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Beyond Screen Time: Compulsive and Distress-Related Profiles of Social Media Use in Young Adults

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Abstract

Time spent on social media is widely used as an indicator of problematic use, yet time may say little about how use becomes problematic. We examined whether young people with similar usage time show different psychological profiles. In this cross-sectional study, 530 young people in Spain (68.3% women; mean age 19.7 years) completed measures of problematic social media use, digital compulsivity, emotional distress, emotion regulation, and self-reported daily social media time. Hierarchical and k-means cluster analyses (three clusters) were conducted on unstandardized scores and complemented by ANOVA, post hoc tests, equivalence tests, and external validation variables. Internal indices indicated modest cluster structure. Three profiles emerged: a compulsive-use profile, with the highest problematic use and compulsivity; a distress-associated profile, with the highest emotional distress despite moderate problematic use; and a functional profile, with lower use, fewer symptoms, and higher emotion regulation. The compulsive-use and distress-associated profiles did not differ in daily time (3.67 vs. 3.43 hours, $p = .642$; equivalent within ± 0.75 hours) but differed markedly in compulsivity, problematic use, and distress. Daily time was the least discriminative variable ($R^2 = .05$), whereas problematic use ($R^2 = .66$) and compulsivity ($R^2 = .49$) discriminated most. On variables not used in the clustering (meaning in life, emotional eating, family communication, and smartphone use), the functional profile differed from both problematic profiles, whereas these two did not differ from each other. These cross-sectional findings suggest that screening and prevention should look beyond screen time, although the cluster structure was weak and the profiles require replication.

1. Introduction

The global proliferation of social media (SM) has transformed human interaction and has sparked an intense debate in psychological research about its impact on mental health. PSMU (Problematic Social Media Use) is not officially recognized as a disorder in either the DSM-5 or the ICD-11. However, it is considered a growing public health problem (WHO, 2024) and mental health disorders more broadly represent a leading source of global disability burden, with depressive disorders ranking as the second highest cause of years lived with disability worldwide (Psychiatry, 2024).

Problematic social media use is defined as a pattern of social media use characterised by loss of control, preoccupation, and functional impairment across personal, professional, and social domains (Cataldo et al., 2022). The theoretical model of PSMU conceptualizes social media use along a continuum that, at its problematic extreme, shares characteristics with behavioural addictions such as excessive preoccupation, loss of control, compulsive use, and interference with vital activities, as described in Griffiths' (2005) components model of behavioural addiction.

The present study focuses on three key dimensions that have been identified as central to understanding heterogeneity in PSMU: (1) compulsivity and problematic use patterns, (2) psychological distress (depression, anxiety, and stress), and (3) emotional regulation. Each of these dimensions is reviewed in turn below.

Compulsivity and impulsivity are related but distinct constructs relevant to additive behaviours. Impulsivity refers to the tendency to act without adequate forethought or consideration of consequences and is associated with reward sensitivity and the pursuit of immediate gratification. Compulsivity, by contrast, refers to repetitive, inflexible behaviours that persist despite negative consequences, and is more closely linked to habitual or automatic responding. In the context of addictions, impulsivity would initially manifest in the pursuit of use for its positive reinforcement, until control is gradually lost and compulsive seeking appears, resulting in problematic use or addiction (Pedrero-Pérez et al., 2021; De Sola et al., 2016). In this sense, impulsivity is considered not only a predictive factor in the development of additive behaviours (Belin et al., 2008; Makarenko et al., 2025), but also a key element in the maintenance of continued social media use (Rothen et al., 2018; Turel & Bechara, 2017; Wu et al., 2013). Compulsivity, in turn, plays a significant role as a precursor to additive behaviours (De Sola et al., 2016) and has been closely linked with difficulties in exercising self-regulated control over social media use (Bocci-Benucci et al., 2025).

The population most affected by this condition is young people (Cambra et al., 2020) because of their age and the stage of neurodevelopment they are undergoing, characterized by neurobiological immaturity and reduced regulatory capacity (Hardy et al., 2019), which favours impulsive behaviours. Furthermore, this stage also involves the formation or search for identity (Granados et al., 2020; Klimstra et al., 2010; Erikson, 1972), often through self-comparison with peer groups (Ragelienė, 2016). Billieux et al. (2015) showed that, in these cases, excessive and problematic use could be driven by the need for excessive reassurance, as a way of seeking interpersonal validation and maintaining social connectedness. This can lead to the emergence of addiction-like symptoms (Pivetta et al., 2019).

Although there is a consistent theoretical and empirical basis associating social media use with various indicators of emotional distress—such as increased symptoms of anxiety, stress and depression, loneliness, low self-esteem, suicidal ideation, and lower life satisfaction (Al Ahbabi et al., 2024; Diaz & Amaya, 2012; Huang et al., 2020; Ko et al., 2014; Lian et al., 2018; Twenge & Martin, 2020), among others —the perception among young people of social media is very positive, as it facilitates communication and entertainment (Varchetta et al., 2023). And certainly, some studies suggest that social media use does not necessarily produce negative or additive effects (Carbonell & Oberst, 2015; Valencia-Ortiz et al., 2021; Wadsley & Ihssen, 2023); on the contrary, it could improve perceived quality of life, as it facilitates communication and social support (Alivi et al., 2023).

One probable reason for these controversies in findings is the traditional methodological approaches used in research, such as cross-sectional studies (Portnoy & Eliason, 2020) and correlation/regression analyses, which present significant limitations. These methods cannot establish causal directionality (Portnoy & Eliason, 2020) and are unable to determine whether pre-existing emotional distress leads to greater social media use or vice versa (Odgers & Jensen, 2020). Furthermore, they are methodologically insufficient to identify whether effects differ across specific subgroups of users (Hair et al., 2019).

In this way, the proposition of reverse causality envisions the use of social networks as an avoidance strategy aimed to alleviate already existing symptoms in individuals (Li et al., 2023; Peng & Liao, 2023), rather than as a direct cause of those symptoms.

The vulnerability-stress model supports this theory, suggesting that the negative impact of social networks is greater in individuals who already have a preexisting vulnerability to mental health problems (Monroe & Simons, 1991; Ellis et al.; 2011; Jiao et al., 2025). Regarding the bidirectional causality perspective, Social Comparison Theory (Festinger, 1954) posits that constant exposure to idealized versions of others' lives online (Kang et al., 2025; Meier & Johnson, 2022) can foster feelings of inadequacy, low self-esteem, and depression (Rüther et al., 2023; Vogel et al., 2014). Likewise, it has been consistently shown that increased use of social networks correlates with greater social comparison, which in turn predicts higher levels of anxiety and depression (Verduyn et al., 2022; Vogel et al., 2014).

Time spent using social media has proven highly relevant for associated consequences. Prolonged use of Instagram and TikTok (more than 3 hours) has been associated with higher levels of self-criticism and body dissatisfaction among young Spaniards aged 18 to 35 (Varaona et al., 2024; Ariana et al., 2024). A greater prevalence of depressive and anxiety symptoms has been reported when use exceeded one hour per day (Mundy et al., 2021), with an approximately 13% increased risk of presenting these symptoms as this threshold is surpassed (Liu et al., 2022). It is also postulated that time is relevant due to its engrossing capacity; the Displacement Theory (Przybylski & Weinstein, 2017) suggests that excessive time spent on social media can replace essential activities beneficial for mental health, such as sleep or face-to-face social interactions (Hökby et al., 2025; Przybylski & Weinstein, 2017). In fact, intensive social media use has been linked with reduced sleep quality—a known risk factor for depression and anxiety (Twenge & Martin, 2020; Woods & Scott, 2016).

Another relevant factor that has been studied within this construct is emotional regulation. In addiction to quantity of use, individual vulnerability factors such as impulsivity or difficulties in emotional regulation are critical. The digitalization of interpersonal communication has profoundly changed the way young people express and manage their emotions (Prikhodko et al., 2020), highlighting that problematic social media use is associated with greater difficulties in emotional regulation (Elkin et al., 2025; Piccerillo & Digennaro, 2025). Specifically, emotional regulation has been observed as a moderating variable in the effects of social media addiction, with findings showing that those individuals who display better self-regulation experience fewer negative impacts, potentially acting as a protective factor (Khan et al., 2021) consistent with the vulnerability-stress model (Monroe & Simons, 1991; Ellis et al., 2011; Jiao et al., 2025).

Despite the considerable volume of existing research, as can be seen, relevant questions surrounding this topic remain unresolved. It is still necessary to coherently integrate variables that have shown to be key, such as impulsivity, emotional regulation, or psychological vulnerability. Examining how these characteristics are jointly expressed could better reflect actual use and its features. With the aim of

shaping a more comprehensive model that allows for an individualized understanding of the various manifestations of the problem, we consider cluster analysis to be a particularly appropriate methodological approach for this purpose (Hair et al., 2019), as it enables the identification of naturally occurring subgroups of users who share similar patterns across multiple variables simultaneously, something that variable-centred approaches such as regression cannot achieve. This person-centred approach is especially suited to capturing the heterogeneity inherent in PSMU, where the same outcome may arise through different combinations of risk and protective factors. A further reason for this approach is that time spent on social media, the most widely used indicator of exposure, may not capture how use becomes problematic: users with similar usage time may differ substantially in compulsivity and distress.

The central research question addressed in this study is therefore: are there empirically distinguishable profiles of social media users that differ in problematic use, compulsivity, psychological distress, and emotional regulation, and do these profiles differ in the time spent on social media? The study is exploratory; we examine whether users with comparable usage time show qualitatively different profiles. Identifying such profiles would allow for a more individualized understanding of PSMU and could inform the development of profile-specific preventive and psychoeducational strategies.

2. Materials and Methods

2.1 Participants

A total of 530 young people took part, recruited through non-probabilistic incidental snowball sampling in two waves (February-April 2024, n = 172; September-November 2024, n = 358), mostly students from the Francisco de Vitoria University. The sample consisted of 362 women (68.3%), 164 men (30.9%), and 4 participants who preferred not to disclose their gender (0.8%), aged between 18 and 25 years (M = 19.70 years; SD = 1.75).

Regarding educational level, 85.1% of the sample were pursuing an undergraduate degree, 7.3% were enrolled in a master's program, and 1.5% were doing a vocational course. Sociodemographic characteristics by cluster are shown in Table 1.

Table 1

Sociodemographic Characteristics by Cluster

Gender	**PCU (n = 131)**	**PAD (n = 164)**	**FP (n = 221)**	**Total (n = 516)**
Women	104 (79.4%)	124 (75.6%)	126 (57.0%)	354 (68.6%)
Men	27 (20.6%)	39 (23.8%)	93 (42.1%)	159 (30.8%)
Prefer not to say	0 (0.0%)	1 (0.6%)	2 (0.9%)	3 (0.6%)
Age				
M (SD)	19.39 (1.53)	19.57 (1.68)	19.95 (1.88)	19.70 (1.75)
Range	17–24	17–25	17–25	17–25

Note. PCU = Problematic Compulsive Use; PAD = Psychological Distress-Associated profile; FP = Functional Profile.

Inclusion criteria consisted of being between 18 and 25 years old, being enrolled in a higher education program, and providing informed consent. Exclusion criteria included being outside the age range, not using any social media, and submitting incomplete responses.

The present study uses the same sample as Carbonell-Colomer et al. (2025), published in Frontiers in Psychology, which reported descriptive analyses of social media use patterns in Spanish university students. The cluster solution reported here is also the one used by Carbonell-Colomer et al. (2026), published in Frontiers in Psychiatry, in which 50 participants from this sample were assigned to the three profiles by nearest centroid for a psychophysiological study (inhibitory control, heart rate variability, salivary alpha-amylase, and oxytocin). That article reported the final cluster centres; the present manuscript provides the full description, internal and external validation, and equivalence testing of the profiles, which were not addressed there.

2.2 Procedure

All participants completed the questionnaire online via the Qualtrics platform in two waves: February 22 to April 2024 (n = 172) and September to November 2024 (n = 358). Researchers visited classrooms outside of scheduled teaching time (during breaks or after class) to present the study and invite participation. Participation was entirely voluntary, and no academic credit, grade benefit, or other incentive was offered. After providing informed consent, participants completed sociodemographic items followed by the instruments described in Section 2.3. On average, completion took 25 minutes. Ethics statement. The study was conducted in accordance with the Declaration of Helsinki. The project (no. 41/2024) was favourably evaluated by the Francisco de Vitoria University Research Ethics Committee on 23 May 2024 (certificate issued 1 September 2024). The 172 participants of the first wave responded before that session. Participants provided informed consent electronically before starting the

questionnaire. A sensitivity analysis restricted to participants who responded after 23 May 2024 is reported in the Results.

2.3 Variables and Instruments

Social Media Usage (Ad hoc questionnaire): daily usage time for each social network was obtained through an ad hoc questionnaire (Carbonell-Colomer et al., 2025) in which participants were asked to report the time displayed in the Digital Well-Being or Screen Time settings of their smartphone for the previous day. Although the figures originate from the device's own usage records, they were transcribed by participants for the previous day and are therefore treated as self-reported data. The platforms assessed were WhatsApp, Instagram, TikTok, and Twitter, which represent the most frequently used social networks among Spanish university students (Carbonell-Colomer et al., 2025). A validated alternative measure was not used, as no standardised instrument currently exists for collecting platform-specific screen time data directly from device settings.

Problematic Smartphone and Social Media Use (PSNUSS). To assess problematic use of social networks, the Problematic Smartphone and Social Networks Use Scale (PSNUSS), developed and validated among Spanish youth by some of the present authors (Luque-Reca et al., 2024; the acronym used in the original validation study is PSSNUS), was used. The scale was previously published and was not developed for this study. This instrument assesses patterns of problematic smartphone and social network use that negatively affect users' personality and social functioning. The scale consists of 18 items assessed on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree) and has a Cronbach's alpha of 0.89 in its validation study; in the present sample, internal consistency was good (Cronbach's α = .842, n = 530). It includes five factors: psychological dependence, preference for online interaction, desire for social recognition, controlling others, and loss of productivity. The overall average is calculated by dividing the total score by the number of items (18), resulting in a mean of 3.12 in the validation (Luque-Reca et al., 2024).

Depression, Anxiety and Stress Scales-21 (DASS-21). The DASS-21 scale is a self-report instrument designed to assess the severity of emotional symptoms of depression, anxiety, and stress. The scale includes 21 items scored on a 4-point Likert scale from 0 (*Did not apply to me at all*) to 3 (*Applied to me most of the time*). It consists of three subscales: Depression, Anxiety, and Stress. The total score for each dimension is obtained by summing the corresponding 7 items and multiplying the result by two. The Spanish version demonstrated excellent reliability, with Cronbach's alpha values as high as 0.96 for the total scale. In the present sample, the scale also demonstrated excellent internal consistency (Cronbach's α = .938, n = 516). Its hierarchical structure and psychometric properties have been confirmed in the Spanish population in studies with large samples (Ruiz et al., 2017). The DASS-21 lacks official clinical cut-off points both in the original and Spanish adaptations (Daza et al., 2002; Fonseca-Pedrero et al., 2010; Ruiz et al., 2017). However, the normative ranges suggested in the literature were used to contextualize general severity: 0–20: very low; 21–40: mild; 41–60: moderate; 61–80: high; >80: very high (Daza et al., 2002; Fonseca-Pedrero et al., 2010; Ruiz et al., 2017).

Obsessive-Compulsive Drug Use Scale adapted to ICT (OCDUS-ICT; Pedrero-Pérez et al., 2021): the OCDUS-ICT is a 12-item self-report scale developed to assess compulsivity associated with mobile phone and social media use. Items are scored on a 7-point Likert scale ranging from 1 (Never) to 7 (All the time), with a maximum possible score of 84. Items 6 and 12 are reverse scored. Higher scores indicate greater compulsivity. The scale demonstrated high internal consistency in its Spanish validation study (Cronbach's α = .87; Pedrero-Pérez et al., 2021), and in the present sample internal consistency was also good (Cronbach's α = .835, n = 530).

Wong and Law Emotional Intelligence Scale (WLEIS). The WLEIS was developed by Wong and Law (2002) and is a self-report questionnaire designed to measure perceived emotional intelligence, based on the Mayer and Salovey ability model. The scale consists of 16 items scored on a 7-point Likert scale from 1 (completely disagree) to 7 (completely agree). A Spanish version has been validated in adults (Extremera et al., 2019), supporting the four-factor structure and showing adequate internal consistency and criterion validity. It includes four subscales: Self-Emotions Appraisal, Others' Emotions Appraisal, Use of Emotion, and Regulation of Emotion (Wong & Law, 2002). In this study, only the last four items of the scale were used, corresponding to the measure of emotional regulation, with a maximum possible score of 28. In the present sample, this four-item subscale demonstrated good internal consistency (Cronbach's α = .877, n = 530).

2.4 Statistical analysis

SPSS version 25 software was used for data processing.

A total of 536 responses were collected. Six were excluded due to incomplete item responses, resulting in a final analytical sample of N = 530. Missing data analysis revealed that the DASS-21 subscale had 20 additional missing values (3.7%), which were handled through listwise deletion for analyses involving this variable (n = 516). The remaining variables presented no missing data beyond the initial exclusions. Given the low proportion of missing data, no imputation procedures were applied.

A hierarchical cluster analysis was performed to find possible homogeneous groups within social media usage patterns, using the average linkage between groups method (BAVERAGE) with squared Euclidean distance as the dissimilarity measure. Variables were entered in their original metric without prior standardization. The resulting dendrogram (see Appendix 1) suggested a three-cluster solution, based on the pronounced increase in agglomeration coefficients when merging from three to two clusters (from 1164.848 to 1898.875, an increment of 733.727), consistent with the elbow criterion, which was used to define the initial cluster centres for the subsequent k-means analysis. The k-means algorithm converged after 6 iterations, with a maximum absolute coordinate change of 0.000 in the final iteration, and a minimum distance between initial centres of 69.788.

To examine the differences between the identified groups, ANOVA was applied after performing Levene's tests of homogeneity of variances for each of the variables. Given the significant overall effects, *post hoc*

tests were performed, specifically the Games-Howell test for variables with heterogeneous variances and Bonferroni for those with homogeneous variances.

Structural quality and internal validity indicators were calculated, including explained variance (R^2) and the sum of squares ratio between groups and total to assess the discriminant capacity of the variables, together with silhouette, Calinski-Harabasz, and Davies-Bouldin indices. Stability was assessed with 500 bootstrap resamples and 500 random split-halves in which k-means was seeded at the final centres (adjusted Rand index, ARI, and Jaccard coefficients). Because clustering was performed on unstandardized scores, variables with greater variance weigh more heavily in the Euclidean distance (in the clustering space, daily hours accounted for 0.7% of the total variance, versus 41.8% for PSNUSS, 27.2% for DASS-21, 26.3% for OCDUS-ICT, and 4.1% for WLEIS), so a sensitivity analysis clustered the standardized variables (k-means, k = 3 and 4, 100 random starts). Equivalence of daily hours between PCU and PAD was tested with two one-sided Welch tests (TOST), using margins of d = ± 0.3 and d = ± 0.5 (± 0.67 and ± 1.12 hours). External validity was examined with variables not used in the clustering (MLQ presence and search for meaning, EEQ, CI, AUDIT, and daily smartphone hours) using Welch ANOVA with Holm correction and Games-Howell post hoc tests. A final sensitivity analysis excluded participants who responded before the Ethics Committee session (23 May 2024).

The k-means algorithm iteratively reassigns cases to the nearest cluster centroid until convergence is achieved (i.e., no further meaningful change in centroid positions occurs). In the present analysis, convergence was reached after 6 iterations, with a maximum absolute coordinate change of 0.000 in the final iteration, confirming a stable solution. For reproducibility, the final cluster centres (Table 3) can be used as initial centres in SPSS QUICK CLUSTER.

3. Results

Firstly, after performing the hierarchical cluster analysis, the resulting dendrogram (Appendix 1) suggested the existence of three main groups, a number that was used as a preliminary criterion to define the number of clusters.

The agglomeration schedule confirmed this decision, showing a pronounced increase in the agglomeration coefficient when moving from three to two clusters (from 1164.848 to 1898.575, an increment of 733.727), indicating that merging beyond three clusters would result in a substantial loss of information. This pattern is consistent with the elbow criterion for cluster selection.

Internal validity indices were computed on the 516 cases with complete data. For the retained three-cluster solution, the silhouette coefficient was 0.23 in the original metric used for clustering (Calinski-Harabasz = 250.6; Davies-Bouldin = 1.46) and 0.15 when variables were standardized, indicating weak cluster structure. With standardized scores, k-means solutions gave silhouette values of 0.27 (k = 2), 0.19 (k = 3), and 0.20 (k = 4), without a clearly superior number of clusters. Three clusters were retained on the basis of the dendrogram, the agglomeration schedule, and the interpretability of the profiles; the

profiles should therefore be read as a useful description of heterogeneity along a continuum rather than as natural groups.

Stability was examined with 500 bootstrap resamples and 500 random split-halves, with k-means seeded at the final centres. Agreement with the original partition was moderate (bootstrap ARI = 0.62, SD = 0.22; split-half ARI = 0.60, SD = 0.22). Jaccard coefficients were 0.68 for PCU, 0.58 for PAD, and 0.83 for FP, so PAD was the least stable profile (below the conventional 0.60 threshold).

Prior to the cluster analysis, Pearson correlations were computed among all primary study variables (see Table 2). All correlations were statistically significant ($p < .01$). Notably, PSNUSS and OCDUS-ICT showed a strong positive correlation ($r = .671$), indicating conceptual overlap between problematic use and compulsivity, while emotional regulation (WLEIS) was negatively associated with psychological distress (r = − .385), consistent with, although not proof of, a protective role.

Table 2
Pearson Correlation Matrix of Primary Study Variables

1. Daily hours on social media	**1**	**2**	**3**	**4**	**5**
2. PSNUSS	.204**				
3. OCDUS-ICT	.235**	.671**			
4. WLEIS (ER)	− .191**	− .261**	− .201**		
5. DASS-21	.205**	.316**	.299**	− .385**	

*Note. ER = Emotional Regulation subscale. N = 516–530. ** p < .01.*

With the aim of finding different profiles in the use of social networks, a cluster analysis was performed using the k-means method with a three-cluster solution previously suggested by the hierarchical analysis.

The results, presented in the following table identified three distinct profiles.

Table 3

Descriptive data of the identified profiles

Variables	Cluster 1(PCU)	Cluster 2 (PAD)	Cluster 3 (FP)
PSNUSS	4.7	3.6	2.8
Daily Hours on RRSS	3.67	3.43	2.66
DASS	44.74	55.12	20.02
OCDUS	58.56	47.13	36.23
WLEIS	18.14	17.51	21.01
N	131	164	221

Note: *All values represent cluster means. PCU = Problematic Compulsive Use profile (n = 131); PAD = Psychological Distress-Associated profile (n = 164); FP = Functional Profile (n = 221). RRSS = Social Networks.*

Cluster 1 (n = 131) is characterised by high social media use, with an average PSNUSS score of 4.7 and an average daily time of 3.67 hours. It also shows considerably higher psychological distress compared to Cluster 3 (DASS = 44.74 vs. 20.02), and notably lower emotional regulation than Cluster 3 (WLEIS = 18.14 vs. 21.01), although these differences were less pronounced than those observed for Cluster 2.

Cluster 2 (n = 164) shows moderate use of social media (PSNUSS = 3.6) which is approximately equivalent to the mean reported in the validation study and an average of 3.43 hours per day. However, it also shows higher levels of psychological distress (DASS = 55.12) and digital compulsivity (OCDUS = 47.13).

Finally, Cluster 3 (n = 221) groups users with lower social media use (PSNUSS = 2.8; 2.66 hours per day), lower levels of psychological distress (DASS = 20.02) and digital compulsivity (OCDUS = 36.23), and higher emotional regulation compared to the other two groups (WLEIS = 21.01). The results of the analysis of variance are presented in Table 4.

Table 4

Results of the analysis of variance (ANOVA) between clusters

PSNUSS	***F* Statistic**	***p* (Sig.)**	**η² parcial**
	496.86	**< .001**	**.660**
OCDUS	247.71	< .001	.491
DASS	116.87	< .001	.313
WLEIS	28.94	< .001	.101
Daily Hours on RRSS	13.04	< .001	.048

Note. *All p-values are two-tailed. Significance level set at α = .05. η² partial indicates the proportion of variance explained by cluster membership.*

Multiple comparisons performed using Bonferroni tests (for WLEIS) and Games–Howell tests for the rest of the variables confirmed statistically significant differences between the three groups in all the variables analysed ($p < .001$). Specifically, the usage pattern associated with additive behaviour had the highest values for problematic social media use (PSNUSS), compulsivity (OCDUS), and daily usage time. The usage profile associated with psychological distress, although showing less compulsive use than the earlier one, was characterised by the highest level of emotional distress. Finally, the functional profile obtained the lowest values in PSNUSS, OCDUS and DASS, and the highest scores in emotional regulation (WLEIS), configuring a profile of regulated and emotionally adaptive use. The differences were significant between all cluster pairs ($p < .001$), except between Clusters 1 and 2 in the WLEIS variable, where no statistically relevant differences were found ($p = .803$). Similarly, no significant differences were found between Clusters 1 and 2 in daily hours of social media use (mean difference = 0.24, 95% CI [− 0.39, 0.86], $p = .642$, Games-Howell).

In terms of effect size, the variables that best differentiated the groups were problematic network use (PSNUSS) and compulsivity (OCDUS), with explained variances of 66% and 49%, respectively. Emotional distress (DASS) also showed significant differentiation ($R^2 = .31$), while emotional regulation (WLEIS) and daily usage time had more modest effects. The distances between the final centres ranged from 24.47 to 31.50, showing an adequate separation between the three identified profiles. The pairwise contrasts between clusters are presented in Table 5.

Table 5
Mean Differences Between Clusters

Variable	Contrast	*p*
PSNUSS	1 > 2 > 3	< .001
OCDUS	1 > 2 > 3	< .001
DASS	2 > 1 > 3	< .001
WLEIS	3 > 1 = 2	< .001
Daily Hours on RRSS	1 = 2 > 3	< .001

Note: *Contrasts reflect post hoc pairwise comparisons. Bonferroni correction was applied for variables with homogeneous variances (WLEIS); Games-Howell test was applied for variables with heterogeneous variances (PSNUSS, OCDUS-ICT, DASS-21, Daily Hours on RRSS). The contrast notation indicates the direction of significant differences (e.g., 1 > 2 > 3 indicates Cluster 1 > Cluster 2 > Cluster 3); = indicates no significant difference between clusters. All p-values are two-tailed*

Significant differences were found between the three clusters in all variables.

Cluster 1 (PCU) showed higher scores in problematic use, compulsivity, and daily use. Cluster 2 (PAD) scored higher than the other clusters on the DASS (depression, anxiety, and stress) score, and cluster 3 (FP), showed a higher score only in emotional regulation. No significant differences were found between clusters 1 and 2 in terms of daily hours of use.

To visualise the profiles obtained, a radar chart was created with the five variables included in the model, which is presented below.

Note

Values normalized as percentage of maximum possible score per scale. PSNUSS max = 126; Daily Hours max = 8h; DASS-21 max = 126; OCDUS-ICT max = 84; WLEIS (Emotional Regulation) max = 28. PCU = Problematic Compulsive Use; PAD = Psychological Distress profile; FP = Functional Profile.

Figure 1 shows the profile of the normalised mean scores in the five study variables for each cluster. The profile associated with compulsive use scores highly on the scales for problematic use (PSNUSS) and compulsivity (OCDUS); the profile associated with distress is characterised by higher levels of emotional distress (DASS); and the adaptive profile is characterised by greater emotional regulation (WLEIS) and lower overall use of social media.

Equivalence in daily time. PCU and PAD did not differ in daily hours (3.67 vs. 3.43; d = 0.11). Two one-sided tests indicated equivalence within ± 0.75 hours (90% CI of the difference [− 0.20, 0.67]; TOST p = .027), within d = ± 0.5 (± 1.12 hours; p < .001), and marginally within d = ± 0.3 (± 0.67 hours; p = .0499), but not within ± 0.5 hours (p = .16).

External validation. Table 6 compares the profiles on variables not used in the clustering. FP differed from PCU and PAD in presence of meaning (MLQ), emotional eating (EEQ), family communication (CI), and daily smartphone use (Holm-adjusted $p < .001$; η^2 between .04 and .16), whereas PCU and PAD did not differ significantly on any of them (all Games-Howell $p \geq .105$). Search for meaning and alcohol use (AUDIT) did not differ after correction. Thus, the external variables separated the functional profile from the two problematic profiles but did not, in this sample, separate PCU from PAD.

Table 6
External validation of the profiles (variables not used in the clustering)

Variable	PCU M (SD)	PAD M (SD)	FP M (SD)	Welch F	η^2	p (Holm)
Presence of meaning (MLQ)	24.92 (6.83)	24.49 (6.37)	28.04 (5.76)	19.3	0.067	< .001
Search for meaning (MLQ)	27.44 (5.85)	27.55 (5.79)	26.76 (7.42)	0.8	0.003	0.461
Emotional eating (EEQ)	14.05 (6.86)	12.45 (6.56)	7.96 (5.39)	49.0	0.156	< .001
Family communication (CI)	35.25 (7.41)	34.47 (7.31)	37.92 (8.22)	10.3	0.040	< .001
Alcohol use (AUDIT)	6.59 (5.27)	6.27 (5.91)	5.21 (5.31)	3.3	0.012	0.076
Daily smartphone hours	5.72 (2.55)	5.32 (2.53)	4.29 (2.01)	19.0	0.066	< .001

Note. PCU = Problematic Compulsive Use profile (n = 131); PAD = Psychological Distress-Associated profile (n = 164); FP = Functional Profile (n = 221). p values are Holm-adjusted across the six variables. PCU vs. PAD: all Games-Howell $p \geq .105$.

Sensitivity analyses. (a) Excluding the 165 participants (of the 516) who responded before the Ethics Committee session (n = 351), cluster means were virtually identical (PSNUSS 84.9/66.2/51.3; OCDUS-ICT 58.0/47.6/35.4); PSNUSS ($\eta^2 = .64$) and OCDUS-ICT ($\eta^2 = .51$) remained the most discriminating variables and daily time the least ($\eta^2 = .06$), and PCU and PAD remained similar in daily hours (difference = 0.31 hours, $p = .32$; equivalence within $d = \pm 0.5$, $p = .010$). (b) When the five variables were standardized, a three-cluster solution (n = 158/195/163) ordered participants along a severity gradient (daily hours 2.36, 3.08, and 4.04) without a distress profile with moderate use, whereas a four-cluster solution (n = 139/103/192/82) reproduced such a profile (daily hours 2.88; DASS-21 = 55.3; WLEIS = 13.3) with the same daily time as a non-distressed moderate-use profile (3.07 hours; DASS-21 = 27.7; equivalence within $d = \pm 0.5$, $p = .001$). The profiles reported here are therefore dependent on the variable weighting used.

4. Discussion

The present study examined whether young people with similar social media use differ in psychologically meaningful ways. Using a person-centred approach, we identified three profiles: PCU, PAD, and FP. The key finding is that the two profiles with the most problematic indicators, PCU and PAD, did not differ significantly in daily time (3.67 vs. 3.43 hours) yet differed markedly in compulsivity, problematic use, and distress, so time spent alone cannot separate them. This offers a coherent framework for integrating apparently contradictory findings in the literature and for moving beyond variable-centred approaches that mask meaningful individual differences.

Three empirically distinguishable profiles emerged, each reflecting a distinct combination of risk and protective factors rather than a simple continuum of severity. The characteristic of problematic use, measured with the PSNUSS, was the variable with the greatest weight for discrimination by groups (R^2 = .66), followed by the neuropsychological characteristic of compulsivity measured with OCDUS (R^2 = .49). These results are consistent with the scientific literature identifying compulsivity and problematic use as core features of behavioural addiction, and with Griffiths' (2005) components model, in which loss of control and compulsive engagement are considered defining characteristics distinguishing problematic from recreational use (Turel & Bechara, 2017).

In contrast to earlier literature, the time spent on social media, despite significant differences between groups, showed low discriminatory power (R^2= .05) and emerged as the least relevant factor in differentiating between groups. These results contrast with the abundant literature showing that the probability of suffering mental health problems induced by social media is directly proportional to the time spent on these platforms (Zubair et al., 2023). This finding may be explained by the fact that, in populations with high connectivity, intensive use of social media becomes normative, which reduces variability between individuals. As a result, even users who do not have problems record a similar number of hours as those in at-risk groups. Therefore, time may no longer reflect qualitative differences in the relationship with the activity (González-Nuevo et al., 2023).

The low discriminatory power of time spent on social media highlights the need to interpret and differentiate behavioural addictions beyond quantity of use. It is true that Griffiths' (2005) addiction components, the most commonly used model, do not refer to exact consumption or time of use as a component, but rather to tolerance, which encompasses this increase in consumption/use, but not a starting point for this or an upper or lower limit of adequate quantity, as we attempt to do with social media. More recently, Ciudad-Fernández et al. (2025) proposed differentiating between core components (relapse, mood modification, abstinence, and conflict) and peripheral components, which include salience and tolerance. Their findings suggest that core components are more strongly associated with negative symptoms whereas peripheral components show limited validity and clinical utility (Castro-Calvo et al., 2021; Razum, Baumgartner, and Glavak-Tkalíc., 2023). In fact, tolerance is not considered a diagnostic criterion for gaming disorder in the ICD-11 (Castro-Calvo et al., 2021; Higuchi et al., 2021).

The same pattern was found for emotional regulation. We found significantly higher emotional regulation in the adaptive/functional use cluster, but no differences were seen between the other two

groups, resulting in low discriminatory power (R^2=.10). This absence of difference between PCU and PAD in emotional regulation is itself a substantive finding: it suggests that emotional regulation difficulties are not specific to any form of problematic use but rather constitute a shared vulnerability factor across both profiles. This challenges models that position emotional dysregulation as a defining feature of compulsive use specifically and instead supports a transdiagnostic interpretation. Given the consistent evidence in the literature of the negative correlation between emotional regulation and problematic social media use (Chen et al., 2025; Granados et al., 2020; Hormes et al., 2014), our results did not show the expected pattern. Nevertheless, emotional regulation is widely recognized as essential for mental health development (Wang et al., 2025), so the higher levels observed in the adaptive cluster may be consistent with a protective role, which cross-sectional data cannot confirm, as has been seen in other problematic online behaviours (Quaglieri et al., 2022) or social media itself (Díaz-Moreno et al., 2023; Estévez et al., 2017; Hormes et al., 2014).

Finally, the psychological variables of depression, anxiety, and stress measured using the DASS-21 showed moderate discriminatory power (R^2 =.31). In this case, the group with the highest score was cluster 2, which was the only cluster to score higher than the functional group on these variables. Consistent with previous literature these findings support the existence of a clear relationship between social media and psychological distress. However, the fact that cluster 2 has the highest scores on psychological distress without also having the highest scores on problematic appears to support a compensatory system (Conkey-Morrison et al., 2025; Kardefelt-Winther et al., 2017) rather than a direct antecedent of social media consumption, although longitudinal designs would be needed to confirm this directionality. This compensatory interpretation is theoretically consistent with the I-PACE model (Brand et al., 2019), which posits that individuals with pre-existing emotional vulnerabilities may use social media as a maladaptive coping strategy rather than developing problematic use through positive reinforcement pathways. The PAD profile thus appears to represent a qualitatively different pathway to distress-associated use, one driven by emotional vulnerability rather than by behavioural dysregulation per se.

These three profiles enable an integrated interpretation of the existing literature, helping to reconcile studies that report no association between social media use and psychological symptoms (Vuorre & Przybylski, 2024) and those suggesting that the nature rather than the quantity of use is the key determinant of outcomes — for instance, Yu et al. (2024) found that active use (posting) was more strongly associated with mental health outcomes than passive use (viewing), a distinction that may map onto the profiles identified here: the PCU profile, characterised by high compulsive and problematic use, may reflect patterns of more active and dysregulated engagement, whereas the PAD profile may involve more passive, avoidance-driven use consistent with a compensatory function and those that discuss the benefits produced by social media (Nagata et al., 2024). This integrative framework also accommodates studies that report clear associations between neuropsychological symptoms characteristic of additive profiles, where social media is compared as a behavioural addiction with substance addiction (Moretta & Wegmann, 2025; Tsilosani et al., 2023), as well as studies that refer to the dilemma of vulnerability, earlier symptoms or behaviour as a defence mechanism (Conkey-Morrison et al., 2025; Shannon et al.,

2024; Tullett-Prado et al., 2023). Furthermore, this broader perspective not only allows for the integration of existing results but also facilitate the proposal of new studies with a more appropriate sample, as well as to explore these variables as potential indicators of risk profiles, which could inform future prevention and intervention strategies pending replication in more diverse samples.

Convergent evidence from a laboratory subsample of this sample (n = 50; Carbonell-Colomer et al., 2026) points in the same direction: the distress-associated profile committed more omissions than the functional profile in a Go/No-Go task (p = .011), whereas biomarker differences between profiles were largely non-significant. Given the subsample size, and because participants were assigned to profiles by nearest centroid, these findings are preliminary and cannot be considered an independent replication.

The study has certain limitations that should be considered when interpreting the findings. First, the cross-sectional design precludes causal inferences regarding the directionality of the associations observed; it cannot be determined whether compulsivity, emotional dysregulation, or psychological distress precede or follow problematic social media use. Second, the use of non-probability sampling limits the ability to generalise the results. The sample was obtained mainly from university students at a single Spanish university, introducing educational and cultural homogeneity and limiting generalisation to other age groups, educational levels, or cultural contexts. Third, the sample was predominantly female (68.3%), which may limit the generalizability of the findings to male populations, given evidence suggesting gender differences in social media use patterns and their psychological correlates. Future studies should seek to replicate these profiles in more diverse and representative samples. Fourth, no formal power analysis was conducted prior to data collection; although the sample size (N = 530) is relatively large for cluster analytic research, the absence of a priori power estimation limits the ability to evaluate whether the study was adequately powered to detect the observed effects. Fifth, the measure of daily social media use was based on a single-day self-reported screen time record from device settings, which may not be representative of habitual usage patterns and is subject to day-to-day variability. Future studies should incorporate multi-day or longitudinal screen time measures to improve ecological validity. Finally, a further limitation concerns the circularity inherent in cluster-based research: the same variables used to generate the cluster solution were subsequently employed in the ANOVA to demonstrate group differences. While this approach is common in exploratory clustering studies, it mathematically guarantees group separation and therefore does not constitute independent validation of the identified profiles. Future studies should examine these profiles using external validation variables not included in the clustering procedure. In addition, cluster structure was weak (silhouette = 0.23), clustering used unstandardized scores so that daily hours contributed little to the solution, the PAD profile was the least stable (Jaccard = 0.58), and the external variables did not separate PCU from PAD. Finally, data were collected in two waves, the first (n = 172) before the Ethics Committee session; a sensitivity analysis excluding that wave yielded the same pattern.

Despite these limitations, the study has several methodological and conceptual strengths. The sample size (N = 530) provides adequate statistical power for cluster analytic research and enhances the robustness of the identified solution. More importantly, the person-centred approach adopted here

addresses a gap that variable-centred methods such as regression cannot fill by grouping individuals rather than variables, cluster analysis reveals naturally occurring combinations of risk and protective factors that would remain hidden in aggregate analyses. The simultaneous inclusion of compulsivity, psychological distress, emotional regulation, and usage frequency allows for a more complete characterisation of PSMU heterogeneity than studies examining these variables in isolation.

5. Conclusion

In conclusion, this study provides empirical evidence that social media use among young people is not a homogeneous phenomenon but is organised into meaningfully distinct profiles that differ in their combinations of compulsivity, psychological distress, emotional regulation, and usage patterns. Importantly, daily time did not distinguish the compulsive-use from the distress-associated profile, so time alone is an insufficient indicator of problematic use. The three profiles identified — PCU, PAD, and FP — suggest that problematic social media use may follow qualitatively different pathways: one characterised by behavioural dysregulation and compulsivity, and another by emotional vulnerability and compensatory use. This person-centred framework helps reconcile apparently contradictory findings in the literature and offers a more nuanced foundation for future research. Pending replication in more diverse samples and longitudinal validation, these profiles may ultimately inform the development of differentiated preventive and psychoeducational strategies tailored to the specific characteristics of each user group.

Declarations

Ethics approval and consent to participate.

This study was conducted in accordance with the Declaration of Helsinki. The project (no. 41/2024) was approved by the Research Ethics Committee of Universidad Francisco de Vitoria (favourable resolution of 23 May 2024). Informed consent to participate was obtained from all participants before they completed the questionnaire.

Consent for publication.

Not applicable.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

Generative AI (Claude, Anthropic) was used to assist with the re-analysis of the data (scripts for cluster validation, equivalence tests, and external validation) and with language editing and restructuring of parts of the manuscript; a generative AI tool was also used to create Figure 1. The authors reviewed and verified all outputs and take full responsibility for the content.

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Author Contribution

M.C.-C. conceived and designed the study and carried out its overall execution as part of her doctoral research. E.B.-B. and C.M.-G. supervised the project, contributed to the methodological design, and participated in the organisation, writing, and critical revision of the manuscript. All authors read and approved the final manuscript.

Data Availability

The dataset supporting the findings of this study is not publicly available due to ethical and privacy considerations related to human participant data. The de-identified data are available from the corresponding author (myriam.carbonell@ufv.es) upon reasonable request.

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Figures

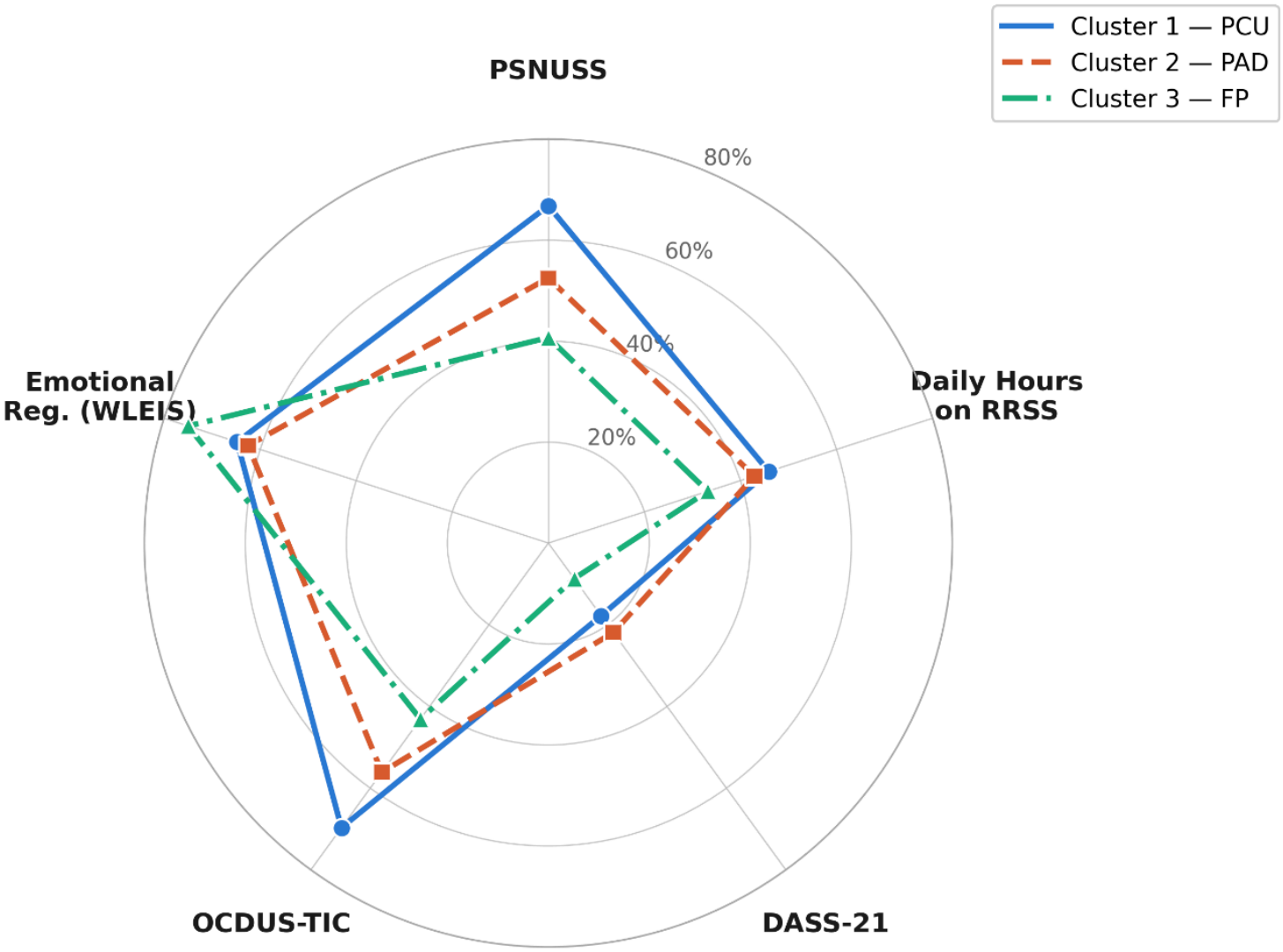

Figure 1

Illustration of differences between groups using a radar chart

Note. Values normalized as percentage of maximum possible score per scale. PSNUSS max = 126; Daily Hours max = 8h; DASS-21 max = 126; OCDUS-ICT max = 84; WLEIS (Emotional Regulation) max = 28. PCU = Problematic Compulsive Use; PAD = Psychological Distress profile; FP = Functional Profile.

Supplementary Files

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- Appendix1.docx