Addictive Behaviors Reports 23 (2026) 100655

Contents lists available at ScienceDirect

Addictive Behaviors Reports

journal homepage: www.elsevier.com/locate/abrep

# The association between fear of missing out and problematic smartphone use: A latent profile analysis of problematic social media use

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ARTICLE INFO

*Keywords:*
Addictive behaviors
Behavioral addiction
Fear of missing out
Latent profile analysis
Online social networking
Problematic social media use
Problematic smartphone use
Social media
Technology addiction

ABSTRACT

Problematic social media use (PSMU) has emerged as a societal and behavioral concern, especially among young adults. However, individual differences in symptom manifestation remain understudied. The present study adopted a person-centered approach to identify distinct profiles of PSMU and to examine the predictive roles of fear of missing out (FoMO), problematic smartphone use (PSU), age, and sex among a sample of 625 Italian university students aged 18 to 40 years ($M = 25.31$ years, $SD = 5.85$) who completed a self-report online survey. Using latent profile analysis (LPA) on a sample of Italian university students who use *Instagram*, five profiles were identified. Salience, tolerance, mood modification, withdrawal, and conflict symptoms sharply differentiated the high-risk with withdrawal symptom group from the other groups, supporting a cross-sectional pattern consistent with (but not demonstrating) a dimensional progression model. FoMO predicted high-risk with withdrawal symptoms and high-risk without withdrawal symptom membership, suggesting its role as an early vulnerability factor, whereas PSU strongly predicted high-risk with withdrawal symptoms classification. Sex differences also emerged, with females being more likely to belong to higher risk with withdrawal symptoms profiles. Analysis also indicated that younger participants were more at risk of belonging to the high-risk PSMU group. The findings offer nuanced insight into how psychological factors shape social online behavior and suggest tailored intervention strategies for users' risk levels. However, the findings should be interpreted within the context of the *Instagram* social platform and the study's sample-specific characteristics.

## 1. Introduction

In recent years, the pervasive use of social media has raised growing concerns regarding its potential for problematic engagement, particularly among younger populations (Brand et al., 2025a; Gori et al., 2024; Shimkhada & Ponce, 2024). Problematic social media use (PSMU), which refers to the uncontrolled and compulsive use of social media that leads to functional impairment in everyday life, can be determined by a range of addiction symptoms such as salience, mood modification, tolerance, withdrawal, conflict, and relapse (Andreassen et al., 2012; Griffiths, 2005) and showing both trait and state-like features (Horváth et al., 2024). These components mirror core features of behavioral addictions, yet their manifestation may vary across individuals and levels of severity. Despite the growing literature on PSMU, most studies have relied on variable-centered approaches, which assume homogeneity in symptom expression across the population (e.g., Lin et al., 2023; Servidio et al., 2025; Soraci et al., 2025). In contrast, person-centered methods such as latent profile analysis (LPA) allow for the identification of qualitatively distinct subgroups of users, offering a more nuanced understanding of how problematic use patterns develop and differ across

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https://doi.org/10.1016/j.abrep.2025.100655
Received 9 September 2025; Received in revised form 14 December 2025; Accepted 16 December 2025
Available online 17 December 2025

individuals (e.g., Smith & Short, 2022).

An important variable, among others, contributing to the emergence of PSMU is the fear of missing out (FoMO), a dispositional tendency characterized by the need to remain continuously connected to others online due to a fear of exclusion or missing rewarding experiences (Przybylski et al., 2013). FoMO has been shown to predict increased social media checking, excessive online use, and reduced offline satisfaction (Servidio et al., 2024), positioning it as a key psychological antecedent of online overuse (Shi et al., 2025; Tao et al., 2024). Alongside FoMO, problematic smartphone use (PSU) has also been identified as a related but distinct construct, reflecting broader patterns of dysfunctional smartphone engagement (Elhai et al., 2020, 2025; Servidio et al., 2024, 2025). Theoretical models such as the Interaction of Person-Affect-Cognition-Execution (I-PACE; Brand et al., 2016; 2019; 2025b) suggest that PSMU and PSU may co-occur as a result of underlying vulnerabilities, including impaired self-regulation and maladaptive coping strategies. The co-occurrence is more likely simply because smartphones are the most common device for accessing social media (Kuss & Griffiths, 2017).

From a theoretical standpoint, the present study was embedded in the Interaction of Person–Affect-Cognition-Execution (I-PACE) model of specific internet-use disorders, which posits that predisposing person variables and situational factors influence affective and cognitive responses to online cues, thereby shaping decision making and executive functions over time (Brand et al., 2016, 2019). In the I-PACE framework, the progression toward dysregulated digital-media use is typically described as a sequence from predisposing vulnerabilities to affective and cognitive responses, which in turn undermine executive functioning and increase the likelihood of compulsive use (Brand et al., 2019). FoMO can therefore be conceptualized as an affective–cognitive vulnerability that heightens sensitivity to socially rewarding cues and amplifies urges to check social media. Conversely, PSU may reflect a behavioral manifestation of reduced executive control and impaired self-regulation, positioning it at a later stage of the I-PACE process. These distinctions suggest that FoMO and PSU should differentially characterize latent profiles varying in severity and symptom configuration. Accordingly, the hypotheses and analytic strategy were explicitly informed by these mechanisms.

In a narrative extension of this framework to social network use disorder, Wegmann and Brand (2019) distinguished between a fear-driven, compensation-seeking pathway, in which individuals use social networking sites to alleviate negative emotions and social concerns, and a reward-driven path, in which use is primarily motivated by the anticipation of positive reinforcement and gratification. In line with this perspective, FoMO was conceptualized as a central fear-related predisposing variable that may motivate harmful reinforcement mechanisms through interaction with social networks. In contrast, smartphone use reflects a broader pattern of dysregulated, reward-driven interaction with digital technologies that can facilitate the development of PSMU. By adopting a person-centered, symptom-based approach to PSMU, the present study empirically explored whether different combinations of addiction-like symptoms correspond to distinct configurations of these theoretically derived risk factors among young adult *Instagram* users.

In recent years, some studies have adopted a person-centered approach to investigate individual differences in problematic internet use (e.g., social media use). For example, Stănculescu and Griffiths (2022) identified three clusters of "social media addiction" through LPA, highlighting the key role of social anxiety, sex, and age in determining the severity of symptoms. Later, Stănculescu and Griffiths (2024) extended the previous model to general internet addictions, showing how profiles characterized by high eudaimonic well-being differ from those dominated by hedonic motivations in online use. However, these studies have not examined the problematic use patterns characteristic of visually oriented platforms, such as *Instagram*. In particular, the architecture based on personalized algorithmic feeds and ephemeral stories generates cycles of intermittent gratification and social reinforcement that are not found on primarily text-based or group-oriented platforms, such as Twitter or Facebook groups.

Therefore, the present study adopted a person-centered approach to examine heterogeneity in PSMU among social media users. More specifically, it aimed to: (i) identify distinct latent profiles of PSMU using LPA; (ii) examine whether FoMO and PSU predict class membership; and (iii) explore the symptom-level composition of each profile to better understand the psychological mechanisms underlying different degrees of social media use risk. By employing LPA, the study sought to identify distinct subgroups of social media users who share constellations of PSMU symptoms, thereby illuminating the heterogeneity that is obscured when a monolithic pattern of problematic engagement is assumed. In doing so, the study not only identifies clusters of individuals whose PSMU manifestations range from relatively mild interference with daily routines to severe disruptions of emotional well-being and interpersonal relationships, but also examines, at the level of individual symptoms, which psychological mechanisms drive these divergent patterns.

This dual emphasis on person-centered and symptom-centered perspectives enables a more nuanced understanding of how constructs such as FoMO and PSU contribute to class membership. Rather than simply correlating FoMO and PSU with overall PSMU severity, the study assesses whether higher levels of FoMO and broader tendencies toward dysfunctional smartphone engagement serve as risk factors that predispose specific users to more severe latent profiles. In this context, a person-centered approach can complement variable-centered evidence by shifting the focus from overall levels of PSMU to distinct configurations of addiction-like symptoms. Rather than simply asking whether FoMO and PSU are associated with higher PSMU scores, the present study investigated whether these risk factors differentially characterize latent profiles defined by the six core components of PSMU. Prior person-centered studies on social media–related constructs have primarily distinguished groups along a general severity continuum and have often relied on global indices or latent factors of problematic use, with limited attention to symptom-level heterogeneity and to the joint role of FoMO and PSU as predictors of profile membership.

As far as the present authors are aware, no previous study in the Italian context has ever combined a symptom-level (item-based) latent profile analysis of PSMU with FoMO and PSU as joint predictors of class membership among a university population, and very few studies have used LPA. By modelling PSMU at the symptom level rather than relying on total scores, the present study extends the existing literature by clarifying how FoMO and PSU differentiate qualitatively distinct patterns of PSMU symptoms among young Italian adult *Instagram* users. Moreover, by investigating sex and age differences, the research extends its applicability to real-world contexts, highlighting how demographic variables interact with underlying psychological predispositions to shape an individual's likelihood of belonging to a high-risk subgroup.

The present study advances a dimensional cross-sectional pattern consistent (but not demonstrating) a dimensional progression model of social media overuse, challenging the conventional binary frame of "problematic versus non-problematic" use. Instead, it empirically examines a cross-sectional pattern through which users may transition over time, showing that risk is not merely present or absent but varies in degree according to the intensity and configuration of underlying symptoms. Such a framework has crucial implications for the design of tailored interventions and online well-being programs. By pinpointing which combinations of FoMO, PSU, sex, and age most strongly predict high-risk profiles, practitioners can develop stratified strategies that address the precise psychological and behavioral needs of different user subgroups.

More specifically, FoMO and PSU are among the most consistently documented psychological correlates of PSMU across contemporary frameworks such as the I-PACE model and compensatory internet use theory (Elhai et al., 2025; Sánchez-Fernández & Borda-Mas, 2023) and therefore provide robust indicators of individual vulnerability to dysregulated online behaviors. Age and sex were included as essential demographic controls given their well-established associations with social media use patterns and addictive-like tendencies. Therefore, the present study not only enriches theoretical discourse on social media overuse (especially among *Instagram* users) but also lays the groundwork for more effective, evidence-based approaches to promoting healthier online behaviors among younger populations.

## 2. Method

### 2.1. Participants

A total of 629 university students participated in a cross-sectional survey study, recruited through convenience sampling. Four cases (0.6 %) were excluded as multivariate outliers based on Mahalanobis distance ($p < 0.001$), yielding a final sample of 625 participants for the subsequent statistical analyses. Participants were recruited through social media posts (e.g., *Instagram*) and during regular campus classroom sessions. The sample comprised 411 females (65.12 %), with ages ranging from 18 to 40 years ($M = 25.31$, $SD = 5.85$). On average, participants reported spending 9.54 h per week on *Instagram* ($SD = 10.32$). All participants were informed about the study's aims and procedures and provided informed consent in accordance with the Declaration of Helsinki. The study protocol was approved by the institutional ethics committee of the first author (No. 0288248/2024).

Inclusion criteria were as follows: (i) having an active *Instagram* social media account. This was to ensure a prevalent social media environment among participants, given that *Instagram* is one of the most widely used social networking platforms among young adults in Italy (CENSIS, 2024), by assessing weekly *Instagram* use as an indicator of online engagement; (ii) being at least 18 years old, and (iii) possessing proficiency in the Italian language. Before data collection, participants were thoroughly informed about the study's objectives and procedures. It was emphasized that participation was anonymous, voluntary, and uncompensated. A link to the survey, hosted on the *LimeSurvey* platform, was provided to enable participants to give informed consent and complete the survey.

It should also be noted that part of the dataset has been used in previous publications that addressed different research questions using a variable-centered, mediation-based approach (i.e., Servidio et al., 2022, 2024). Both previous studies used the same instruments to assess the key constructs of interest (i.e., FoMO, PSU, and PSMU). These studies followed highly comparable procedures for recruitment strategy, inclusion criteria, and data collection setting. These previous studies addressed different research questions using variable-centered, mediation-based models, and no person-centered or latent profile analyses were conducted or reported. In the present study, the two datasets were merged to increase statistical power and to enable a person-centered examination of latent profiles of PSMU and their psychosocial predictors.

### 2.2. Measures

*Demographic information*. The survey included questions relating to sex, age, and education level. Participants were asked to report their average weekly time spent on *Instagram* by selecting one of four categories: "less than two hours," "between two and four hours," "between four and six hours," or "more than six hours.".

*Problematic social media use.* PSMU was assessed using the six-item Bergen Social Media Addiction Scale (BSMAS; Andreassen et al., 2016; Italian version: Monacis et al., 2017). As aforementioned, the six items of the scale correspond to the symptoms described by the components model of addiction (salience, mood modification, tolerance, withdrawal, conflict and relapse) (Griffiths, 2005). Items (e.g., *"You use social media to forget about personal problems"*) are rated on a five-point Likert-type scale ranging from 1 (*never*) to 5 (*very often*). The total score ranges from 6 to 30, with higher scores indicating a greater risk of PSMU. In the present study, the internal consistency was good (Cronbach's $\alpha = 0.79$; McDonald's $\omega = 0.79$).

*Fear of missing out.* FoMO was assessed using the 10-item Fear of Missing Out Scale (FoMOS; Przybylski et al., 2013; Italian version: Casale & Fioravanti, 2020). Items (e.g., *"I fear others have more rewarding experiences than me"*) are rated on a five-point Likert-type scale ranging from 1 (*not at all true of me*) to 5 (*extremely true of me*). The total score ranges from 10 to 50, with higher scores indicating higher levels of FoMO. In the present study, the internal consistency was good ($\alpha = 0.77$; McDonald's $\omega = 0.77$).

*Problematic smartphone use.* PSU was assessed using the short 10-item version of the Smartphone Addiction Scale (Kwon et al., 2013; Italian version: Servidio et al., 2023). Items (e.g., *"I have used my smartphone longer than I had intended"*) are rated on a six-point Likert-type scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). The total score ranges from 10 to 60, with higher scores indicating greater risk of PSU. In the present study, the internal consistency was good ($\alpha = 0.79$; McDonald's $\omega = 0.84$).

### 2.3. Statistical analysis

All statistical analyses were performed using *R* software (version 4.4.2; R Core Team, 2024). Preliminary assumptions of univariate and multivariate normality were assessed using the *MVN* package (Korkmaz et al., 2014). Missing data were negligible for a small subset of variables not included in the latent profile analysis (e.g., age: 22.24 %; PSU: 5.04 %; *Instagram*: 15.64 %). However, there were no missing data for the six BSMAS items used as profile indicators. For all analyses requiring complete observations (e.g., ANOVAs and multinomial regression), complete-case analysis (listwise deletion) was adopted, consistent with recommended practices when missingness is non-systematic and does not involve key model indicators. No imputation procedures were applied. Descriptive statistics, including means, standard deviations, frequencies, percentages, skewness, and kurtosis, were computed for the study variables. Given violations of the normality assumption, robust procedures were adopted for the primary analyses. Pearson correlation coefficients were calculated to examine associations between the main study constructs. Internal consistency was assessed using both Cronbach's $\alpha$ and McDonald's $\omega$, computed using the *psych* package (Revelle, 2025).

To identify distinct subgroups of participants, based on PSMU symptoms, LPA was conducted using the *tidyLPA* package (Rosenberg et al., 2018). The package *tidyLPA* applies casewise deletion by default. Although the observed variables exhibited significant deviations from multivariate normality, particularly in skewness and kurtosis, these violations were not deemed critical for the present analyses. Moreover, LPA remains appropriate in this context because it models local normality within each latent class rather than assuming global multivariate normality across the entire sample (Ferguson et al., 2020).

Prior to model estimation, each BSMAS item was z-standardized ($M = 0$, $SD = 1$), so that profile means could be interpreted as deviations from the sample grand mean for each symptom and to avoid undue influence of differences in item variance. Participants were classified based on their responses to the six items of the BSMAS. A series of latent profile models was estimated using the *tidyLPA* package (Rosenberg et al., 2018). For each solution (1–9 classes), three parameterizations were fitted: (i) equal variances and zero covariances (Model 1), (ii) varying variances and zero covariances (Model 2), and (iii) varying variances and varying covariances (Model 3). This strategy allowed profile solutions to be compared across increasing levels of model complexity and to evaluate their relative fit. Model selection was based on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size adjusted BIC (SABIC), and classification entropy, as well as theoretical interpretability and minimum class size (>5%). Profiles representing less than 5 % of the sample were excluded from interpretation to ensure the stability and interpretability of the results.

In the estimation package adopted (*tidyLPA*), bootstrap likelihood-ratio test (BLRT) statistics were unavailable and were therefore not used as a decision criterion. Based on these criteria, a five-profile solution was retained as the final model. The correlation matrix of the BSMAS items and the full set of fit indices for the nine profile models are reported in the Supplementary Materials [Tables S1 and S2]. Moreover, to verify the robustness of the retained five-profile solution, adjacent class solutions were examined. The six-class solution was degenerate, yielding a class with zero estimated members and a minimum posterior probability of 0 %, indicating that the additional class did not represent a meaningful or statistically identifiable subgroup. On this basis, robustness was evaluated by comparing the five-class model primarily against the four-class solution. Fit indices and comparison plots are reported in Supplementary Table S3 and Fig. S1.

To assess the external validity of the profiles, a series of one-way analyses of variance (ANOVAs) were conducted with class membership as the predictor variable and FoMO, PSU, and weekly *Instagram* use as outcome variables. Where overall effects were significant, Tukey's Honestly Significant Difference (HSD) post-hoc tests were conducted to identify pairwise differences between groups. Eta-squared (η2) effect size was used to determine the magnitude and significance of the observed differences. The homogeneity of variance was tested using Levene's test. Because Levene's test indicated a violation of the homogeneity-of-variance assumption for PSMU, Welch's ANOVA was conducted, which is robust to heteroscedasticity. When overall effects were significant, group differences were examined using Games-Howell post hoc tests, which do not assume equal variances or sample sizes. Effect sizes were reported using eta-squared (η2) with 95 % confidence intervals. Finally, following profile identification, a multinomial logistic regression was performed using the *nnet* package (Venables & Ripley, 2002) to examine predictors of latent profile membership. FoMO, PSU, age, and sex (coded as: 0 = male, 1 = female) were entered as predictors, with the no-risk class profile serving as the reference group. Prior to model estimation, multicollinearity diagnostics were conducted. Multicollinearity was assessed using variance inflation factors (VIFs) computed on auxiliary regression models including the same set of predictors. All VIF values were low (1.01–1.21), indicating no issues with multicollinearity. Results are reported as odds ratios (OR) with corresponding 95 % confidence intervals. All visualizations were produced using *ggplot2* (Wickham, 2016).

## 3. Results

### 3.1. Preliminary analyses

Before conducting the LPA, the assumptions of multivariate and univariate normality were examined. Results from the Henze-Zirkler test indicated a significant deviation from multivariate normality, $HZ = 5.61, p < 0.001$, suggesting that the overall data structure did not follow a multivariate normal distribution. This finding was also supported by Mardia's multivariate skewness statistic, which was significant, $\chi^2 = 573.60, p < 0.001$. In contrast, Mardia's multivariate kurtosis statistics were significant, $z = 6.43, p < 0.0001$, indicating that the shape of the data in terms of kurtosis was deviant from normality.

These results indicated that none of the proposed variables were normally distributed. However, despite these deviations from normality, the observed skewness and kurtosis values were within acceptable limits (see Table 1), suggesting asymmetric distributions. Given the relatively large sample size (N = 625) and considering that the primary analyses involved latent profile analysis and multinomial logistic regression, both of which are robust to moderate non-normality, no data transformations were applied (Bouckenooghe et al., 2025). Descriptive statistics for the study variables are presented in Table 1.

Given that the six items of the Bergen Social Media Addiction Scale (BSMAS) served as indicator variables in the latent profile analysis, it is informative to report item-level descriptive statistics in addition to the total scale score. Table 2 presents the means, standard deviations, skewness, and kurtosis for each PSMU item. Bivariate correlations among the study variables are shown in Table 3.

**Table 1**
Descriptive statistics (N = 625).

| Variable | Mean | SD | Skewness | Kurtosis | $A^2$ |
|---|---|---|---|---|---|
| PSU | 2.54 | 0.93 | 0.50 | −0.19 | $3.48^{***}$ |
| FoMO | 1.94 | 0.61 | 0.71 | 0.19 | $6.93^{***}$ |
| PSMU | 2.25 | 0.77 | 0.45 | −0.35 | $4.85^{***}$ |
| Age | 25.31 | 5.85 | 1.23 | 0.76 | $22.07^{***}$ |

*Note.* PSU = Problematic smartphone use. FoMO = Fear of missing out. PSMU = Problematic social media use. $A^2$ = Anderson-Darling statistic. $^{***}p < 0.001$.

### 3.2. Determining the number of latent profiles

Model fit indices for latent profile models ranging from one to nine classes are reported in Table 4. The five-class model was selected as the optimal solution based on a combination of statistical and substantive criteria. Therefore, the five-class model exhibited a good entropy value (0.82), suggesting clear class separation, and none of the classes had a proportion below 5 % in dimension. Taken together, these results support the five-class model as the most parsimonious and interpretable solution. The results in Table 4 highlight these accuracy rates, reflecting the effectiveness of the model in achieving accurate participant classification.

Fig. 1 displays the mean scores across the six indicators of problematic social media (salience, tolerance, mood modification, relapse, withdrawal, conflict) for the five profiles identified through LPA: high-risk with withdrawal symptoms, high-risk without withdrawal symptoms, withdrawal-conflict risk, low-risk, and no-risk. The high-risk with withdrawal symptoms group comprised 85 participants (13.6 %; 95 % CI [69.13, 103.73]). They exhibited uniformly elevated means across all six BSMAS indicators, with exceptionally high levels of withdrawal and conflict (around 2 and 1 *SD* above the mean, respectively). This pattern reflects a pervasive and severe form of dysregulated social media use, involving intense craving, failed attempts to cut down, and marked negative consequences. The second profile (high-risk without withdrawal symptoms) comprised 123 individuals (19.7 %; 95 % CI [104.23, 144.17]). They exhibited elevated scores on salience, tolerance, and mood modification (around 1 *SD* above the mean) and moderately high scores on relapse and conflict. At the same time, withdrawal was close to the sample mean. This configuration suggests a high-risk level of problematic use, characterized by strong involvement and emerging negative consequences, but less extreme withdrawal symptoms than in the high-risk with withgrawal symptoms group.

The third profile (withdrawal-conflict risk) comprised 45 participants (7.2 %; 95 % CI [33.47, 59.93]). They exhibited relatively low salience and tolerance (below the sample mean), near-average mood modification, moderately elevated relapse, and clearly elevated withdrawal and conflict (about 1 *SD* above the mean). This pattern indicated a group of participants who experience pronounced withdrawal and interpersonal problems despite not reporting high levels of salience or tolerance, suggesting a more specific symptom configuration rather than a simple intermediate severity level. Participants in the fourth profile

**Table 2**
Descriptive statistics for PSMU items (N = 625).

| Variable | Range | Mean | SD | Skewness | Kurtosis |
|---|---|---|---|---|---|
| Salience | 1–5 | 2.96 | 1.21 | −0.06 | −0.99 |
| Tolerance | 1–5 | 2.79 | 1.15 | 0.11 | −0.83 |
| Mood | 1–5 | 2.41 | 1.27 | 0.46 | −0.90 |
| Relapse | 1–5 | 1.89 | 1.00 | 0.88 | −0.04 |
| Withdrawal | 1–5 | 1.58 | 0.87 | 1.38 | 1.02 |
| Conflict | 1–5 | 1.88 | 1.10 | 1.12 | 0.44 |

**Table 3**
Bivariate Pearson correlations with 95 % confidence intervals (N = 625).

| Variable | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1. PSU | | | | |
| 2. FoMO | 0.41*** 0[.34, 0.47] | | | |
| 3. PSMU | 0.62*** 0[.56, 0.66] | 0.40*** 0[.33, 0.46] | | |
| 4. Age | −0.16*** [-0.25, −0.07] | −0.19*** [-0.27, −0.10] | −0.21*** [-0.30, −0.13] | |
| 5. Sex | 0.09* 0[.01, 0.17] | −0.04 [-0.11, 0.04] | 0.16*** 0[.08, 0.24] | −0.10* [-0.18, −0.01] |

*Note.* Values in square brackets indicate the 95 % confidence interval for each correlation. Sex is a point bi-serial correlation (coded as a dummy variable: 0 = Male, 1 = Female). *$p < 0.05$. ***$p < 0.001$.

(low-risk) comprised 169 participants (27.0 %; 95 % CI [147.68, 192.11]). They exhibited slightly elevated salience and near-average tolerance, but below-average mood modification, relapse, withdrawal, and conflict. This pattern is consistent with a low-risk group, characterized by relatively frequent or salient use but few addiction-like symptoms or negative consequences. Finally, participants in the fifth profile (no-risk) comprised 203 participants (32.5 %; 95 % CI [180.30, 227.07]). The exhibited consistently low scores across all six BSMAS components (about 0.5–1 *SD* below the mean), indicating minimal or absent PSMU symptoms.

Assumption checks showed that the homogeneity-of-variance assumption was violated for PSMU (Levene's test: $F(4, 620) = 6.253$, $p < 0.001$). Consistent with this, Welch's ANOVA was applied, which is robust to heteroscedasticity. The ANOVA showed a strong, statistically significant effect of latent profile membership on PSMU scores, $F(4, 199.57) = 506.45$, $p < 0.001$. Means (and SDs) for each profile were as follows: high-risk with withdrawal symptoms, $M = 3.30$ (0.51); 95 % CI [3.19, 3.41]; high-risk without withdrawal symptoms, $M = 3.04$ (0.37); 95 % CI [2.98, 3.10]; withdrawal-conflict risk, $M = 2.29$ (0.30); 95 % CI [2.20, 2.38]; low-risk, $M = 2.09$ (0.28); 95 % CI [2.05, 2.13]; and no-risk, $M = 1.47$ (0.32); 95 % CI [1.43, 1.51]. Games-Howell post-hoc tests confirmed that all pairwise differences between profiles were statistically significant (all $p$-values $< 0.001$). The largest contrasts were observed between the high-risk with withdrawal symptoms and no-risk profiles (difference = 1.83, 95 % CI [1.66, 2.00]) and between the high-risk without withdrawal symptoms and no-risk profiles (difference = 1.57, 95 % CI [1.46, 1.68]). Although the difference between the high-risk with withdrawal symptoms and high-risk without withdrawal symptoms profiles was smaller, it remained statistically significant ($p < 0.001$; difference = 0.26, 95 % CI [0.085, 0.442]). Overall, these findings highlighted substantial heterogeneity in problematic social media use across profiles, reflecting a clear gradient of symptom severity.

**Table 4**
LPA Fit indices for 1–9 class solutions (z-standardized BSMAS items) (N = 625).

| Classes | LogLik | AIC | BIC | SABIC | Entropy | Smallest class size (%) | Min. posterior prob. (%) |
|---|---|---|---|---|---|---|---|
| 1 | −5318 | 10,660 | 10,713 | 10,675 | 1.000 | 100.0 | 100.0 |
| 2 | −4892 | 9822 | 9906 | 9846 | 0.825 | 43.7 | 93.9 |
| 3 | −4733 | 9517 | 9633 | 9550 | 0.825 | 20.2 | 87.3 |
| 4 | −4687 | 9440 | 9586 | 9481 | 0.776 | 17.1 | 83.6 |
| **5** | **−4627** | **9334** | **9512** | **9385** | **0.820** | **7.2** | **75.1** |
| 6 | −4669 | 9432 | 9641 | 9492 | 0.670 | 0.0 | 0.0 |
| 7 | −4470 | 9047 | 9287 | 9115 | 0.779 | 0.0 | 0.0 |
| 8 | −4463 | 9048 | 9319 | 9125 | 0.765 | 0.0 | 0.0 |
| 9 | −4463 | 9062 | 9364 | 9148 | 0.740 | 0.0 | 0.0 |

*Note.* LogLik = Log-likelihood; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample-adjusted BIC.

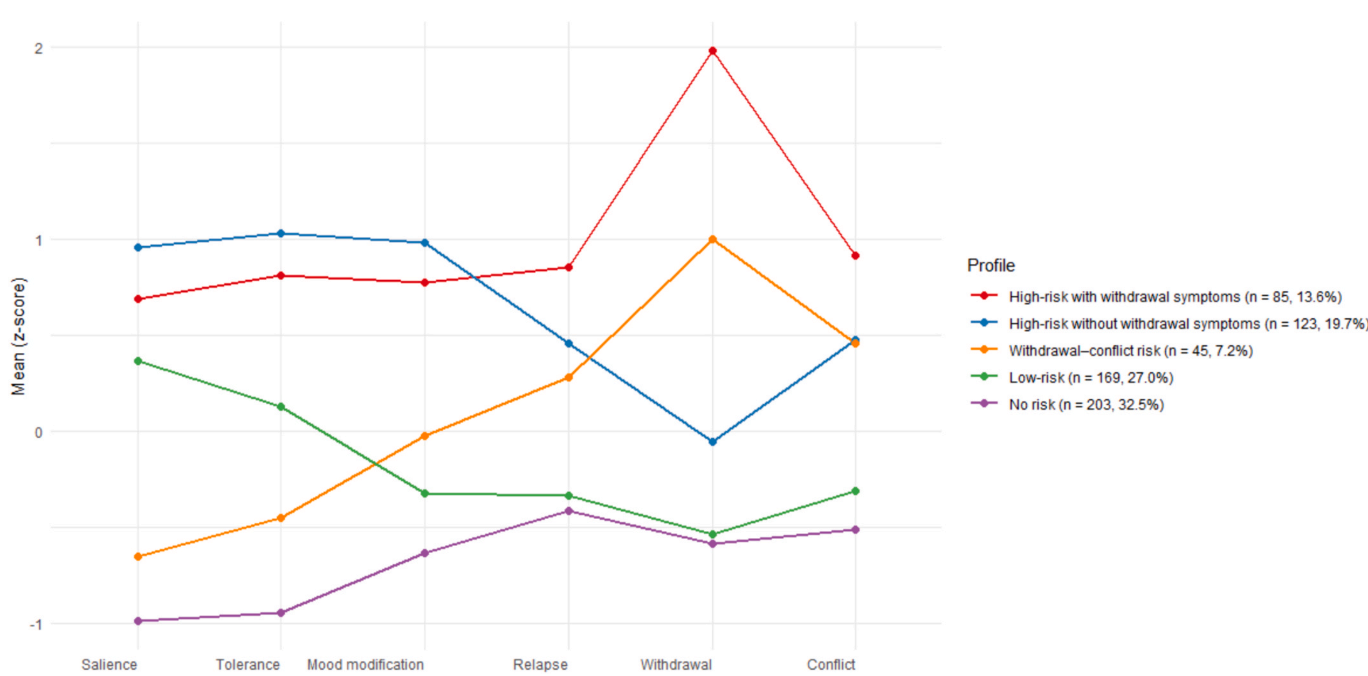


**Fig. 1.** Mean scores across the five dimensions of problematic social media use by latent profile membership.

### 3.3. Group differences

To examine how the five latent profiles differed on FoMO, PSU, and age, Welch's ANOVAs were conducted due to violations of the homogeneity-of-variance assumption across all variables. Effect sizes (η2) and Games-Howell post hoc tests were used to evaluate the magnitude and significance of pairwise differences. The ANOVA results are presented in Table 5. Additionally, Fig. 2 displays the mean levels of FoMO, PSU, and age across the five latent profiles, with error bars representing standard errors.

Overall, these findings provided evidence for the external validity of the proposed six latent profiles, highlighting meaningful psychological and behavioral differences among the identified groups of participants.

### 3.4. Predicting profile membership

A multinomial logistic regression model was conducted to examine whether FoMO, PSU, age, and gender predicted membership in the five latent profiles, using the no-risk profile as the reference category. The model showed good explanatory power (residual deviance = 1230.83; AIC = 1270.83). Table 6 reports the significant predictors for each contrast. All predictors showed low VIF values (1.01–1.21), confirming the absence of multicollinearity in the multinomial model.

PSU emerged as the strongest and most consistent predictor of profile membership. Every one-unit increase in PSU was associated with higher odds of belonging to the high-risk with withdrawal symptoms profile (OR = 11.09), the high-risk without withdrawal symptoms profile (OR = 3.92), low-risk (OR = 1.63), and withdrawal-conflict profiles (OR = 4.06), relative to the no-risk group. FoMO also predicted membership in three profiles: higher FoMO increased the odds of belonging to the high-risk with withdrawal symptoms (OR = 2.91), high-risk without withdrawal symptoms (OR = 3.07), and low-risk (OR = 1.81) profiles, compared to the no-risk profile. Age did not significantly predict membership in any of the profiles. Sex significantly predicted membership in two profiles: females were more likely than males to belong to the high-risk with withdrawal symptoms (OR = 2.39) and high-risk without withdrawal symptoms profiles (OR = 3.13), relative to the no-risk group. Finally, none of the predictors significantly distinguished the withdrawal-conflict profile from the no-risk profile on FoMO or gender, nor the low-risk profile on gender, indicating that PSU was the most robust predictor of latent profile membership.

## 4. Discussion

The present study used a person-centered approach to identify latent profiles of problematic social media use (PSMU) among *Instagram*-using students in Italy. It also examined whether fear of missing out (FoMO), conceptualized as a psychological antecedent, and problematic smartphone use (PSU) predicted membership in these profiles. Using latent profile analysis (LPA), five interpretable profiles emerged: high-risk with withdrawal symptoms (n = 85, 13.6 %), high-risk without withdrawal symptoms (n = 12, 19.7 %), withdrawal-conflict risk (n = 45, 7.2 %), low-risk (n = 169, 27.0 %), no-risk (n = 203, 32.5 %).

Based on the findings, profile-by-profile theoretical interpretation and practical recommendations are provided here, mapping symptom constellations onto process-oriented models (I-PACE; Brand et al., 2016, 2019) and PSMU-specific distinctions between fear-driven and reward-driven pathways (e.g., Wegmann & Brand, 2019). This clarifies whether the profiles reflect mere gradations of severity or qualitatively distinct mechanisms and suggests tailored prevention and intervention strategies.

Participants of the high-risk with withdrawal symptoms profile showed uniformly elevated scores across all six core indicators, with particularly marked increases in withdrawal and conflict. Within the I-PACE framework, this constellation is consistent with convergent vulnerabilities: strong predisposing factors (e.g., affective dysregulation, high FoMO), intense affective and cognitive reactivity to social cues (craving, attentional biases), and impaired executive control that fails to inhibit use online applications and technological tools (Brand et al., 2016, 2019). Moreover, the prominence of withdrawal and conflict suggests that use is maintained by both reward processes and negative reinforcement (continued use to avoid distress), consistent with a clinically salient addictive presentation. Clinically, individuals in this profile should be prioritized for multi-component interventions (e.g., relapse-prevention strategies, inhibitory-control training), thorough functional assessment, and, where appropriate, referral to specialized mental health services.

Participants in high-risk without withdrawal symptoms profile exhibited clearly elevated salience, tolerance, and mood modification, with moderately increased relapse and conflict but less extreme withdrawal than in the high-risk group. This pattern points toward intensifying reward sensitivity and habit formation (e.g., reward-driven processes) that are beginning to yield negative outcomes but may still be amenable to early, selective interventions. For these users, brief, targeted prevention efforts (digital-hygiene measures, notification management, scheduled offline periods), psychoeducation regarding FoMO, and short emotion-regulation skills training may help prevent progression toward higher severity.

Participants of the withdrawal conflict profile, which was the smallest profile, was notable because withdrawal and conflict scores were clearly elevated despite relatively low salience and tolerance and near-average mood modification. Such a profiled suggests that interpersonal problems and withdrawal symptoms can emerge even in the absence of pervasive continuous engagement, possibly due to situational dependence, relationship conflict, or specific contextual reinforcers. This pattern appeared to be qualitatively different from a simple mid-severity step on a continuum. Intervention for this group should focus on interpersonal and contextual factors (e.g., family or couple interventions, conflict-resolution work, targeted psychoeducation), investigating the situational triggers that produce withdrawal and conflict rather than focusing solely on reducing frequency of use.

The low-risk profile included participants with slightly elevated salience and near-average tolerance, with mood modification, relapse, withdrawal, and conflict lying clearly below the sample mean. This pattern suggests relatively frequent or salient social media use without substantial dysregulation or functional impairment. Within the I-PACE architecture, these users may present early-stage involvement or habitual use driven by reward and social convenience rather than loss-of-control addiction. Practical responses should prioritize universal or selective prevention (general digital-literacy and digital-hygiene programs, promotion of balanced online/offline routines), rather than intensive clinical intervention.

**Table 5**
Welch ANOVA results and significant pairwise comparisons.

| Variable | *F*(df1, df2) | *p*; $\eta^2$ | Significant pairwise differences (Games-Howell) |
|---|---|---|---|
| FoMO | 21.81 (4, 201.64) | < 0.001; $\eta^2$ = 0.30 | High-risk with withdrawal symptoms > No-risk; High-risk with withdrawal symptoms > Low-risk; High risk without withdrawal symptoms > No-risk; Low-risk > No-risk; Withdrawal-conflict risk > No-risk |
| PSU | 69.26 (4, 196.94) | < 0.001; $\eta^2$ = 0.58 | High-risk with withdrawal symptoms > All profiles; High risk without withdrawal symptoms > No-risk; High risk without withdrawal symptoms > Low-risk; High risk without withdrawal symptoms > Withdrawal-conflict risk; Withdrawal-conflict risk > No-risk; Low-risk > No-risk |
| Age | 4.28 (4, 171.24) | = 0.003; $\eta^2$ = 0.09 | High-risk with withdrawal symptoms < No-risk |

*Note*. PSU = Problematic smartphone use. FoMO = Fear of missing out.

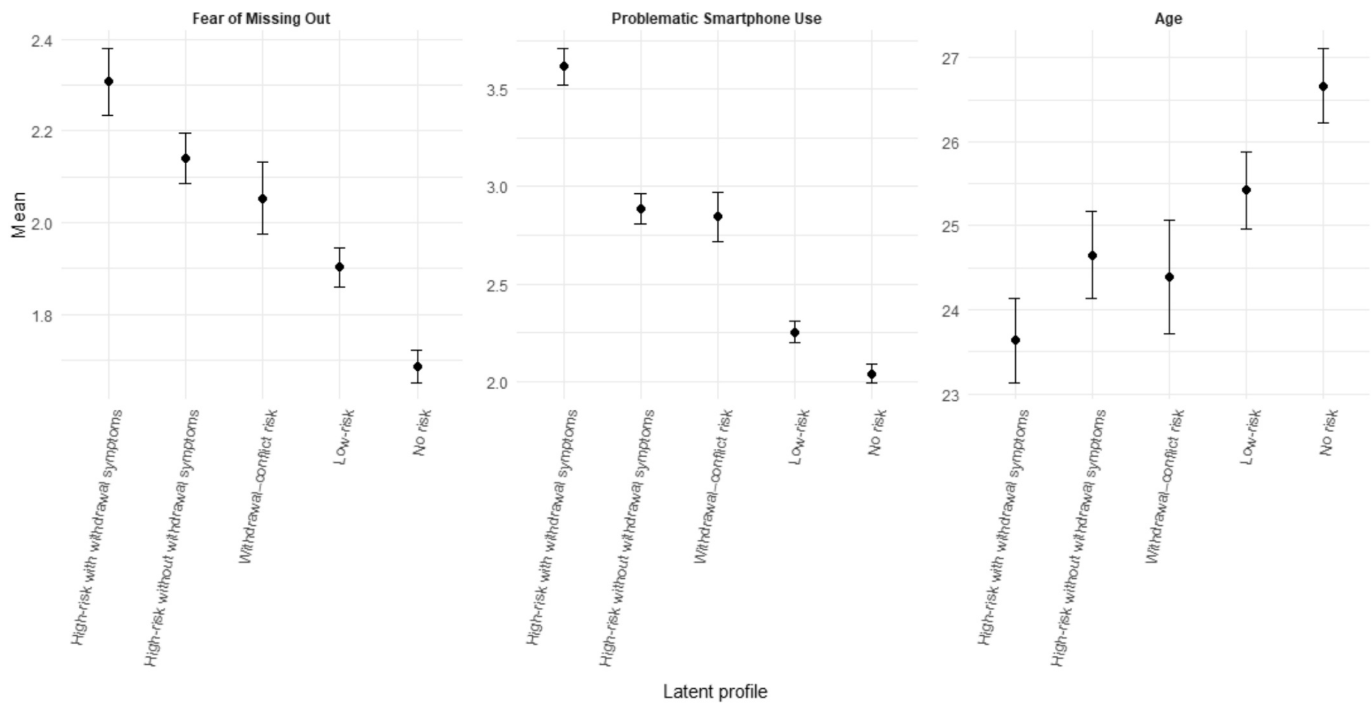


**Fig. 2.** Mean levels of fear of missing out (FoMO), problematic smartphone use (PSU), and age across the five latent profiles of problematic social media use (PSMU. Profiles are ordered by severity. Bars represent standard errors of the mean.

**Table 6**
Multinomial logistic regression predicting profile membership.

| Class | Predictor | B | SE | z | p | OR |
|---|---|---|---|---|---|---|
| High-risk with withdrawal symptoms | FoMO | 1.07 | 0.34 | 3.17 | 0.002 | 2.91 |
| | PSU | 2.41 | 0.26 | 9.18 | < 0.001 | 11.09 |
| | Sex (1 = female) | 0.87 | 0.40 | 2.15 | 0.031 | 2.39 |
| High risk without withdrawal symptoms | FoMO | 1.12 | 0.28 | 4.03 | < 0.001 | 3.07 |
| | PSU | 1.37 | 0.21 | 6.63 | < 0.001 | 3.92 |
| | Sex (1 = female) | 1.14 | 0.32 | 3.54 | < 0.001 | 3.13 |
| Low-risk | FoMO | 0.60 | 0.25 | 2.42 | 0.016 | 1.81 |
| | PSU | 0.49 | 0.18 | 2.70 | 0.007 | 1.63 |
| Withdrawal-conflict risk | PSU | 1.40 | 0.27 | 5.28 | < 0.001 | 4.06 |

*Note*. Reference group: No-risk. PSU = Problematic smartphone use. FoMO = Fear of missing out.

Finally, the no-risk profile includes participants with uniform low scores across all six indicators indicating normative engagement with minimal or absent PSMU symptoms. For this group, prevention efforts are best conceptualized as universal and educational rather than clinical, focusing on maintaining healthy habits and awareness of potential risks rather than attempting to modify problematic patterns that are not yet present.

These results are consistent with previous research suggesting that university students may be more vulnerable to PSMU compared to general population samples (Bányai et al., 2017; Cheng et al., 2022; Cui et al., 2023). Unlike prior LPA studies that classified users into three broad profiles (e.g., high, moderate, and mild-risk: Li et al., 2020; Stănculescu & Griffiths, 2022), the five-profile solution identified in this study provided a more nuanced picture of risk, particularly distinguishing between mild-stage engagement, mood-driven use, and at-risk. Moreover, the symptom-level analysis demonstrated essential differences in how addiction components are expressed across profiles.

Salience and tolerance were clearly elevated in the high-risk with withdrawal symptoms and high-risk without withdrawal symptoms profiles, consistent with their conceptualization as early indicators of intensified engagement and habitual use (Andreassen et al., 2012; Peng & Liao, 2023). These symptoms showed a graded decrease across the withdrawal–conflict, low-risk, and no-risk profiles, supporting their role as markers of general involvement rather than severe dysregulation. Withdrawal and conflict showed a more specific pattern: both were highest in the high-risk with withdrawal symptoms profile and remained substantially elevated in the withdrawal-conflict profile, in line with their interpretation as core symptoms signaling functional impairment and emotional dependency (Moretta et al., 2022).

Therefore, these dimensions appear to capture the progression from intensive involvement to dysregulated use. Mood modification, in contrast, was highest in both the high-risk with withdrawal symptoms and high-risk without withdrawal symptoms profiles, with intermediate levels in the withdrawal-conflict profile and clearly lower values in the low-risk and no-risk groups. This suggests that mood regulation motives characterize users at multiple risk levels, particularly those with heightened but not necessarily dysfunctional engagement (Yang et al., 2025). Rather than distinguishing the low-risk profile, mood modification appears to operate as a transitional or cross-cutting symptom. Overall, this pattern is consistent with the dual-process perspective proposed by Billieux et al. (2019), in which "peripheral" symptoms (e.g., salience, tolerance) reflect heightened engagement, whereas "core" symptoms (e.g., withdrawal, conflict) index more severe dysregulation. The configurations observed across profiles strengthen the value of integrating person-centered and symptom-centered approaches to capture heterogeneous developmental pathways of problematic social media use.

Consistent with theoretical expectations and previous empirical evidence, the present study's results confirm the association between PSMU and PSU (Elhai et al., 2025; Li et al., 2023; Marino et al., 2021; Soraci et al., 2025). Individuals in the high-risk with withdrawal symptoms group reported significantly higher PSU scores, with nearly a tenfold increase in the odds of classification compared with the other group profiles. These findings align with the I-PACE model (Brand et al., 2016, 2019), which posits that problematic online use stems from a dynamic interplay between predisposing variables (e.g., personality, affective symptoms), cognitive responses (e.g., fear of missing out), and reinforcement processes (Servidio et al., 2025). High PSU among some participants may reflect the adoption of maladaptive coping strategies, reward sensitivity, and impaired inhibitory control.

FoMO also emerged as a significant predictor for several profiles in the multinomial logistic model. Higher FoMO scores were associated with greater odds of membership in the high-risk with withdrawal symptoms, high-risk without withdrawal symptoms, and low-risk profiles compared to the no-risk group. In contrast, FoMO did not significantly predict membership in the withdrawal-conflict risk profile. Overall, these findings indicate that FoMO functions as a psychological vulnerability factor that increases the likelihood of belonging to profiles characterized by elevated, but not necessarily dysregulated, patterns of social media use. This interpretation aligns with previous research showing that FoMO heightens sensitivity to online social cues, intensifies checking behaviors, and reduces satisfaction with offline interactions (Przybylski et al., 2013; Servidio et al., 2024).

Sex differences also emerged in the prediction of profile membership. Females were significantly more likely than males to belong to the high-risk with withdrawal symptoms and high-risk without withdrawal symptoms profiles, whereas no sex differences were found for the other profiles. This result is consistent with prior studies suggesting that females tend to use smartphones and social media for relational maintenance, emotional communication, and social connection (Bányai et al., 2017; Stănculescu & Griffiths, 2022; Su et al., 2020), which may increase vulnerability to problematic use when such interactions become compulsive or emotionally driven.

Significant group differences in FoMO and PSU provided external validity for the profiles. The high-risk with withdrawal symptoms group consistently showed the highest values on both indicators, reinforcing the theoretical coherence of the latent classification. Games-Howell post hoc comparisons showed that PSU scores were significantly higher in the high-risk with withdrawal symptoms, high-risk without withdrawal symptoms, withdrawal-conflict risk, and low-risk profiles compared to the no-risk group. Similar patterns emerged for FoMO, with the high-risk with withdrawal symptoms, high-risk without withdrawal symptoms, and withdrawal-conflict risk profiles scoring significantly higher than the no-risk profile. Across all variables, the no-risk group consistently reported the lowest levels, confirming the robustness of the latent profiles.

Overall, the present study advances a person-centered understanding of PSMU, highlighting how combinations of psychological factors contribute to qualitatively distinct use profiles. The results have meaningful implications for intervention design. For instance, prevention programs targeting FoMO and PSU might be more effective for those at high-risk without withdrawal symptoms. At the same time, behavioral regulation strategies and digital hygiene education could be better suited for individuals in the high-risk with withdrawal symptoms category. In sum, the integration of theory-driven predictors with LPA methodology provided a refined framework for understanding individual differences in PSMU.

### *4.1. Limitations and future directions*

Although the results of the present study are promising, several limitations should be acknowledged. First, the sample consisted exclusively of university students (N = 625), with a notable overrepresentation of female participants (72.5 %) and a mean age of approximately 22.6 years. Recruitment via *Instagram* social media postings and in-class invitations may have selectively attracted individuals who were already highly engaged online, potentially limiting the generalizability of the findings to adolescents, older populations, or non-university settings. The voluntary and uncompensated nature of participation may also have introduced self-selection bias, potentially inflating levels of PSMU and PSU relative to the general population.

Moreover, the generalizability of the findings is constrained by the convenience sampling strategy, the female overrepresentation, and the exclusive focus on *Instagram*. Because *Instagram* is a visually oriented platform characterized by algorithmically curated feeds, social comparison dynamics, and short-lived content, its affordances may elicit distinct patterns of problematic use that differ from those emerging on platforms such as TikTok, Snapchat, or Facebook. Therefore, the present results should be interpreted as specific to *Instagram*-using university students in Italy rather than to social media users more broadly. Future studies should employ multi-platform assessments or stratified sampling strategies to determine whether similar symptom configurations and predictors emerge across different digital environments and demographic groups.

A further limitation concerns the reliance on self-report measures, administered via an online survey platform (*LimeSurvey*). While facilitating large-scale data collection, self-report instruments are vulnerable to social desirability bias and recall inaccuracies, particularly regarding estimated weekly *Instagram* use and self-perceived addiction symptoms. The absence of objective usage data (e.g., app-based tracking) precludes validation of self-reported behaviors. Additionally, the cross-sectional design prevents causal inferences about the directionality of associations between FoMO, PSU, and PSMU. Although the findings align with theoretical models such as I-PACE, unmeasured factors (e.g., academic stress, social support) may have influenced the observed relationships. Moreover, the instruments differed in their temporal reference: PSMU symptoms were rated with respect to the past 12 months, whereas FoMO and problematic smartphone use were assessed in line with their original, non-specified time-frame and referred to participants' typical experiences. Although these constructs are generally regarded as relatively stable tendencies among young adults, such discrepancies in recall periods may have introduced additional measurement error and should be addressed in future studies by harmonizing time frames or combining self-reports with objective usage indicators.

Methodologically, the choice of a five-profile LPA solution, though supported by fit indices and interpretability, reflects subjective judgment and may not replicate across different samples or cultural contexts. The identification of distinct profiles, such as high-risk without withdrawal symptoms or low-risk, might vary in prevalence or configuration in other populations. Furthermore, while PSU emerged as the most consistent and robust predictor of profile membership, FoMO played a more nuanced role, primarily associated with high-risk with withdrawal symptoms and high-risk without withdrawal symptoms profiles. This highlights the need to replicate and extend these findings in more heterogeneous, longitudinal samples.

Additionally, another limitation of the present study is that LPA was conducted using *tidyLPA*, which, while correcting standard errors, does not estimate additional parameters available in other software such as *Mplus* (e.g., within-class variance–covariance structures). Although primary parameter estimates typically remain consistent across these approaches, the absence of these advanced modelling techniques may affect the accuracy of the profiles. Future research should replicate these analyses using software such as *Mplus* to verify and, if possible, enhance the robustness of the identified profiles.

Although additional constructs (e.g., emotion regulation, loneliness, impulsivity) could have broadened the model's explanatory scope, the present study aimed to test whether core, theoretically central predictors were sufficient to differentiate symptom-level heterogeneity in PSMU. Expanding the set of covariates would have increased model complexity and reduced the interpretability of profile differentiation, contrary to recommendations for maintaining parsimony in person-centered analyses. However, future research should integrate a wider range of psychological variables to situate symptom-level profiles within broader models of behavioral addiction.

Finally, the present study assessed only *Instagram* use as an indicator of social media engagement. This narrow focus may not fully capture the diversity of digital habits across emerging platforms such as *TikTok* or *BeReal*, which could involve distinct patterns and dynamics of problematic use. Future research should adopt a broader scope, incorporating platform-specific behaviors to provide a more comprehensive understanding of online habits and their clinical implications. Additionally, longitudinal studies are needed to explore how dispositional, relational, and contextual factors interact over time to shape trajectories of digital media engagement and risk.

## 5. Conclusions

The present study employed a person-centered approach to identify distinct latent profiles of problematic social media use (PSMU) among university students, resulting in five interpretable profiles: high-risk with withdrawal symptoms, high-risk without withdrawal symptoms, withdrawal-conflict risk, low-risk, and no-risk. These profiles differed in their patterns of addiction-related symptoms, highlighting the heterogeneity in PSMU manifestations. The findings underscore the importance of considering both symptom severity and configuration when assessing risk, because different profiles exhibited unique combinations of salience, tolerance, mood modification, withdrawal, relapse, and conflict.

Consistent with theoretical expectations, PSU, FoMO, and sex were found to be significant predictors of profile membership. Individuals in the high-risk with withdrawal symptoms profile reported substantially higher PSU levels, aligning with the perspective of the I-PACE model, which underlines that maladaptive coping and reward sensitivity experiences contribute to compulsive digital behaviors. FoMO was particularly associated with high-risk with withdrawal symptoms, high-risk without withdrawal symptoms, and low-risk profiles, reinforcing its role as both an early vulnerability factor and a maintaining mechanism in PSMU. Notably, sex differences were observed, with females more likely to belong to the high-risk profiles, possibly due to heightened social and emotional engagement motives. These findings align with prior research suggesting sex-specific patterns in digital media use.

Overall, this research advances the understanding of PSMU by integrating person-centered and symptom-centered approaches, offering a distinguishing framework for identifying at-risk individuals and tailoring interventions based on distinct psychological and behavioral profiles. Future studies should explore longitudinal trajectories to determine how risk profiles evolve over time and further examine the interplay between PSMU, PSU, and underlying psychological mechanisms.

Although the study provides meaningful insight into symptom-level heterogeneity in PSMU, the findings should be interpreted with caution given the reliance on a convenience sample of predominantly female *Instagram* users. The platform-specific nature of *Instagram* may also limit generalizability to other social media ecosystems with different affordances. Future research using multi-platform designs or more representative sampling procedures is needed to determine the extent to which these latent profiles extend beyond this demographic and platform context.

## Author agreement

All authors have seen and approved the final version of the manuscript.

## Compliance with ethical standards

- Informed consent was obtained from all participants included in the study.

## Role of funding sources

- This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
- ZH has received financial support from the National Research, Development and Innovation Fund. Project no. STARTING 150862 whch was implemented with support provided by the Ministry of Culture and Innovation of Hungary from the National Research, Development and Innovation Fund, financed under the STARTING_24 funding scheme.

## CRediT authorship contribution statement

**Rocco Servidio:** Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Paolo Soraci:** Methodology, Data curation, Conceptualization. **Zsolt Demetrovics:** Writing – review & editing, Writing – original draft. **Zsolt Horváth:** Formal analysis, Data curation. **Mark D. Griffiths:** Writing – review & editing, Writing – original draft.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.abrep.2025.100655.

## Data availability

Data will be made available upon reasonable request to the first author.

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