AMERICAN PSYCHOLOGICAL ASSOCIATION

Psychology of Addictive Behaviors

ISSN: 0893-164X

2026, Vol. 40, No. 4, 422–431
https://doi.org/10.1037/adb0001142

Is Problematic Internet Use Always Problematic? An Experience-Sampling Study of Compulsive and Avoidance-Driven Internet Behaviors and Momentary Mood

Joseph Ciarrochi[1], Cristóbal Hernández[2, 3], Eman Hamed[4], Damminda Alahakoon[5], Achini Adikari[5], Keong Yap[4], Isuru Ranapanada[5], Steven C. Hayes[6], Madeleine I. Fraser[4], and Baljinder Sahdra[1]

[1] Institute of Positive Psychology and Education, Australian Catholic University
[2] Escuela de Psicología, Universidad Adolfo Ibáñez
[3] Instituto Milenio para la Investigación en Depresion y Personalidad, Santiago, Región Metropolitana, Chile
[4] School of Behavioural Health Sciences, Australian Catholic University, Strathfield Campus
[5] Centre for Data Analytics and Cognition, La Trobe Business School, La Trobe University
[6] Department of Psychology, University of Nevada, Reno

Objective: The internet has transformed communication and entertainment. Population-level studies typically find that higher problematic internet use (PIU) is associated with lower well-being. We explored how well that average describes individuals using an idionomic (within-person-first) design. ***Method:*** Over 10 days, 84 young adults (M_{age} = 23.5) completed five daily surveys assessing four Young's (1998) PIU-related behaviors (two time control/compulsivity; two emotion dysregulation/avoidance) and six bipolar mood states. We estimated within-person associations using idiographic autoregressive integrated moving average with exogenous inputs, summarized heterogeneity with random-effects and Bayesian multilevel meta-analysis, and explored subgroups via partitioning around medoids and growing self-organizing Maps. ***Results:*** At the within-person level, being above one's own PIU baseline generally linked to lower immediate mood, though effects varied: For some, higher-than-usual PIU coincided with better mood, for others, with worse mood. At the between-person level, individuals with habitually higher PIU reported lower average mood. ***Conclusions:*** Findings support measurement-based tailoring: If higher-than-usual PIU lifts mood now but carries later costs, practitioners might emphasize delay-of-gratification strategies; if it dampens mood immediately, they may use awareness/functional mapping approaches. Future studies should test whether person-specific measures improve intervention choice.

Public Health Significance Statement
Most research treats problematic internet use as uniformly harmful, but this study shows that its effects on mood vary widely from person to person. We found that while some individuals felt worse when their internet use was higher than usual, others felt better or showed no change at all. Rather than applying a one-size-fits-all approach, practitioners can use each person's own pattern of internet use and mood to tailor intervention, focusing on building awareness of immediate harms for some and on managing short-term benefits that may carry longer term costs for others.

Keywords: behavioral addiction, problematic internet usage, well-being, individual differences, idionomic

Supplemental materials: https://doi.org/10.1037/adb0001142.supp

Carla J. Rash served as action editor.

Joseph Ciarrochi https://orcid.org/0000-0003-0471-8100

This work was funded by Agencia Nacional de Investigación y Desarrollo (ANID) Fondecyt Regular No. 1240103 awarded to Cristóbal Hernández.

Joseph Ciarrochi played a lead role in conceptualization, data curation, formal analysis, writing–original draft, and writing–review and editing. Cristóbal Hernández played a supporting role in writing–original draft and an equal role in conceptualization, data curation, and writing–review and editing. Eman Hamed equal role in formal analysis, writing–original draft, and writing–review and editing. Damminda Alahakoon played a supporting role in writing–review and editing and an equal role in formal analysis. Achini Adikari played a supporting role in formal analysis and writing–review and editing. Keong Yap played a supporting role in writing–review and editing. Isuru Ranapanada played a supporting role in formal analysis. Steven C. Hayes played a supporting role in conceptualization and writing–review and editing. Madeleine I. Fraser played a supporting role in conceptualization, project administration, writing–original draft, and writing–review and editing. Baljinder Sahdra played a supporting role in formal analysis, writing–original draft, and writing–review and editing and an equal role in conceptualization.

Correspondence concerning this article should be addressed to Joseph Ciarrochi, Institute of Positive Psychology and Education, Australian Catholic University, Level 9, 33 Berry Street, North Sydney, NSW 2060, Australia. Email: jociarrochi@acu.edu.au

Global internet usage is rising at an unprecedented rate, with 67% of the world's population—approximately 5.4 billion people—now online, a nearly 5% increase from 2022 (International Telecommunication Union, 2023). This rapid growth has heightened concerns about compulsive internet use and its potential negative impact on well-being, particularly among young people who have been labeled "digital natives" (Al-Samarraie et al., 2021; Ciarrochi et al., 2016). While problematic internet use (PIU; Young, 1998) is often linked to negative outcomes such as poorer mental health, academic difficulties, and lower life satisfaction, research findings remain inconsistent. Some studies report small negative effects (Hernández et al., 2024), particularly for compulsive internet use (Ciarrochi et al., 2016; Donald et al., 2022, 2024), while others find no significant association with well-being (Ansari et al., 2024). This variability suggests that the relationship is more complex than initially assumed.

One common view is that PIU has a small, consistent negative effect for everyone. This treats both person-to-person differences and null findings as noise and leans on group averages, implicitly assuming that people are interchangeable over time. That same-for-everyone stance is the ergodic assumption (Molenaar, 2004). We test a different view: PIU's impact varies by individual—some show immediate harms, others little to none, and some even short-term benefits. If so, group averages can cancel out opposing effects and hide the true spread of outcomes. If our hypothesis holds, intervention should shift from one-size-fits-all to personalized, measurement-based approaches to problematic use.

To address this limitation, we adopt an idionomic approach—a method that begins by modeling individuals rather than assuming group-level effects apply uniformly (Ciarrochi, Sahdra, Fraser, et al., 2024; Hayes et al., 2022). Rather than relying on averages that may obscure substantial variability, this approach examines each person's unique pattern of PIU and well-being before drawing broader conclusions. By identifying subgroups with distinct response profiles, an idionomic framework provides a more precise and personalized understanding of PIU's impact (Ciarrochi, Sahdra, Fraser, et al., 2024; Sahdra et al., 2024).

The present study uses PIU as a strong test case for the heterogeneity hypothesis given its widely recognized negative association with well-being (Ciarrochi et al., 2016; Den Eijnden et al., 2010; Donald et al., 2022, 2024; Hernández et al., 2024). We operationalize PIU in terms of Young's original instrument (Young, 1998), which frames the construct as internet addiction. We use the term "problematic internet use" given its historical prevalence while recognizing it as an umbrella label focused on the medium rather than the domain of engagement. Our analysis, therefore, centers on cross-cutting processes—compulsivity (time-control difficulties) and avoidance-driven use (emotion dysregulation)—rather than any specific online activity. This choice enhances comparability with prior PIU work, but it limits construct specificity. We did not assess the domain of use (e.g., gaming, pornography, gambling, social networking), which we now foreground as a limitation.

Most existing research in this area relies on between-person designs or longitudinal studies with fewer than five time points—approaches that lack the statistical power to model individual-level, within-person effects (Ansari et al., 2024; Ciarrochi et al., 2016; Donald et al., 2022, 2024; Hernández et al., 2024). As a result, they cannot adequately test whether PIU is harmful for some individuals, but not for others. To address this gap, we use an intensive longitudinal design to estimate each person's daily response to PIU. Drawing on past idionomic research (e.g., Sahdra et al., 2024), we hypothesize that the pooled negative association masks significant variation and that PIU's impact will vary substantially from person to person.

PIU

Throughout the literature, PIU has also been referred to as compulsive internet use, internet dependence, and internet addiction (Andreassen et al., 2017; Hamutoglu et al., 2020; Hernández et al., 2024). Although PIU shares features with addictive disorders—such as compulsiveness (the tendency to repeat actions in an urge-driven, hard-to-interrupt manner), withdrawal symptoms, and negative social consequences—its classification as an addiction remains debated (Arness & Ollis, 2023; Donald et al., 2022, 2024). Critics argue that framing PIU as an addiction risks pathologizing a widespread behavior in modern society, potentially overlooking its adaptive uses and the role of context and individual differences in shaping its effects.

Instead, PIU is best understood as persistent, excessive internet use that continues despite adverse consequences, including compulsiveness (a strong urge to stay online) and avoidance (using the internet to escape responsibilities, negative emotions, or real-world problems). These behaviors can disrupt daily life by interfering with work, relationships, and mental well-being. Therefore, the term "problematic internet use" is preferred, as it acknowledges the dysfunctional aspects of excessive use without automatically classifying it as an addiction (Billieux et al., 2015).

However, we would go a step further. Even if internet use is compulsive and avoidant, it may not necessarily be problematic, at least in terms of its immediate effects on mood. Some individuals may experience short-term relief, enjoyment, or even social connection through their internet use, despite its compulsive or escapist nature. For example, using the internet to avoid real-world stressors might temporarily reduce anxiety or provide a sense of control (Scott et al., 2024). Similarly, compulsive engagement in online activities—such as gaming or social media—may offer positive reinforcement, fostering feelings of competence, belonging, or pleasure (Ryan et al., 2006).

Thus, the distinction between problematic and nonproblematic PIU is not solely about compulsiveness or avoidance but also depends on context, long-term consequences, and individual differences. For some, internet use may serve as a functional coping strategy, while for others, it may exacerbate distress and lower mood. This complexity underscores the importance of idionomic approaches that account for individual variability rather than assuming a universal negative impact.

Is Problematic Internet Usage Problematic?

In this article, we focus on immediate mood because it steers what people do next. Well-being encompasses having fewer negative emotions and more positive ones (Diener, 2000), and mood—a sustained affective tone—shapes how people interpret and respond to events in real time (Forgas & Ciarrochi, 2002). Mood-management theory explains why people turn to media when they feel bad: They seek quick relief and pleasure (Zillmann, 1988). This helps explain PIU: Some users turn to the internet—especially social media—to lift

mood or escape distress (Coyne et al., 2020). The compensatory internet use model extends this logic: People go online to meet unmet needs (connection, achievement, regulation), and chronic reliance can foster PIU (Kardefelt-Winther, 2014).

The internet delivers clear benefits in communication, information, and entertainment (Castellacci & Tveito, 2018; Du et al., 2021). However, PIU correlates, on average, with depression, anxiety, lower mindfulness, lower life satisfaction, and poorer sleep (Chan et al., 2022; Gong et al., 2024; Shensa et al., 2017; Uram & Skalski, 2022; Vannucci et al., 2017). A meta-analysis has linked PIU to a diminished quality of life (Noroozi et al., 2021), and its prevalence appears to be higher in countries with longer commutes, higher pollution, and lower GDP (Cheng & Li, 2014).

While these findings suggest that PIU is associated with poor mood, the study outcomes primarily depend on a between-person or nomothetic approach. Most research focuses on aggregated patterns of results (i.e., averages) that often downplay within-person variation (Molenaar, 2004). Typically, this nomothetic approach is adopted in statistical analysis and psychological research, which is founded on the ergodic assumption that a group mean can be simply applied to a process in time for a given individual (Molenaar, 2004; Sahdra et al., 2024b). This notion of psychological homogeneity fails to consider or embrace the complexity and diversity of individuals, which is relevant to the present study due to the range of factors that impact both PIU and well-being. Recent work demonstrates the importance of a within-person lens (Beyens et al., 2020, 2024; Valkenburg et al., 2021). For instance, while social networking use correlates with lower well-being among individuals, daily changes in use did not predict daily well-being within individuals (Stavrova & Denissen, 2021).

The differential susceptibility to media effects model (Valkenburg & Peter, 2013) embraces this person-specific approach and posits that individual reactions to media use are influenced by dispositional factors (e.g., personality traits and mood), developmental factors (i.e., age), and social contexts (e.g., family dynamics and cultural norms), which modify how individuals respond to media content and subsequently impact their well-being. It challenges broad displacement accounts that treat all screen time as harmful by crowding out healthier activities (Lin, 1993). Consistent with this view, different media types show different links to well-being: Social media and TV relate to low self-esteem and depression, whereas gaming does not (Boers et al., 2019). Effects also vary depending on how people use social media: Many show no change, some exhibit only negative or only positive effects, and a tiny fraction shows both (Beyens et al., 2024). Other work finds no reliable within-person link between social media use and depression (Jensen et al., 2019).

Idionomic Analysis of PIU

We use an idionomic strategy (Ciarrochi, Sahdra, Hayes, et al., 2024; Sahdra et al., 2024): Model each person first (idiographic), and then look for group or subgroup regularities only when they mirror those individual patterns. Groups are not the goal; they are a lens through which to view the world. They help spot recurring processes, contexts, or response patterns and generate hypotheses about when and for whom certain dynamics appear, without overriding person-level evidence. To accomplish our idionomic goals, we will model within-person links between PIU and mood (e.g., Ciarrochi, Sahdra, Hayes, et al., 2024; Sahdra et al., 2024). After estimating these person-specific relations, we examine whether common trends emerge and use a growing self-organizing map (GSOM) and clustering to identify subgroups with shared profiles. This clarifies individual differences and supports more precise, process-based clinical formulations (Ciarrochi, Sahdra, et al., 2024; Hayes et al., 2022).

We target cross-cutting processes that are implicated across online behaviors (Hernández et al., 2024), thereby complementing domain-specific work. Because we analyze processes, not online domains, we do not make claims about platform-specific harms/benefits. We return to these implications in the Discussion section.

We expect that on average, higher PIU relates to poorer mood (aggregated-effects hypothesis). However, the strength and direction of the PIU–mood link vary across individuals (idionomic). If we do find substantial heterogeneity is present, subgroup patterns derived from GSOM/clustering will be used to summarize person-level profiles without averaging away or masking individual effects.

Method

Preregistration

The design and analytic plan of this study were preregistered on the Open Science Framework before data analysis. The analyses presented here include exploratory extensions that build on that preregistered plan (Hamed et al., 2024).

Participants and Procedure

This study utilized existing de-identified archival data collected by Hernández et al. (2024). Ethics approval was obtained before data collection by the Committee of Ethics in Science of Universidad Adolfo Ibáñez (Project Number: 17/2022; Hernández et al., 2024). Eligibility criteria included being 18–29 years old, living in Chile, and having a smartphone with a consistent internet connection. The study was advertised through social media and led to a recruitment of 122 participants, of which 53% were male and 47% were female (M_{age} = 23.3 years, SD = 3.06). See Table 1 of Hernández et al.'s (2024) study for additional demographic characteristics of study participants.

Following their registration to the survey platform, participants were contacted by research assistants who explained the study in further detail and instructed them to answer short surveys five times a day (10:00 a.m., 1:00 p.m., 4:00 p.m., 7:00 p.m., and 9:00 p.m.) for 10 days. Participants who answered 80% or more of the surveys received a gift card worth 10.000 CLP as an incentive. To obtain sufficient power for individual-level estimates, the present study focused on the 84 participants who completed at least 20 measurement points (44 males, 36 females, four undeclared; M_{age} = 23.5, SD = 2.96; $M_{observations}$ = 39) and on contemporaneous relationships. This within-person sample size is consistent with that in past research (Ciarrochi, Sahdra, Fraser, et al., 2024). We ran a Monte Carlo power analysis (see Supplemental Material S10). In the lowest n scenario (N = 20), power was modest: For effects of $\beta \geq .60$, power exceeded .73.

Measures

The present study utilized a range of self-report measures, which are outlined below and in Table 1. For additional details and information about the validity of each measure, refer to Hernández et al.'s (2024) study. PIU was assessed using four items that were

Table 1
Within-Person Correlations Between Problematic Internet Use and Mood Variables

Variable	Tired	Unhappy	Agitated	No energy	Bad	Tense
Just a few more minutes	−0.05**	−.01	0	−.05**	−.01	−.02
Failed to decrease internet time	−0.07**	−.04	−.02	−.07**	−.04	−.05**
Felt bad offline	−0.05**	−.07**	−.08**	−.04	−.1**	−.09**
Preferred the internet over people	0.01	−.02	−.04	0	−.03	−.03

Note. The table above presents correlation (*r*) values. Mood items were bipolar (<0 = negative; >0 positive), so a negative correlation indicates that above-average problematic internet use levels were associated with below-average mood levels, closer to the negative polarity.
** $p < .01$.

adapted from the short Spanish version of Young's Internet Addiction Test (Hernández & Rivera, 2018; Young, 1998) specifically the Emotion Dysregulation (e.g., "I felt bad when I wasn't connected to the Internet," and "I chose to spend more time online than going out with other people.") and Time Control subscales (e.g., "I tried to decrease the time I spent on the internet and failed to do so," and "I found myself saying 'just a couple more minutes' while online."). We do not average these scales; instead, we examine items separately. Although we do not aggregate these items into subscale scores, we refer to them collectively for interpretive clarity as avoidance-driven internet use (Emotion Dysregulation) and compulsive internet use (Time Control) to better reflect the underlying psychological processes. Items were rated on a Likert scale ranging from 1 (*not at all*) to 7 (*to a great extent*). Intraclass correlations (ICCs) showed person-to-person separation but still clear within-person variance: ICC(1)s ranged from 0.41 to 0.58 ($M = 0.49$), indicating that variance splits roughly evenly, with about half between persons and half due to occasion-to-occasion fluctuations within individuals. ICC(2)s ranged from 0.972 to 0.985 ($M = 0.979$), indicating excellent precision of person-level means given repeated observations.

Mood was measured in the moment using the six bipolar dimensions of affect defined by Wilhelm and Schoebi (2007): tired–awake, discontent–content, agitated–calmed, without energy–full of energy, unwell–well, and tense–relaxed. Participants responded to the prompt "In this moment, I feel" using slider scales ranging from –6 to +6, where –6 indicated the extreme of the first state (e.g., very tired) and +6 indicated the extreme of the second state (e.g., very awake), with 0 representing a neutral point. We translated the momentary mood items into Spanish using a committee approach and oriented all scales toward positive valence; full procedures and final wording are shown in Supplemental Material S11 (Wilhelm & Schoebi, 2007). ICCs underscored strong within-person dynamics: ICC(1)s ranged from 0.26 to 0.39 ($M = 0.32$), indicating that roughly two thirds of the variance reflected fluctuations within individuals across occasions rather than stable between-person differences. At the same time, ICC(2)s ranged from 0.94 to 0.97 ($M = 0.96$), indicating that the person-level means are estimated with excellent precision given the repeated observations.

Analysis Plan

The analysis examined the within-person association between PIU and well-being (i.e., exploring if PIU links with contemporaneous moment-to-moment mood) and between-person association (i.e., whether people above average in PIU also tend to have poorer mood). Analyses were conducted in R (R Core Team, 2024). The first step included conducting a descriptive analysis on all variables (PIU and mood). The proposed steps are outlined below and follow the data analytical steps proposed by Sahdra et al. (2024). The data file was long for the time-series analysis and wide for the person-level data.

Idiographic Modeling

We applied idiographic autoregressive integrated moving average with exogenous inputs models (individual autoregressive integrated moving average with exogenous covariate), which estimate the link between PIU and mood separately for each participant. These models control for three key time-series components: autoregression (p), which accounts for past values of the outcome variable; integration (d), which adjusts for nonstationarity by differencing; and moving average (q), which accounts for past error terms. By modeling these temporal dynamics, idiographic autoregressive integrated moving average with exogenous inputs controls for autocorrelation and trends that might otherwise confound the observed associations, enabling a more accurate estimation of the unique contribution of PIU to mood within individuals. As outlined by Ciarrochi, Sahdra, et al. (2024), this approach treats each individual as a separate study, generating β estimates and standard errors for every PIU–mood pairing. For each participant, we modeled the relationship between four PIU behaviors and six mood outcomes, resulting in 24 effect estimates and associated standard errors per person. These idiographic results were then used to estimate pooled effects across individuals and to assess the degree of heterogeneity in those effects (Ciarrochi, Sahdra, Fraser, et al., 2024).

Nomothetic and Heterogeneity Analyses

To assess overall trends and individual variability, we conducted random-effects meta-analyses following established guidelines (Borenstein et al., 2021; Harrer et al., 2021). These models provided a pooled effect estimate of the relationship between PIU and mood, along with key statistics such as the 95% confidence interval for precision, between-person variance (τ^2), Cochran's Q for testing heterogeneity, I^2 to quantify the proportion of variance due to heterogeneity, and a 95% prediction interval to estimate the range of effects expected in future samples. We also used forest plots and other visualizations to illustrate variability across individuals and highlight the distribution of effects.

To formally assess heterogeneity in these idiographic models, we conducted a Bayesian multilevel meta-analysis, where effects were nested within individuals, and each individual was treated as a

separate study (Marsh et al., 2023). This approach allowed us to compare models assuming a common (fixed) effect against those allowing random effects, providing an omnibus test of heterogeneity. The Bayesian framework offers a flexible and robust way to handle nested structures and quantify uncertainty in the presence of individual-level variability (Harrer et al., 2021).

Subgroup Identification and Pattern Discovery

To explore whether patterns of PIU and mood can be meaningfully grouped, we used partitioning around medoids (PAM; Schubert & Rousseeuw, 2019) and GSOM (Alahakoon et al., 2000, 2001). These unsupervised clustering techniques allowed us to systematically identify subgroups of participants who exhibit similar within-person dynamics across the 24 PIU–mood relationships. In addition to identifying core clusters, we also examined complex or outlier cases—participants whose response patterns do not align with any major subgroup. This approach supports a more nuanced understanding of individual variability and may highlight atypical or clinically significant profiles that would be obscured in aggregated analyses.

Results

We hypothesized that PIU is associated with lower levels of mood at the aggregate level. To test this hypothesis, we conducted within- and between-person correlations, focusing on contemporaneous relationships. The average within-person correlations suggest a complex picture. Overall, using Funder and Ozer's (2019) effect size guidelines, increased PIU behaviors show a small association with lower mood (ranging from −0.12 to −0.04), as evident in Table 1. On average, when individuals are above their own PIU baseline, their mood is lower.

Turning to stable differences between people, the between-person correlations were medium in size based on Funder and Ozer's criteria (Supplemental Table S1). For example, "failed to decrease internet time" showed significant negative correlation, indicating that people who engaged in this behavior were more tired ($r = -0.29$, $p < .01$) and unhappy ($r = -0.21$, $p = .05$; items are bipolar with higher scores being more positive). Similarly, individuals who endorsed "preferred internet over people" significantly were more agitated ($r = -0.23$, $p = .05$), had less energy ($r = -0.24$, $p = .03$), felt bad ($r = -0.31$, $p = .01$), and were more tense ($r = -0.25$, $p = .02$). These findings indicate that individuals with above-average levels of PIU tend to experience above-average unpleasant mood and lower levels of positive mood compared with people with below-average PIU, supporting the hypothesis that PIU is associated with poorer mood at the group level. From these correlations based on aggregation, the within-person and between-person analyses produced outcomes at a different order of magnitude. However, it is important to note that these correlations are based on average within- and average between-person effects and do not consider individual variability.

Heterogeneity Analysis

We hypothesized that significant heterogeneity between PIU and well-being among individuals reduces the accurate application of group averages to individuals. To test this hypothesis, an idiographic autoregressive integrated moving average with exogenous inputs analysis was employed to investigate the heterogeneity in the data further. This allowed us to estimate a pooled effect of the link between PIU and mood across all subjects, as well as the standard deviation or variability in these links. A meta-analysis was conducted using the brms package (V2.14.4; Bürkner, 2017). Our Bayesian model showed a small average negative link between PIU and mood (pooled effect $\bar{\beta} = -0.06$, 95% confidence interval [−0.11, −0.02]). Variation across people was large ($SD = 0.18$, $SE = 0.02$), indicating heterogeneous effects. Using a ±2 *SD* band (≈95% of individuals), estimated effects ranged from −0.42 (2 *SD*s below the mean) to +0.30 (2 *SD*s above). Thus, while the average trend is negative, some individuals exhibit sizable mood drops when PIU rises, others show little change, and other individuals experience short-term mood gains.

To further examine this heterogeneity and perform sensitivity analysis using an alternative to Bayes, we conducted a traditional meta-analysis using metafor 4.2-0 in R (Viechtbauer, 2010) to explore the heterogeneity of the link between each PIU and mood pair. We focused on I^2 values, which indicate the percentage of variation across individuals due to genuine heterogeneity rather than chance (Ciarrochi, Sahdra, Hayes, et al., 2024). Our I^2 values ranged from 53.95% to 77.21%, suggesting significant heterogeneity among participants (refer to the Supplemental Table S2 for specific I^2 values). This variation reflects the diverse ways participants experience and respond to PIU. As Higgins et al. (2003) suggested, if I^2 values exceed 50%, it is advisable to explore heterogeinty and the possibility of subgroups. In the following analysis, we examine these subgroups in more detail.

Exploring Heterogeneity

The former analyses established that there is significant heterogeneity in the impact of PIU on well-being among participants. Therefore, cluster analysis was conducted to identify more homogeneous subgroups. We used PAM as the clustering algorithm that groups data points into a specified number of clusters (Ciarrochi, Sahdra, Fraser, et al., 2024). Unlike *k* means, which uses the mean of cluster points as the center, PAM selects actual data points (medoids) as centers, making it more robust to noise and outliers.

Two clusters were identified using the silhouette method, which helps determine how accurately each data point fits within its assigned cluster relative to neighboring clusters (Rousseeuw, 1987). The first cluster ($n = 50$) comprises participants for whom PIU had a slight positive or neutral effect on their mood, as indicated by most medoid values being close to zero or slightly positive, with an average of 0.02 and none exceeding 0.15. By contrast, the second cluster ($n = 34$) comprises participants wherein PIU was clearly linked to poorer well-being, with most values negative and the majority below −0.2. For interpretative convenience, we labeled the first cluster PIU neutral positive and the second group PIU negative, acknowledging that these labels are descriptive summaries of observed patterns rather than fixed groupings. Refer to Supplemental Table S3 for specific values within the clusters.

Although the PAM analysis revealed distinct groups, many participants did not fit well into either cluster, as evidenced by the low-average silhouette width of 0.22 (Supplemental Figures S1 and S2). This weak silhouette score suggests that the two-cluster solution may not fully capture the complexity of individual responses to PIU. Moreover, while PAM effectively grouped participants, it did not allow for an intuitive visualization of the gradual

transitions between individuals, making it difficult to explore how mood responses to PIU varied along a spectrum rather than as discrete categories.

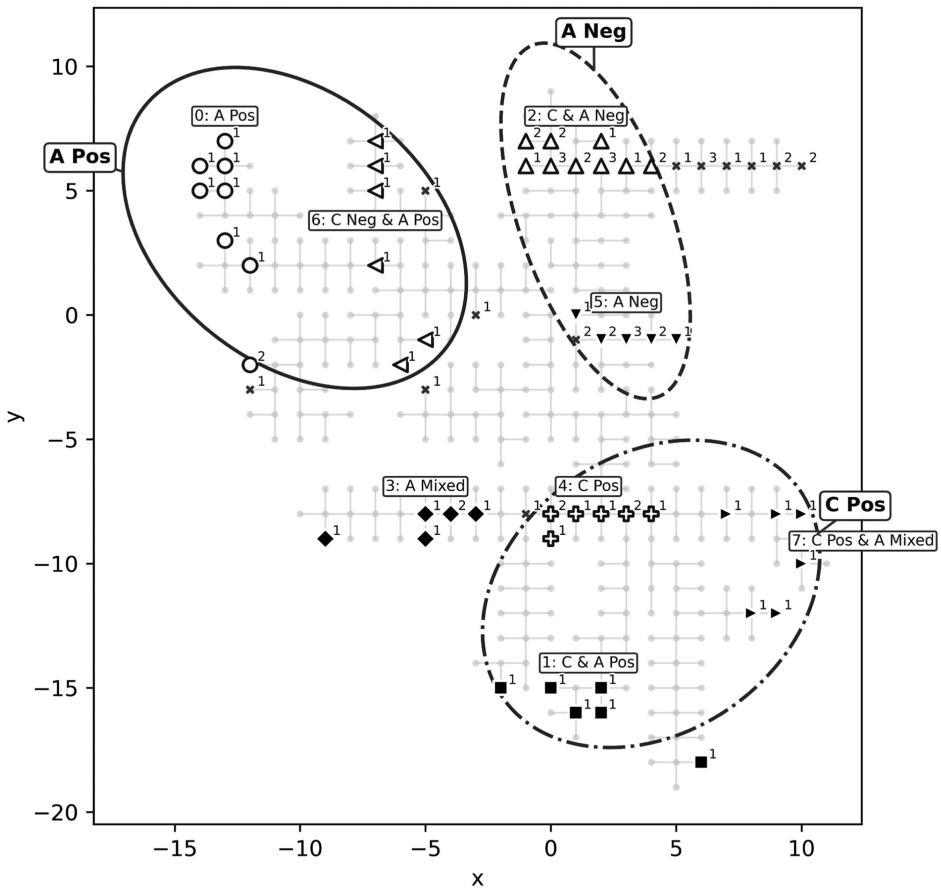
To address this limitation, we applied GSOM, a neural network–based unsupervised learning method that captures the underlying structure of the data while enabling more flexible and interpretable visualizations (GSOM; Alahakoon et al., 2000). GSOM deviates from traditional clustering methods, as it generates a latent representation of data as a topology-preserving mapping of the input space. A key feature of the GSOM is that it is neighborhood preserving, and therefore neighboring groups of data points can be identified as clusters once the GSOM has captured the underlying topological relationships in the data. Unlike PAM, which forces data into predefined clusters, GSOM expands its structure dynamically (in terms of size and shape of the network), thereby better capturing the gradual variations in PIU's impact across individuals. This allowed us to explore fine-grained patterns of heterogeneity, identifying potential subgroups beyond those detected by PAM while preserving the continuum.

To help interpret the GSOM map, we performed *K*-means clustering on the resulting GSOM nodes. Based on the Davies–Bouldin index (Supplemental Figure S4), the average silhouette score across different cluster solutions (Supplemental Figure S5), we identified nine clusters with reasonable fit (silhouette value over .50; see Supplemental Figure S6). However, some cases were close to the group edges and did not fit well into any region (i.e., silhouette score of .10 or less). This group was named "unclassified." The final map is presented in Figure 1.

Figure 1 presents the GSOM clustering analysis, which identifies subgroups of individuals based on their compulsive internet use (Comp) and avoidance-driven internet use (Avoid), as well as the association of these behaviors with mood. The clusters reveal meaningful distinctions in how compulsive and avoidant internet behaviors relate to mood. The analysis identified several distinct clusters (see Supplemental Figure S7 for details of relationships). Some individuals, such as those in Cluster 0 (Avoid Pos) and Cluster 4 (Comp Pos), tend to experience more positive mood when they

Figure 1

Growing Self-Organizing Map Clustering Visualization Illustrating That Avoidance and Compulsive Internet Behaviors Are Linked to Positive and Negative Mood for Subsets of People



Note. Each point represents one or more participants. Numbers on nodes indicate the number of participants mapped to that node. Proximity reflects similarity—closer nodes are more similar. C = compulsive internet use; A = avoidance-driven internet use; Pos = problematic internet use linked to more positive mood; Neg = problematic internet use linked to more negative mood; Mixed = problematic internet use behaviors had different effects on mood.

engage in avoidance or compulsive internet use, respectively. By contrast, Cluster 2 (Comp and Avoid Neg) and Cluster 5 (Avoid Neg) include individuals for whom these behaviors are associated with poorer mood. Other groups, such as Cluster 6 (Comp Neg, Avoid Pos) and Cluster 7 (Comp Pos, Avoid Mixed), reflect more complex patterns, where compulsive and avoidant behaviors correspond to both positive and negative mood outcomes depending on the individual.

Because the GSOM generates nodes to reflect both local and global patterns and structures in the data, each data point is positioned relative to (based on the values of the variables) all the other points in the data set. The neighborhood and topology preservation feature of GSOM has positioned the negative clusters toward the upper right in Figure 1, while the positive effects are spread across, showcasing the diversity. The dynamic and input-driven growth of the GSOM enabled the underlying variation in the data to dictate its directions of growth, and it can be seen that Avoid Pos pushed the growth toward the top left while Comp Pos toward the bottom right. A further observation is that the most intense and pure Pos groups (Comp and Avoid Pos, at the bottom right and Avoid Pos at the top left) distanced themselves furthest away from the negative clusters. It can also be seen that the inputs mapped to negative clusters are more closely positioned compared with the variation in the positive clusters.

Discussion

This study examined the relationship between PIU and mood using an idionomic approach to better capture individual differences and extend on prior understandings of PIU, which have been limited to group-level findings (Noroozi et al., 2021). The current findings highlight a key limitation of aggregated estimates: They obscure meaningful variability at the individual level. While the pooled effect suggests that PIU is linked to more negative mood, this association is small, consistent with prior research (Beyens et al., 2024; Orben et al., 2019; Valkenburg et al., 2021). However, substantial heterogeneity in the data suggests that this small effect does not accurately reflect what is happening at the individual level.

Rather than a uniform negative impact, PIU's effects varied widely across individuals. Some experienced strong negative associations, while others showed neutral or even positive links between PIU and positive mood. Because these opposing effects tend to cancel out in pooled analyses, traditional approaches may underestimate the actual impact of PIU, whether beneficial or harmful. This finding challenges the assumption that PIU is inherently detrimental, at least in the short term, and aligns with research advocating for more nuanced, person-centered analyses (Beyens et al., 2020; Hayes et al., 2022; Stavrova & Denissen, 2021).

By contrast, the between-person pattern points in one direction: People who, on average, used the internet more problematically—struggling to cut back or preferring it over people—also, on average, reported more agitation, tiredness, and low energy. That traitlike association suggests that even if PIU sometimes lifts mood in the short term, habitually higher PIU may be linked to poorer mood overall. However, between-person comparisons cannot answer within-person questions: They do not show that raising one's own PIU causes later mood to drop, and they may reflect other stable differences (e.g., stress, sleep, support). We should consider the between-person correlations as suggestive, rather than causal, and use them as a reason to track both within-person fluctuations and between-person differences in future work.

The identification of substantial heterogeneity in the relationship between PIU and mood within the sample is perhaps the most significant finding of this study. Due to this significant heterogeneity, we conducted a cluster analysis, which identified two distinct subgroups within the sample: one in which PIU had a clear negative effect on mood and another in which it had a neutral or slightly positive effect. From this approach, we found that only around 24% of participants reported a significant negative impact on mood. This is noteworthy, as if we only considered the overall pooled correlations, we would have generalized that PIU has a slight negative effect on mood for the group as a whole.

The findings from the GSOM clustering analysis highlight substantial individual differences in how compulsive internet use (Comp) and avoidance of being offline (Avoid) relate to mood. While some individuals exhibit positive associations between these behaviors and mood, others experience negative effects, and some show mixed patterns wherein compulsive or avoidant behaviors are beneficial in some contexts but detrimental in others. These results challenge the assumption that compulsive internet use is uniformly harmful, instead suggesting that its effects depend on individual and contextual factors. A traditional pooled estimate of the relationship between PIU and mood fails to capture this heterogeneity, as the aggregation of opposing individual-level effects likely underestimates both the positive and negative consequences of PIU. This aligns with prior research demonstrating that media effects are not uniform but vary based on individual susceptibility, motivation, and environmental influences (Beyens et al., 2020, 2024; Valkenburg et al., 2021). The differential susceptibility to media effects model (Valkenburg & Peter, 2013) further supports this perspective, suggesting that the impact of internet use is contingent on a range of personal and situational factors.

The heterogeneity observed in the present study is also consistent with broader psychological theories that emphasize the importance of person-specific variability in behavioral and mood outcomes. Research on self-regulation and compulsive behaviors suggests that the immediate effects of PIU may differ from its long-term consequences, with some individuals experiencing short-term relief or engagement benefits while ultimately suffering negative cumulative effects (Brevers & Turel, 2019; Duckworth et al., 2018). Similarly, studies on emotional regulation and coping strategies indicate that while some individuals use internet engagement adaptively, others may rely on it in ways that reinforce avoidance and distress over time (Casale et al., 2018; Hou et al., 2019). This suggests that while PIU may not always present immediate harm, chronic engagement in compulsive or avoidant internet use may lead to long-term declines in mood. Taken together, these findings reinforce the importance of moving beyond group-level assumptions and adopting idionomic approaches that model individual trajectories before drawing broader conclusions (Sahdra et al., 2024a).

These findings also have implications for the ongoing debate about whether PIU should be classified as an addiction (Arness & Ollis, 2023; Donald et al., 2024). The substantial heterogeneity we observed suggests that a uniform addiction framework may be too simplistic. For some individuals, PIU displays patterns consistent with addiction: compulsive use that persists despite negative mood consequences. For others, however, PIU coincided with neutral or even improved mood in the short term. However, these positive

immediate effects do not rule out problems; many addictive behaviors initially provide positive reinforcement. The critical question may be whether PIU represents a local maximum: a behavior that provides moderate well-being in the moment but crowds out opportunities for greater flourishing (Duckworth et al., 2019; Rachlin & Green, 1972). From this perspective, the problem is opportunity cost rather than direct harm. This variability supports process-based rather than categorical approaches. Rather than asking whether PIU is an addiction, it may be more productive to ask: Does PIU persist because individuals are avoiding discomfort, struggling to delay gratification, or simply unaware of what they are forgoing? This aligns with calls to move beyond broad diagnostic categories toward precision approaches that target specific mechanisms (Hayes et al., 2022). The idionomic approach offers possible insights for tailoring interventions to individuals rather than relying on broad group-level assumptions. It may enable practitioners to assess how compulsive or avoidant internet use functions in an individual's daily life, determining whether it provides short-term benefits, contributes to distress, or leads to a combination of both. This aligns with the shift toward process-based therapy, which focuses on identifying the mechanisms behind an individual's behavior rather than applying symptom-based classifications that may not capture the full complexity of their experience (Sahdra et al., 2024).

Intervention strategies could be tailored to these patterns. For individuals who experience immediate distress while engaging in compulsive or avoidant internet use, interventions may focus on building awareness of the negative consequences of their behavior, helping them recognize dysfunctional coping mechanisms. Strategies such as mindfulness training, stimulus control, and cognitive defusion could enable these individuals to step back from automatic internet use and consider alternative responses. By contrast, individuals who experience short-term mood benefits from compulsive or avoidant internet use may require a different approach, one focused on promoting delay-of-gratification strategies. For example, interventions could explore the short-term benefits and potential long-term costs of internet use and jointly develop strategies that provide immediate and longer term emotional or psychological benefits. This could involve promoting meaningful offline or online activities, enhancing social connections, or fostering engagement in intrinsically rewarding pursuits. An individualized approach ensures that interventions are not only effective but also aligned with each person's motivational and emotional context, ultimately increasing the likelihood of sustainable behavior change.

Limitations and Future Directions

While this study offers valuable insights into the relationship between PIU and mood, several limitations should be considered. First, we did not systematically assess the object of online engagement (e.g., gaming, pornography, gambling, social networking) or motives. Because PIU is an umbrella term, our inferences concern processes (compulsivity, avoidance) rather than object-specific effects. Future work should integrate process measures with detailed assessments of objects and motives. Second, the use of self-report measures introduces potential social desirability biases and a lack of introspective abilities, especially due to participants' varying levels of emotional awareness and recall accuracy, which may impact on the validity of self-report. Future studies may benefit from incorporating objective measures such as screen-time trackers as recommended and utilized by Hoong (2021), who used screen-time reports that provided objective data readily available and accessible in modern devices. Third, this study utilized a short-term (10 days) longitudinal design, which does not capture the long-term effects of PIU on mood. While this study allowed for the examination of moment-to-moment changes in mood and PIU, longitudinal studies are needed to ascertain if these short-term fluctuations translate into lasting effects on mood. Third, due to the myriad of ways that the internet can be used, it is important to differentiate between participants' online activities (e.g., social media, gaming, research), which were not accounted for in this study. Future research should include this distinction, reflecting the widespread use of the internet in modern society, which would clarify how different types of internet use may uniquely affect mood over time.

It would also be helpful to examine the underlying motives for internet usage. Recent research on happiness reveals that prioritizing positivity versus experiential attachment to enjoyable activities can have distinct effects on happiness at both within-person and between-person levels (Sahdra et al., 2025). The extent to which someone spends time on the internet due to experiential attachment may indicate a clinging or craving for positive online experiences, which can negatively impact their mood. On the other hand, spending time on the internet accentuating positivity (e.g., for prosocial activities, joyful connection with their community, or raising awareness of important issues to their community) will likely benefit mood. Further research is needed to clarify the role of experiential attachment in problematic internet usage.

Conclusion

This study is the first to examine PIU–mood links idiographically. PIU sometimes aligned with short-term mood benefits within persons, whereas chronically higher PIU related to lower average mood between persons. The pattern fits longer run costs, but causal claims remain tentative; longitudinal and time-series approaches with appropriate controls (e.g., lagged models) are needed to evaluate directionality. The time course information could guide personalized interventions. Future research is needed to evaluate if measurement strategies such as those described here have treatment utility for personalization (Hayes et al., 1987).

References

Al-Samarraie, H., Bello, K.-A., Alzahrani, A. I., & Smith, A. P. (2021). *Young users' social media addiction: Causes, consequences and preventions Chikezie Emele*. https://doi.org/10.1108/ITP-11-2020-0753

Alahakoon, D., Halgamuge, S. K., & Srinivasan, B. (2000). Dynamic self-organizing maps with controlled growth for knowledge discovery. *IEEE Transactions on Neural Networks*, *11*(3), 601–614. https://doi.org/10.1109/72.846732

Alahakoon, D., Halgamuge, S. K., & Srinivasan, B. (2001). Mining a growing feature map by data skeleton modelling. In A. Kandel, M. Last, & H. Bunke (Eds.), *Data mining and computational intelligence* (Studies in Fuzziness and Soft Computing, Vol. 68, pp. 217–250). Physica-Verlag. https://doi.org/10.1007/978-3-7908-1825-3_9

Andreassen, C. S., Pallesen, S., & Griffiths, M. D. (2017). The relationship between addictive use of social media, narcissism, and self-esteem: Findings from a large national survey. *Addictive Behaviors*, *64*, 287–293. https://doi.org/10.1016/j.addbeh.2016.03.006

Ansari, S., Iqbal, N., Asif, R., Hashim, M., Farooqi, S. R., & Alimoradi, Z. (2024). Social media use and well-being: A systematic review and meta-analysis. *Cyberpsychology, Behavior and Social Networking*, *27*(10), 704–719. https://doi.org/10.1089/cyber.2024.0001

Arness, D. C., & Ollis, T. (2023). A mixed-methods study of problematic social media use, attention dysregulation, and social media use motives. *Current Psychology*, *42*(28), 24379–24398. https://doi.org/10.1007/s12144-022-03472-6

Beyens, I., Pouwels, J. L., van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2020). The effect of social media on well-being differs from adolescent to adolescent. *Scientific Reports*, *10*(1), Article 10763. https://doi.org/10.1038/s41598-020-67727-7

Beyens, I., Pouwels, J. L., van Driel, I. I., Keijsers, L., & Valkenburg, P. M. (2024). Social media use and adolescents' well-being: Developing a typology of person-specific effect patterns. *Communication Research*, *51*(6), 691–716. https://doi.org/10.1177/00936502211038196

Billieux, J., Schimmenti, A., Khazaal, Y., Maurage, P., & Heeren, A. (2015). Are we overpathologizing everyday life? A tenable blueprint for behavioral addiction research. *Journal of Behavioral Addictions*, *4*(3), 119–123. https://doi.org/10.1556/2006.4.2015.009

Boers, E., Afzali, M. H., Newton, N., & Conrod, P. (2019). Association of screen time and depression in adolescence. *JAMA Pediatrics*, *173*(9), 853–859. https://doi.org/10.1001/jamapediatrics.2019.1759

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2021). *Introduction to meta-analysis* (2nd ed.). John Wiley & Sons. https://www.scirp.org/reference/referencespapers?referenceid=3424312

Brevers, D., & Turel, O. (2019). Strategies for self-controlling social media use: Classification and role in preventing social media addiction symptoms. *Journal of Behavioral Addictions*, *8*(3), 554–563. https://doi.org/10.1556/2006.8.2019.49

Bürkner, P. C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. https://doi.org/10.18637/JSS.V080.I01

Casale, S., Rugai, L., & Fioravanti, G. (2018). Exploring the role of positive metacognitions in explaining the association between the fear of missing out and social media addiction. *Addictive Behaviors*, *85*, 83–87. https://doi.org/10.1016/j.addbeh.2018.05.020

Castellacci, F., & Tveito, V. (2018). Internet use and well-being: A survey and a theoretical framework. *Research Policy*, *47*(1), 308–325. https://doi.org/10.1016/j.respol.2017.11.007

Chan, S. S., Van Solt, M., Cruz, R. E., Philp, M., Bahl, S., Serin, N., Amaral, N. B., Schindler, R., Bartosiak, A., Kumar, S., & Canbulut, M. (2022). Social media and mindfulness: From the fear of missing out (FOMO) to the joy of missing out (JOMO). *Journal of Consumer Affairs*, *56*(3), 1312–1331. https://doi.org/10.1111/JOCA.12476

Cheng, C., & Li, A. Y.-L. (2014). Internet addiction prevalence and quality of (real) life: A meta-analysis of 31 nations across seven world regions. *Cyberpsychology, Behavior and Social Networking*, *17*(12), 755–760. https://doi.org/10.1089/cyber.2014.0317

Ciarrochi, J., Parker, P., Sahdra, B., Marshall, S., Jackson, C., Gloster, A. T., & Heaven, P. (2016). The development of compulsive internet use and mental health: A four-year study of adolescence. *Developmental Psychology*, *52*(2), 272–283. https://doi.org/10.1037/dev0000070

Ciarrochi, J., Sahdra, B., Fraser, M. I., Hayes, S. C., Yap, K., & Gloster, A. T. (2024). The compassion connection: Experience sampling insights into romantic attraction. *Journal of Contextual Behavioral Science*, *32*, Article 100749. https://doi.org/10.1016/j.jcbs.2024.100749

Ciarrochi, J., Sahdra, B., Hayes, S. C., Hofmann, S. G., Sanford, B., Stanton, C., Yap, K., Fraser, M. I., Gates, K., & Gloster, A. T. (2024). A personalised approach to identifying important determinants of well-being. *Cognitive Therapy and Research*, *48*(4), 1–22. https://doi.org/10.1007/s10608-024-10486-w

Coyne, S. M., Rogers, A. A., Zurcher, J. D., Stockdale, L., & Booth, M. (2020). Does time spent using social media impact mental health? An eight year longitudinal study. *Computers in Human Behavior*, *104*, Article 106160. https://doi.org/10.1016/J.CHB.2019.106160

Den Eijnden, R. J. J. M., Spijkerman, R., Vermulst, A. A., Van Rooij, T. J., & Engels, R. C. M. E. (2010). Compulsive internet use among adolescents: Bidirectional parent–child relationships. *Journal of Abnormal Child Psychology*, *38*(1), 77–89. https://doi.org/10.1007/s10802-009-9347-8

Diener, E. (2000). Subjective well-being: The science of happiness and a proposal for a national index. *American Psychologist*, *55*(1), 34–43. https://doi.org/10.1037/0003-066X.55.1.34

Donald, J. N., Ciarrochi, J., & Guo, J. (2024). Connected or cutoff? A 4-year longitudinal study of the links between adolescents' compulsive internet use and social support. *Personality and Social Psychology Bulletin*, *50*(2), 299–313. https://doi.org/10.1177/01461672221127802

Donald, J. N., Ciarrochi, J., & Sahdra, B. K. (2022). The consequences of compulsion: A 4-year longitudinal study of compulsive internet use and emotion regulation difficulties. *Emotion*, *22*(4), 678–689. https://doi.org/10.1037/emo0000769

Du, J., Kerkhof, P., & van Koningsbruggen, G. M. (2021). The reciprocal relationships between social media self-control failure, mindfulness and wellbeing: A longitudinal study. *PLOS ONE*, *16*(8), Article e0255648. https://doi.org/10.1371/JOURNAL.PONE.0255648

Duckworth, A. L., Milkman, K. L., & Laibson, D. (2018). Beyond willpower: Strategies for reducing failures of self-control. *Psychological Science in the Public Interest*, *19*(3), 102–129. https://doi.org/10.1177/1529100618821893

Duckworth, A. L., Taxer, J. L., Eskreis-Winkler, L., Galla, B. M., & Gross, J. J. (2019). Self-control and academic achievement. *Annual Review of Psychology*, *70*(1), 373–399. https://doi.org/10.1146/annurev-psych-010418-103230

Forgas, J. P., & Ciarrochi, J. V. (2002). On managing moods: Evidence for the role of homeostatic cognitive strategies in affect regulation. *Personality and Social Psychology Bulletin*, *28*(3), 336–345. https://doi.org/10.1177/0146167202286005

Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science*, *2*(2), 156–168. https://doi.org/10.1177/2515245919847202

Gong, Z., Guo, Y., Fan, S., Sun, X., & Wu, Y. (2024). Examining the influence of problematic internet use on sleep quality in Chinese adolescents: A study using the extended Stressor–Strain-Outcome (SSO) model. *Frontiers in Psychology*, *15*, Article 1447852. https://doi.org/10.3389/fpsyg.2024.1447852

Hamed, E., Ciarrochi, J., Fraser, M., Sahdra, B. K., & Contreras, C. E. H. (2024, July 7). *Idionomic links between problematic internet use and wellbeing*. OSF. https://doi.org/10.17605/OSF.IO/5UHQ2

Hamutoglu, N. B., Topal, M., & Gezgin, D. M. (2020). Investigating direct and indirect effects of social media addiction, social media usage and personality traits on FOMO. *International Journal of Progressive Education*, *16*(2), 248–261. https://doi.org/10.29329/ijpe.2020.241.17

Harrer, M., Cuijpers, P., Furukawa, T. A., & Ebert, D. D. (2021). *Doing meta-analysis with R: A hands-on guide*. Chapman and Hall/CRC press. https://doi.org/10.1201/9781003107347

Hayes, S. C., Ciarrochi, J., Hofmann, S. G., Chin, F., & Sahdra, B. (2022). Evolving an idionomic approach to processes of change: Towards a unified personalized science of human improvement. *Behaviour Research and Therapy*, *156*, Article 104155. https://doi.org/10.1016/j.brat.2022.104155

Hayes, S. C., Nelson, R. O., & Jarrett, R. B. (1987). The treatment utility of assessment: A functional approach to evaluating assessment quality. *American Psychologist*, *42*(11), 963–974. https://doi.org/10.1037/0003-066X.42.11.963

Hernández, C., Ferrada, M., Ciarrochi, J., Quevedo, S., Garcés, J. A., Hansen, R., & Sahdra, B. (2024). The cycle of solitude and avoidance: A daily life evaluation of the relationship between internet addiction and symptoms of social anxiety. *Frontiers in Psychology*, *15*, Article 1337834. https://doi.org/10.3389/fpsyg.2024.1337834

Hernández, C., & Rivera, D. (2018). Adaptación Transcultural y Evaluación de las Estructuras Factoriales del Test de Adicción a internet en Chile: Desarrollo de una Versión Abreviada [Cross-cultural adaptation and evaluation of the factorial structures of the internet addiction test in Chile: Development of an Abbreviated Version]. *Revista Iberoamericana de Diagnóstico y Evaluación Avaliação Psicológica*, *4*, 143–155. https://www.redalyc.org/journal/4596/459657524013/html/

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *The BMJ*, *327*(7414), 557–560. https://doi.org/10.1136/bmj.327.7414.557

Hoong, R. (2021). Self control and smartphone use: An experimental study of soft commitment devices. *European Economic Review*, *140*, Article 103924. https://doi.org/10.1016/J.EUROECOREV.2021.103924

Hou, Y., Xiong, D., Jiang, T., Song, L., & Wang, Q. (2019). Social media addiction: Its impact, mediation, and intervention. *Cyberpsychology*, *13*(1), Article 4. https://doi.org/10.5817/CP2019-1-4

International Telecommunication Union. (2023). *Measuring digital development: Facts and figures 2023*. ITU Publications. https://www.itu.int/en/ITU-D/Statistics/Documents/facts/FactsFigures2023.pdf

Jensen, M., George, M. J., Russell, M. R., & Odgers, C. L. (2019). Young adolescents' digital technology use and mental health symptoms: Little evidence of longitudinal or daily linkages. *Clinical Psychological Science*, *7*(6), 1416–1433. https://doi.org/10.1177/2167702619859336

Kardefelt-Winther, D. (2014). A conceptual and methodological critique of internet addiction research: Towards a model of compensatory internet use. *Computers in Human Behavior*, *31*(1), 351–354. https://doi.org/10.1016/j.chb.2013.10.059

Lin, C. A. (1993). Exploring the role of VCR use in the emerging home entertainment culture. *Journalism & Mass Communication Quarterly*, *70*(4), 833–842. https://doi.org/10.1177/107769909307000409

Marsh, H. W., Fraser, M. I., Rakhimov, A., Ciarrochi, J., & Guo, J. (2023). The bifactor structure of the Self-Compassion Scale: Bayesian approaches to overcome Exploratory Structural Equation Modeling (ESEM) limitations. *Psychological Assessment*, *35*(8), 674–691. https://doi.org/10.1037/pas0001247

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Noroozi, F., Hassanipour, S., Eftekharian, F., Eisapareh, K., & Kaveh, M. H. (2021). Internet addiction effect on quality of life: A systematic review and meta-analysis. *The Scientific World Journal*, *2021*, Article 2556679. https://doi.org/10.1155/2021/2556679

Orben, A., Dienlin, T., & Przybylski, A. K. (2019). Social media's enduring effect on adolescent life satisfaction. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(21), 10226–10228. https://doi.org/10.1073/pnas.1902058116

R Core Team. (2024). *R: A language and environment for statistical computing* [Computer software]. R Foundation for Statistical Computing. https://www.R-project.org/

Rachlin, H., & Green, L. (1972). Commitment, choice and self-control. *Journal of the Experimental Analysis of Behavior*, *17*(1), 15–22. https://doi.org/10.1901/jeab.1972.17-15

Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, *20*, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7

Ryan, R. M., Rigby, C. S., & Przybylski, A. (2006). The motivational pull of video games: A self-determination theory approach. *Motivation and Emotion*, *30*(4), 344–360. https://doi.org/10.1007/s11031-006-9051-8

Sahdra, B. K., Ciarrochi, J., Klimczak, K. S., Krafft, J., Hayes, S. C., & Levin, M. (2024). Testing the applicability of idionomic statistics in longitudinal studies: The example of 'doing what matters'. *Journal of Contextual Behavioral Science*, *32*, Article 100728. https://doi.org/10.1016/j.jcbs.2024.100728

Sahdra, B. K., Shin, A., Fraser, M., Levin, M. E., Klimczak, K. S., Krafft, J., Hayes, S. C., Hernández, C., & Ciarrochi, J. (2025). One size does not make all happy: Idionomic links between striving for positive states and happiness in experience sampling. *Journal of Happiness Studies*, *26*(6). https://doi.org/10.1007/s10902-025-00933-0

Schubert, E., & Rousseeuw, P. J. (2019). *Faster k-Medoids clustering: Improving the PAM, CLARA, and CLARANS algorithms*. arXiv. https://doi.org/10.48550/arxiv.1810.05691

Scott, R. A., Zimmer-Gembeck, M. J., Gardner, A. A., Hawes, T., Modecki, K. L., Duffy, A. L., Farrell, L. J., & Waters, A. M. (2024). Daily use of digital technologies to feel better: Adolescents' digital emotion regulation, emotions, loneliness, and recovery, considering prior emotional problems. *Journal of Adolescence*, *96*(3), 539–550. https://doi.org/10.1002/jad.12259

Shensa, A., Escobar-Viera, C. G., Sidani, J. E., Bowman, N. D., Marshal, M. P., & Primack, B. A. (2017). Problematic social media use and depressive symptoms among U.S. young adults: A nationally-representative study. *Social Science & Medicine*, *182*, 150–157. https://doi.org/10.1016/J.SOCSCIMED.2017.03.061

Stavrova, O., & Denissen, J. (2021). Does using social media jeopardize well-being? The importance of separating within- from between-person effects. *Social Psychological and Personality Science*, *12*(6), 964–973. https://doi.org/10.1177/1948550620944304

Uram, P., & Skalski, S. (2022). Still logged in? The link between Facebook addiction, FoMO, self-esteem, life satisfaction and loneliness in social media users. *Psychological Reports*, *125*(1), 218–231. https://doi.org/10.1177/0033294120980970

Valkenburg, P. M., Beyens, I., Loes Pouwels, J., Van Driel, I. I., & Keijsers, L. (2021). *Social media browsing and adolescent well-being: Challenging the "passive social media use hypothesis."* https://academic.oup.com/jcmc/article/27/1/zmab015/6413702

Valkenburg, P. M., & Peter, J. (2013). The differential susceptibility to media effects model. *Journal of Communication*, *63*(2), 221–243. https://doi.org/10.1111/jcom.12024

Vannucci, A., Flannery, K. M., & Ohannessian, C. M. C. (2017). Social media use and anxiety in emerging adults. *Journal of Affective Disorders*, *207*, 163–166. https://doi.org/10.1016/j.jad.2016.08.040

Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*(3), 1–48. https://doi.org/10.18637/jss.v036.i03

Wilhelm, P., & Schoebi, D. (2007). Assessing mood in daily life. *European Journal of Psychological Assessmentt*, *23*(4), 258–267. https://doi.org/10.1027/1015-5759.23.4.258

Young, K. S. (1998). Internet addiction: The emergence of a new clinical disorder. *Cyberpsychology and Behavior*, *1*(3), 237–244. https://doi.org/10.1089/CPB.1998.1.237

Zillmann, D. (1988). Mood management through communication choices. *American Behavioral Scientist*, *31*(3), 327–340. https://doi.org/10.1177/000276488031003005

Received April 28, 2025
Revision received February 1, 2026
Accepted February 6, 2026 ■