu, Z., Xu, J., Chen, H., Liu, Q., Hu, M., Tong, J., Hao, W., Wei, B., & Liao, Y. (2021). Determination the cut-off point for the Bergen social media addiction (BSMAS): Diagnostic contribution of the six criteria of the components model of addiction for social media disorder. *Journal of Behavioral Addictions*, *10*(2), 281–290. https://doi.org/10.1556/2006.2021.00025

Marciano, L., Ostroumova, M., Schulz, P. J., & Camerini, A.-L. (2022). Digital media use and adolescents' mental health during the Covid-19 pandemic: A systematic review and meta-analysis. *Frontiers in Public Health*, *9*, 793868. https://doi.org/10.3389/fpubh.2021.793868

Masi, C. M., Chen, H.-Y., Hawkley, L. C., & Cacioppo, J. T. (2011). A meta-analysis of interventions to reduce loneliness. *Personality and Social Psychology Review*, *15*(3), 219–266.

Meng, S.-Q., Cheng, J.-L., Li, Y.-Y., Yang, X.-Q., Zheng, J.-W., Chang, X.-W., Shi, Y., Chen, Y., Lu, L., Sun, Y., Bao, Y.-P., & Shi, J. (2022). Global prevalence of digital addiction in general population: A systematic review and meta-analysis. *Clinical Psychology Review*, *92*, 102128. https://doi.org/10.1016/j.cpr.2022.102128

Meynadier, J., Malouff, J. M., Loi, N. M., & Schutte, N. S. (2024). Lower mindfulness is associated with problematic social media use: A meta-analysis. *Current Psychology*, *43*(4), 3395–3404. https://doi.org/10.1007/s12144-023-04587-0

Monteiro, R. P., Coelho, G. L. de H., Hanel, P. H. P., de Medeiros, E. D., & da Silva, P. D. G. (2022). The efficient assessment of self-esteem: Proposing the Brief Rosenberg Self-Esteem Scale. *Applied Research in Quality of Life*, *17*(2), 931–947. https://doi.org/10.1007/s11482-021-09936-4

Nurudeen, M., Abdul-Samad, S., Owusu-Oware, E., Koi-Akrofi, G. Y., & Tanye, H. A. (2023). Measuring the effect of social media on student academic performance using a social media influence factor model. *Education and Information Technologies*, *28*(1), 1165–1188. https://doi.org/10.1007/s10639-022-11196-0

Nylund, K. L., Asparouhov, T., & Muthén, B. O. (2007). Deciding on the number of classes in latent class analysis and growth mixture modeling: A monte carlo simulation study. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 535–569. https://doi.org/10.1080/10705510701575396

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science*, *4*(4), 440–461. https://doi.org/10.1037/tps0000176

O'Day, E. B., & Heimberg, R. G. (2021). Social media use, social anxiety, and loneliness: A systematic review. *Computers in Human Behavior Reports*, *3*, 100070. https://doi.org/10.1016/j.chbr.2021.100070

Orben, A., & Przybylski, A. K. (2019). The association between adolescent well-being and digital technology use. *Nature Human Behaviour*, *3*(2), 173–182. https://doi.org/10.1038/s41562-018-0506-1

Park, C., Majeed, A., Gill, H., Tamura, J., Ho, R. C., Mansur, R. B., Nasri, F., Lee, Y., Rosenblat, J. D., Wong, E., & McIntyre, R. S. (2020). The effect of loneliness on distinct health outcomes: A comprehensive review and meta-analysis. *Psychiatry Research*, *294*, 1–12. https://doi.org/10.1016/j.psychres.2020.113514

Peng, P., & Liao, Y. (2023). Six addiction components of problematic social media use in relation to depression, anxiety, and stress symptoms: A latent profile analysis and network analysis. *BMC Psychiatry*, *23*(1), 321. https://doi.org/10.1186/s12888-023-04837-2

Perlman, D., & Peplau, L. A. (1981). Toward a social psychology of loneliness. In S. Duck & R. Gilmour (Eds.), *Personal relationships. 3: Personal relationships in disorder*. Academic Press.

Plackett, R., Blyth, A., & Schartau, P. (2023). The impact of social media use interventions on mental well-being: Systematic review. *Journal of Medical Internet Research*, *25*, e44922. https://doi.org/10.2196/44922

Rao, K., John, S., Trivedi, G., & Gupta, S. (2024). Exploring the relationship between nocturnal social media usage, quality of sleep, indecisiveness and irritability in emerging adults. *International Journal of Interdisciplinary Approaches in Psychology*, *2*(11), 9–26.

Rosenberg, M. (1965). *Society and the Adolescent Self-Image*. Princeton University Press.

Schivinski, B., Brzozowska-Woś, M., Stansbury, E., Satel, J., Montag, C., & Pontes, H. M. (2020). Exploring the role of social media use motives, psychological well-being, self-esteem, and affect in problematic social media use. *Frontiers in Psychology*, *11*, 617140. https://doi.org/10.3389/fpsyg.2020.617140

Schmelzer, N., Westphal, T., Pichardo, A., Buckner, D., Smith, N., Shaaban, N., Johnson, M., Bennett, J., & Estep, J. (2022). The relationship between problematic social media use and time spent on social media: Exploring neuroticism as a moderator. *Psi Beta Research Journal*, *2*(1), 29–35. https://doi.org/10.54581/JWJB5363

Shannon, H., Bush, K., Villeneuve, P. J., Hellemans, K. G., & Guimond, S. (2022). Problematic social media use in adolescents and young adults: Systematic review and meta-analysis. *JMIR Mental Health*, *9*(4), e33450. https://doi.org/10.2196/33450

Shi, X., Wang, A., & Zhu, Y. (2023). Longitudinal associations among smartphone addiction, loneliness, and depressive symptoms in college students: Disentangling between– And within–person associations. *Addictive Behaviors*, *142*, 107676. https://doi.org/10.1016/j.addbeh.2023.107676

Ślusarska, B., Nowicki, G., Piasecka, H., Zarzycka, D., Mazur, A., Saran, T., & Bednarek, A. (2019). Validation of the Polish language version of the Patient Health Questionnaire-9 in a population of adults aged 35–64. *Annals of Agricultural and Environmental Medicine*, *26*(3), 420–424. https://doi.org/10.26444/aaem/99246

Smith, R., Wuthrich, V., Johnco, C., & Belcher, J. (2021). Effect of group cognitive behavioural therapy on loneliness in a community sample of older adults: A secondary analysis of a randomized controlled trial. *Clinical Gerontologist*, *44*(4), 439–449. https://doi.org/10.1080/07317115.2020.1836105

Soothram, S., & Prakash, P. (2024). Impact of social media usage on sleep and eye health: A survey study among university students. *International Journal For Multidisciplinary Research*, *6*(4), 25868. https://doi.org/10.36948/ijfmr.2024.v06i04.25868

Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A brief measure for assessing Generalized Anxiety Disorder: The GAD-7. *Archives of Internal Medicine*, *166*(10), 1092–1097. https://doi.org/10.1001/archinte.166.10.1092

Stinson, L., & Dallery, J. (2023). Reducing problematic social media use via a package intervention. *Journal of Applied Behavior Analysis*, *56*(2), 323–335. https://doi.org/10.1002/jaba.975

Throuvala, M. A., Griffiths, M. D., Rennoldson, M., & Kuss, D. J. (2020). Mind over matter: Testing the efficacy of an online randomized controlled trial to reduce distraction from smartphone use. *International Journal of Environmental Research and Public Health*, *17*(13), 4842. https://doi.org/10.3390/ijerph17134842

Tullett-Prado, D., Doley, J. R., Zarate, D., Gomez, R., & Stavropoulos, V. (2023). Conceptualising social media addiction: A longitudinal network analysis of social media addiction symptoms and their relationships with psychological distress in a community sample of adults. *BMC Psychiatry*, *23*(1), 509. https://doi.org/10.1186/s12888-023-04985-5

Twenge, J. M., Joiner, T. E., Rogers, M. L., & Martin, G. N. (2018). Increases in depressive symptoms, suicide-related outcomes, and suicide rates among U.S. adolescents after 2010 and links to increased new media screen time. *Clinical Psychological Science*, *6*(1), 3–17. https://doi.org/10.1177/2167702617723376

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., & Kross, E. (2017). Do social network sites enhance or undermine subjective well-being? A critical review. *Social Issues and Policy Review*, *11*(1), 274–302. https://doi.org/10.1111/sipr.12033

Waldo, A. D. (2014). Correlates of Internet Addiction among Adolescents. *Psychology*, *05*(18), Article 18. https://doi.org/10.4236/psych.2014.518203

Wang, Z., Yang, H., & Elhai, J. D. (2022). Are there gender differences in comorbidity symptoms networks of problematic social media use, anxiety and depression symptoms? Evidence from network analysis. *Personality and Individual Differences*, *195*, 111705. https://doi.org/10.1016/j.paid.2022.111705

Weaver, J. L., & Swank, J. M. (2019). Mindful connections: A mindfulness-based intervention for adolescent social media users. *Journal of Child and Adolescent Counseling*, *5*(2), 103–112. https://doi.org/10.1080/23727810.2019.1586419

Wiederhold, B. K. (2020). Connecting through technology during the coronavirus disease 2019 pandemic: Avoiding "zoom fatigue." *Cyberpsychology, Behavior, and Social Networking*, *23*(7), 437–438. https://doi.org/10.1089/cyber.2020.29188.bkw

Wu, P., Feng, R., & Zhang, J. (2024). The relationship between loneliness and problematic social media usage in Chinese university students: A longitudinal study. *BMC Psychology*, *12*(1), 13. https://doi.org/10.1186/s40359-023-01498-4

Xiong, W., Yu, L., & Chai, J. (2025). Mindfulness cognitive-based therapy combined with metaphor therapy can improve problematic social media use. *Frontiers in Psychiatry*, *16*, 1503049. https://doi.org/10.3389/fpsyt.2025.1503049

Yigiter, M. S., Demir, S., & Dogan, N. (2024). The Relationship Between Problematic Social Media Use and Depression: A Meta-Analysis Study. *Current Psychology*, *43*(9), 7936–7951. https://doi.org/10.1007/s12144-023-04972-9

Zajac, K., Ginley, M. K., Chang, R., & Petry, N. M. (2017). Treatments for Internet gaming disorder and Internet addiction: A systematic review. *Psychology of Addictive Behaviors*, *31*(8), 979–994. https://doi.org/10.1037/adb0000315

Zhang, K., Li, P., Zhao, Y., Griffiths, M. D., Wang, J., & Zhang, M. X. (2023). Effect of Social Media Addiction on Executive Functioning Among Young Adults: The Mediating Roles of Emotional Disturbance and Sleep Quality. *Psychology Research and Behavior Management*, *Volume 16*, 1911–1920. https://doi.org/10.2147/PRBM.S414625

SUPPLEMENTARY MATERIALS

Figure S1. Percentage Distribution of Problematic Social Media Use– Bergen Social Media Addiction Scale (BSMAS) Items

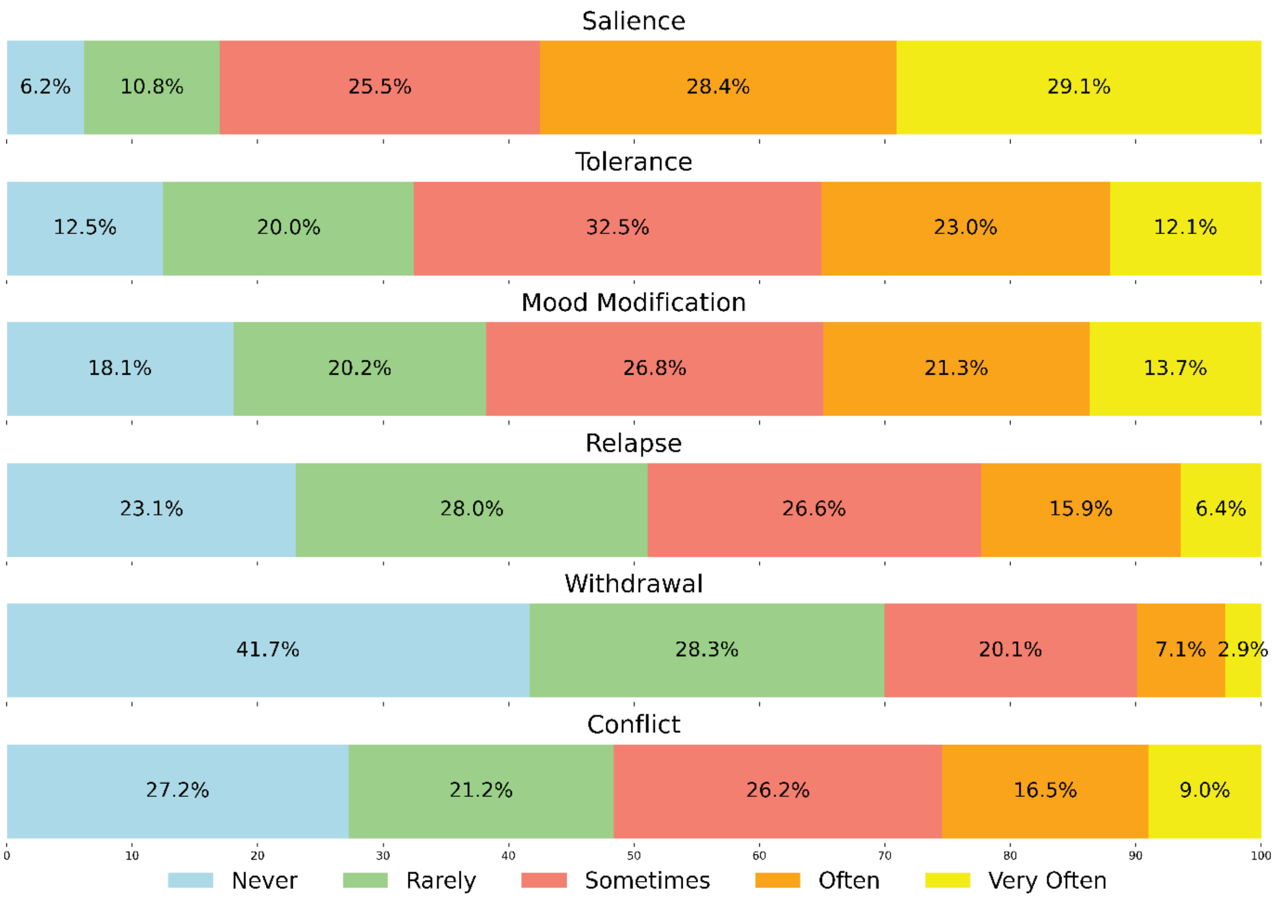
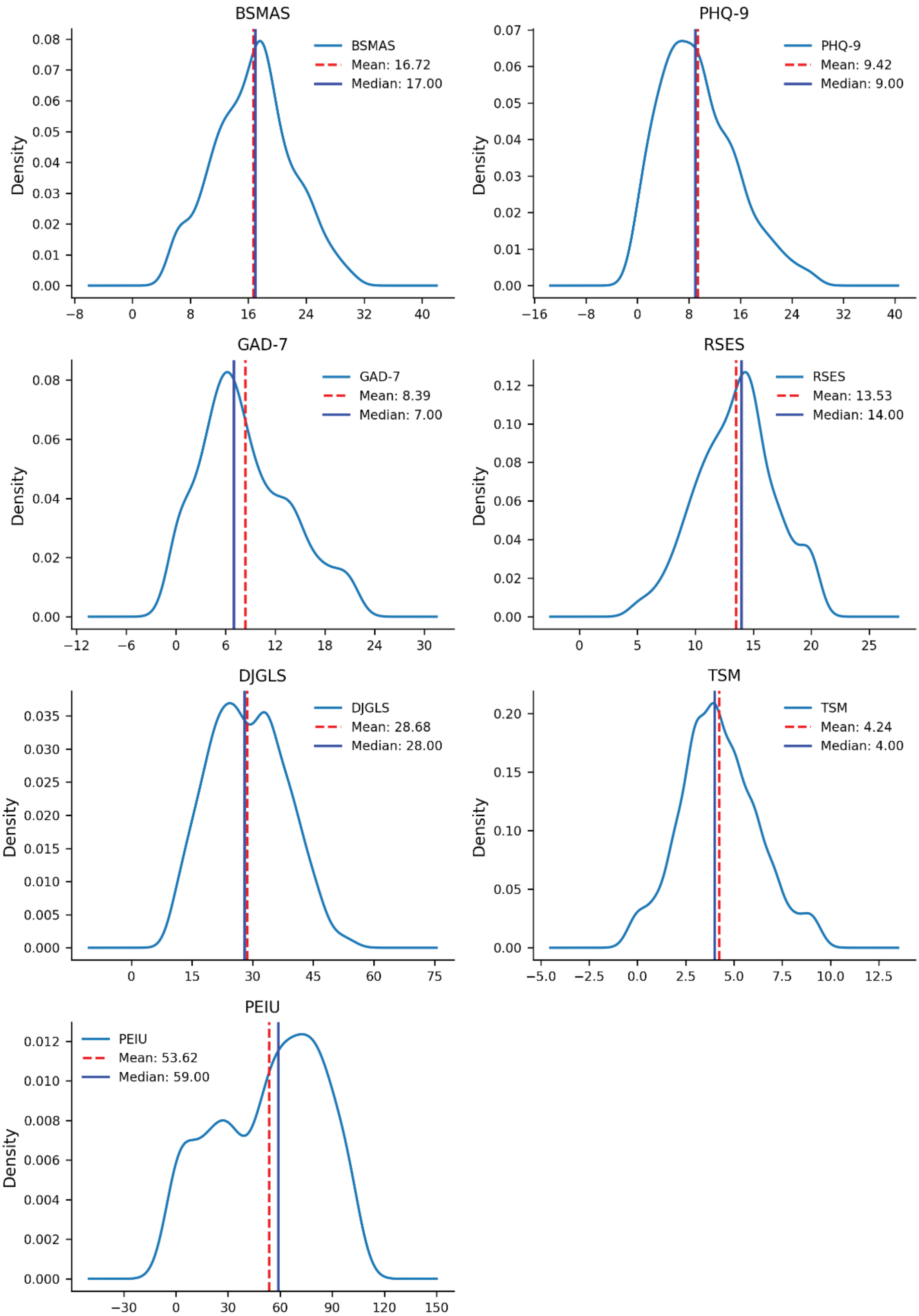


Figure S2. Kernel Density Estimates for BSMAS, PHQ-9, GAD-7, RSES, DJGLS, TSM, and PEIU



Note. BSMAS represents problematic social media use based on the Bergen Social Media Addiction Scale; PHQ refers to depressive symptoms measured using the Patient Health Questionnaire-9; GAD captures anxiety symptoms assessed with the Generalized Anxiety Disorder scale; DJGLS represents loneliness based on the De Jong Gierveld Loneliness Scale; TSM reflects the self-reported average number of hours per day spent on social media; and PEIU denotes perceived excessive internet use.

Table S1. Descriptive statistics and intercorrelations of BSMAS Symptoms: Salience, Mood Modification, Tolerance, Withdrawal, Conflict, and Relapse

Variable	*M*	*SD*	1	2	3	4	5
1. Salience	3.63	1.18					
2. Mood Modification	3.02	1.19	.63**				
3. Tolerance	2.92	1.30	.44**	.61**			
4. Withdrawal	2.55	1.19	.27**	.43**	.44**		
5. Conflict	2.01	1.08	.24**	.49**	.47**	.46**	
6. Relapse	2.59	1.29	.36**	.48**	.52**	.53**	.48**

Note. N = number of cases. M = mean. SD = standard deviation. ** indicates $p < .01$.

Table S2. Descriptive statistics and intercorrelations between Problematic Social Media Use (BSMAS), Depression Symptoms (PHQ-9), Anxiety Symptoms (GAD-7), Self-Esteem (RSES), Loneliness (DJGLS), Time Spent on Social Media (TSM), and Passive Engagement in Internet Use (PEIU)

Variable	*M*	*SD*	1	2	3	4	5	6
1. BSMAS	16.72	5.36						
2. PH-9	9.42	5.92	.36**					
3. GAD-7	8.39	5.39	.35**	.71**				
4. RSES	13.53	3.35	-.22**	-.58**	-.46**			
5. DJGLS	28.68	9.27	.13**	.48**	.43**	-.55**		
6. TSM	4.24	1.99	.52**	.23**	.19**	-.18**	.09**	
7. PEIU	53.62	30.00	.42**	.34**	.26**	-.23**	.23**	.37**

Note. N = number of cases. M = mean. SD = standard deviation. ** indicates $p < .01$.

Table S3. Pairwise comparisons between latent classes on study variables (Tukey HSD post hoc tests)

Variable	Group 1	Group 2	Mean Diff	p-adj	Lower CI	Upper CI
PHQ	1	2	6.58	<0.001	5.06	8.1
PHQ	1	3	3.95	<0.001	2.73	5.16
PHQ	1	4	2.04	<0.001	0.74	3.35
PHQ	2	3	-2.63	<0.001	-4.07	-1.19
PHQ	2	4	-4.54	<0.001	-6.05	-3.03
PHQ	3	4	-1.9	<0.001	-3.12	-0.69
GAD	1	2	6.09	<0.001	4.70	7.47
GAD	1	3	2.98	<0.001	1.87	4.1
GAD	1	4	1.5	0.01	0.31	2.69
GAD	2	3	-3.11	<0.001	-4.42	-1.79
GAD	2	4	-4.59	<0.001	-5.97	-3.21
GAD	3	4	-1.48	<0.001	-2.59	-0.37
DJGLS	1	2	3.93	<0.001	1.40	6.45
DJGLS	1	3	2.7	<0.001	0.67	4.73
DJGLS	1	4	1.77	0.15	-0.40	3.95
DJGLS	2	3	-1.23	0.55	-3.63	1.16
DJGLS	2	4	-2.15	0.12	-4.67	0.36
DJGLS	3	4	-0.92	0.64	-2.94	1.1
TSM	1	2	2.75	<0.001	2.26	3.23
TSM	1	3	1.73	<0.001	1.34	2.12
TSM	1	4	0.92	<0.001	0.50	1.33
TSM	2	3	-1.01	<0.001	-1.47	-0.55
TSM	2	4	-1.83	<0.001	-2.31	-1.35
TSM	3	4	-0.82	<0.001	-1.21	-0.43
PEIU	1	2	38.07	<0.001	30.56	45.58
PEIU	1	3	24.58	<0.001	18.55	30.61
PEIU	1	4	19.33	<0.001	12.87	25.79
PEIU	2	3	-13.49	<0.001	-20.61	-6.37
PEIU	2	4	-18.74	<0.001	-26.22	-11.26
PEIU	3	4	-5.25	0.11	-11.25	0.75

Note. PHQ refers to depressive symptoms measured using the Patient Health Questionnaire-9; GAD captures anxiety symptoms assessed with the Generalized Anxiety Disorder scale; DJGLS represents loneliness based on the De Jong Gierveld Loneliness Scale; TSM reflects the self-reported average number of hours per day spent on social media; and PEIU denotes perceived excessive internet use. Mean Diff indicates the difference between the mean scores of the two compared groups (Group 1 minus Group 2). The p-adj column presents p-values adjusted for multiple comparisons using Tukey's Honest Significant Difference (HSD) procedure. Lower CI and Upper CI specify the bounds of the 95% confidence interval for the mean difference. The Significant column indicates whether the observed difference between groups is statistically significant at the $\alpha = .05$ level.