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Co-developmental trajectories of specific problematic usage of the internet: Associations with microsystem predictors and adolescents' mental health outcomes

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FULL-LENGTH REPORT

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ABSTRACT

Background and aims: The Spectrum Hypothesis posits that various forms of problematic usage of the internet (PUI) constitute distinct yet related constructs. However, empirical validation of this hypothesis has largely relied on cross-sectional data, leaving gaps in understanding the co-developmental trajectories of these behaviors during adolescence, their microsystem predictors, and how identified trajectories are associated with mental health outcomes. This study thus aimed to: (a) identify the heterogeneous co-developmental trajectories of problematic social media use, short video use, and internet game use; (b) examine the microsystem-level factors that predict membership in these distinct trajectories; and (c) investigate how these trajectory classes are associated with mental health outcomes. *Methods:* A total of 1,975 Chinese middle school students (M_{age} = 13.51, 52.56% girls) completed measures on three occasions across one year.Results: Parallel process latent class growth modeling revealed five distinct trajectory groups: Low-Stable (61.0%), High-Increasing (8.1%), High-Stable Gaming and Moderate-Decreasing Social Media (15.5%), High-Stable Social Media and Short Video (6.9%), and Moderate-Increasing Social Media (8.4%). Harsh parenting, teacher-student conflict, and bullying victimization predicted worsening co-developmental trajectories. In addition, the High-Increasing class had higher risks for adverse mental health outcomes (i.e., depression, anxiety, and suicidality) compared to the Low-Stable class, whereas other high-risk classes also showed poorer outcomes (though less severe). *Conclusions:* These findings support the Spectrum Hypothesis from a developmental perspective, highlighting the importance of considering heterogeneity in understanding the co-developmental patterns of PUI forms, their microsystem predictors, and cumulative effects on adolescent mental health.

KEYWORDS

trajectories, problematic usage of the internet, adolescents, microsystem predictors, mental health outcomes

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INTRODUCTION

The contemporary digital landscape has become deeply integrated into adolescent life, with social media, short videos, and internet games forming key components of daily activities. Adolescence is a critical neurodevelopmental period characterized by immature brain development, limited self-control, and altered prefrontal cortex connectivity (Pyeon et al., 2021; Qiu, Liu, Yu, Li, & Nie, 2022), making adolescents particularly vulnerable to digital environments. While these platforms offer avenues for entertainment, learning, emotional coping, and peer social support, a significant segment of young users develops patterns of use that become compulsive or excessive, leading to a spectrum of adverse consequences. Specifically, problematic use patterns constitute risk factors for mental health disorders such as depression, anxiety, and suicidal ideation (Liu, Zhuang, Norvilitis, & Xiao, 2024; Xiao, Meng, Brown, Keyes, & Mann, 2025). The risks are not limited to particular pathologies but encompass a broader range of functional impairments, such as conflicting relationships, academic difficulties (Bender, Kim, & Gentile, 2020; Oberst, Wegmann, Stodt, Brand, & Chamarro, 2017; Yıldız Durak, 2020), and physical health issues (Jiang & Yoo, 2024; Männikkö, Billieux, & Kääriäinen, 2015; Sümen & Evgin, 2021; Zamani, Chashmi, & Hedayati, 2009).

The simultaneous proliferation and unique psychological appeals of social media (fulfilling needs for connection and validation), short video (offering rapid, often passive, entertainment), and internet games (providing immersive experiences and achievement-oriented goals) create a triple threat within the modern digital ecosystem (Lin, He, Zheng, & Ai, 2025). Adolescents are not merely exposed to a single form of potentially problematic content but navigate a complex environment where these experiences coexist and may synergize. While previous studies have examined either the developmental trajectories of problematic usage of the internet (PUI) as a monolithic entity (Huang et al., 2023; Tóth-Király, Morin, Hietajärvi, & Salmela-Aro, 2021) or various forms of PUI in isolation in adolescents, the co-developmental patterns of these different forms during adolescence remain poorly understood. Understanding these interconnected developmental patterns is crucial for validating their nature from a temporal perspective and for informing precise, pattern-specific interventions. We therefore examined the co-developmental trajectories of PUI during adolescence, i.e., problematic internet game use (PIGU), problematic social media use (PSMU), and problematic short video use (PSVU), and how multi-contextual factors contributed to these developmental trajectories and predicted adolescent mental health outcomes.

Scholarly discourse on PUI has moved from broad constructs like internet use toward behavior-specific frameworks. This shift recognizes that broad terms lack the precision needed for research, diagnosis, and targeted interventions (Baggio et al., 2024; Lin et al., 2025), as the internet primarily serves as a delivery mechanism for diverse content rather than being inherently addictive (Flayelle et al., 2023; Starcevic & Aboujaoude, 2017). Indeed, adolescents develop problems with specific applications and their psychological rewards—such as games, social media interactions, or short videos—rather than with the abstract internet concept (Busch & McCarthy, 2021; Cha & Seo, 2018). In line with this, current diagnostic frameworks now emphasize precision while exercising conceptual caution. For instance, gaming disorder is recognized in ICD-11 and listed as a condition requiring further study in DSM-5 (APA, 2013; Billieux, Stein, Castro-Calvo, Higushi, & King, 2021), the most formally recognized form of PUI to date. Yet even this established diagnosis remains contested, with ongoing debates about its diagnostic validity, the risk of pathologizing normal gaming behavior, and concerns about premature formalization before sufficient evidence accumulates (Li, Zhao, et al., 2025). These debates are more pronounced for other behaviors, such as excessive social media or short video consumption, which lack any formal diagnostic status. To avoid overpathologizing everyday behavior while acknowledging its potential severity, we used the umbrella term PUI to encompass these excessive online activities associated with functional impairment and adopted behavior-specific terms such as PIGU, PSMU, and PSVU to capture problematic use patterns across the behavioral spectrum (Fineberg et al., 2022; Zare-Bidoky et al., 2025).

Within this framework, the Spectrum Hypothesis proposes that various forms of PUI represent related but distinguishable constructs (Baggio et al., 2018, 2022, 2024; Starcevic & Aboujaoude, 2017). This differentiation is critical because the motivations driving engagement, usage patterns, the nature of reward mechanisms, and core symptomatology may vary across different online activities (Brand, Young, Laier, Wölfling, & Potenza, 2016). For instance, PSMU involves fear of missing out and social comparison (Brailovskaia & Margraf, 2024; Servidio, Soraci, Griffiths, Boca, & Demetrovics, 2024); PSVU features passive consumption driven by instant gratification (Zhang, Hazarika, Chen, & Shi, 2023); and PIGU involves immersive experiences and achievement-seeking (Brown, Smith, Zarate, Griffiths, & Stavropoulos, 2024). Recent empirical evidence using the dominant DSM-5 and ICD-11 diagnostic frameworks has robustly demonstrated that different forms of PUI cluster into distinct communities, with the relationships between symptoms of the same behavior substantially stronger than those between symptoms of different behaviors (Baggio et al., 2024).

While the Spectrum Hypothesis emphasizes that these behaviors are distinct, empirical validation has relied predominantly on cross-sectional observations, ignoring their potential overlap and co-development. Existing longitudinal studies of PUI have typically examined average developmental paths (Tóth-Király et al., 2021), but this approach assumes all adolescents follow similar trajectories. However, a small but growing body of research using person-centered analytic methods (e.g., latent class growth modeling) has revealed heterogeneous trajectories for various types of PUI when examined independently, with studies documenting two to four developmental trajectories across specific forms of PUI. For instance, Coyne et al. (2020) followed 385 American adolescents (ages 14 to 16 years at baseline) annually for six years and identified three PIGU trajectories: increasing symptoms (10%), moderate symptoms (18%), and nonpathological (72%). In a larger cross-cultural study, Peng et al. (2025) tracked 16,833 Chinese adolescent gamers (mean age 13.40 years at baseline) across three waves over two years, revealing four trajectories: high-risk decreasing (4.5%), moderate-risk stable (19.5%), moderate-risk increasing (3.0%), and low-risk stable (73.0%). Parallel findings emerged in PSMU research. Xiong, Xu, Chen, and Zhang (2025) examined 357 Chinese adolescents (ages 12 to 15 years at baseline) across three waves over one year, showing three trajectory classes: high risk-gradual increase (37%), low risk-sharp increase (39%), and low risk-stable (24%). Most recently, Xiao et al. (2025) followed 4,285 U.S. adolescents (mean age 10.00 years at baseline) from the Adolescent Brain Cognitive Development Study across four years, documenting three social media trajectories (high-peaking: 9.6%, increasing: 31.3%, low: 59.1%) and two gaming trajectories (high: 41.1%, low: 58.9%).

Although the above studies provided important knowledge about the developmental trajectories of specific forms of PUI in adolescents, key questions remain. First, it is unclear whether and for whom PSVU persists, increases, or decreases over time, as this emerging form of PUI has received limited longitudinal attention. Second, researchers have typically examined different types of PUI separately, overlooking their potential overlap and co-development. Given the high co-occurrence and significant correlations among different forms of PUI, these behaviors may jointly change over time rather than developing independently. Thus, it is critical to validate the Spectrum Hypothesis from a developmental perspective by investigating how multiple forms of PUI simultaneously develop and interact over time.

Beyond identifying these co-developmental trajectories, exploring their antecedents is crucial for developing targeted intervention programs, particularly for adolescents whose problematic behaviors persist rather than desist naturally. According to ecological systems theory, adolescent developmental outcomes are shaped by five nested systems, including the microsystem, mesosystem, exosystem, macrosystem, and chronosystem (Bronfenbrenner, 1979). We focused on the microsystem as it encompasses the immediate settings (e.g., family, school, and peer contexts) that directly and persistently affect adolescents. Based on this theory, there is increasing evidence that family, school, and peer factors can directly or indirectly predict the risk of PUI. Within the family context, harsh parenting can increase the likelihood of adolescents engaging in PUI, as they may turn to digital platforms as escape mechanisms to seek social support (Wang, Wang, & Lei, 2023). The school context also poses risks, with teacher-student conflict failing to fulfill the fundamental psychological needs of adolescents and undermining their feelings of security, consequently heightening the risk of PUI (Tan et al., 2024). Additionally, peers play an important role in shaping adolescent PUI; adolescents who experience bullying victimization are more likely to engage in PUI, potentially as a means of regaining confidence and satisfying psychological needs (Zhao, Li, Zhou, Nie, & Zhou, 2020). The above studies have provided initial evidence for identifying the family, school, and peer predictors of PUI trajectories. However, it remains unclear whether these factors differentially influence different forms of PUI. For example, bullying victimization may underlie certain trajectories of PIGU (Peng et al., 2025), yet whether it affects PSMU or PSVU development remains unexplored, highlighting the need for behavior-specific analyses.

Equally important is understanding how these co-developmental trajectories impact adolescent mental health. Identifying which trajectory patterns confer the greatest risk can inform intervention priorities and resource allocation. In this regard, the Interaction of Person-Affect-Cognition-Execution (I-PACE) model (Brand et al., 2016) and the compensatory internet use theory (Kardefelt-Winther, 2014) posit that PUI may initially lead to short-term positive experiences and gratification. However, as the problematic process progresses, the level of gratification decreases while users increasingly rely on internet use as a coping mechanism to manage negative feelings and life stress. With prolonged maladaptive internet use, negative consequences may accumulate over time and become increasingly detrimental to adolescent mental health outcomes such as depression and anxiety. This temporal process is particularly concerning during adolescence, a period vulnerable to emotional dysregulation and the adoption of maladaptive coping strategies (Casey, Getz, & Galvan, 2008).

Recent longitudinal studies support these theoretical predictions. For example, using longitudinal data spanning three years within a Chinese sample, one study found that trajectories characterized by moderate-risk increasing levels of PIGU were linked to significantly higher risks for depression and anxiety (Peng et al., 2025). Similarly, a six-year longitudinal study following adolescents into emerging adulthood revealed that trajectories characterized by increasing PIGU were associated with higher levels of depression and anxiety compared to stable low symptom trajectories (Coyne et al., 2020). Most notably, a large-scale U.S. cohort study demonstrated that both high and increasing PUI trajectories for social media and internet games, when examined separately, were associated with elevated risks for suicide-related behaviors and worse mental health outcomes compared to low problematic use trajectories (Xiao et al., 2025). However, these studies have primarily focused on individual types of PUI, without considering the potential interactive or cumulative effects of multiple concurrent PUI trajectories on adolescent mental health. This represents a critical gap given that adolescents are increasingly exposed to multiple forms of PUI simultaneously.

In summary, despite the Spectrum Hypothesis positing that different forms of PUI represent distinguishable constructs (Baggio et al., 2018), empirical validation of this framework has relied predominantly on cross-sectional data. It remains unclear whether adolescents exhibit heterogeneous co-developmental patterns that reflect the behavior-specific nature proposed by the Spectrum Hypothesis. Furthermore, there is limited longitudinal research examining predictors from multiple microsystems (e.g., family, school, and peer) and mental health outcomes (such as depression, anxiety, and suicidality) associated with PUI trajectories. The present study, therefore, addressed these gaps through three principal aims. Based on a three-wave longitudinal design, the first aim was to identify the heterogeneous co-developmental trajectories of PIGU, PSMU, and PSVU. The second aim was to examine the microsystem-level factors that differentiated membership in the identified trajectory classes, focusing on predictors from the family, school, and peer contexts. The third aim was to investigate how these co-developmental trajectories are associated with mental health outcomes.

METHOD

Participants

Participants were drawn from three middle schools in a city located in South China for a larger longitudinal project on adolescent mental health and well-being. These data have not been published previously. Data collection occurred in January 2024 (T1), July 2024 (T2), and January 2025 (T3). A total of 1,986 participants completed assessments at T1, with 1,821 participants at T2 and 1,955 participants at T3. The decrease in participation at T2 was primarily due to school-level scheduling conflicts, whereas attrition at T3 was mainly due to routine reasons (e.g., school transfers or student absences). Missing data analyses suggested no systematic attrition bias (detailed analyses in Supplementary Materials). The final analytical sample included 1,975 participants who completed assessments at T1 and either T2 or T3 (M_{age} = 13.51 years, SD = 0.53; 937 boys and 1,038 girls), excluding 11 participants who only completed T1. Data were also collected on parental education and per capita monthly household income. For maternal education, 17.82% had a college degree or above, 21.01% had a high school degree, and 61.17% had a middle school degree or below. For paternal education, 22.13% had a college degree or above, 26.73% had a high school degree, and 51.14% had a middle school degree or below. Regarding per capita monthly household income, 15.19% had less than 1,000 yuan, 61.42% had 1,000–5,000 yuan, 19.09% had 5,000–10,000 yuan, and 4.30% had more than 10,000 yuan.

Measures

Problematic usage of the internet (PUI; T1-T3). **Problematic Social Media Use (PSMU).** The Facebook Intrusion Questionnaire (FIQ) was utilized to assess PSMU (Elphinston & Noller, 2011), as adapted by Wang et al. (2018). In this version, the word "Facebook" is replaced with "social media" to encompass a broader range of platforms. A sample item is, "I often think about social networking sites when I am not using it." All items were rated on a 7-point Likert scale (from 1 = *never* to 7 = *always*). Mean scores were calculated by averaging the responses, with higher scores indicating a higher risk of PSMU. This adapted version of the FIQ has been validated among Chinese adolescents, demonstrating good reliability (Dong, Li, & Wang, 2023). In the current study, the scale showed high internal consistency across the three waves (Cronbach's α = 0.92–0.93; McDonald's ω = 0.92–0.94).

Problematic Short Video Use (PSVU). To measure PSVU, we used an 8-item scale adapted by Wang and Lei (2022) from Young's (1998) widely used Internet Addiction Test. This adaptation replaced "the internet" with "short videos" in each item (e.g., "Have you repeatedly made unsuccessful efforts to control, cut back, or stop using short videos?"). All items were rated on a 5-point Likert scale (from 1 = *strongly disagree* to 5 = *strongly agree*). A higher mean score reflects a higher level of PSVU. This scale has been used with Chinese adolescents and demonstrated good psychometric properties (Dai, Wang, Yang, Gao, & Wei, 2025; Li, Yang, et al., 2025). For the present study, Cronbach's alphas revealed good internal consistency across the three waves (Cronbach's α = 0.90–0.92; McDonald's ω = 0.91–0.93).

Problematic Internet Game Use (PIGU). The nine-item Internet Gaming Disorder Scale–Short-Form (IGDS9-SF) was utilized to evaluate the severity of PIGU (Pontes & Griffiths, 2015). Each of the nine items corresponds to one of the nine diagnostic criteria for Internet Gaming Disorder proposed in the DSM-5 (APA, 2013). Participants rated each item on a 5-point scale (from 1 = *never* to 5 = *very often*) based on their gaming experiences. A higher mean score indicates a higher level of PIGU. This scale has shown excellent psychometric properties among Chinese adolescents (Li, Zhao, et al., 2025). For the present study, the scale demonstrated high internal consistency from T1 to T3 (Cronbach's α = 0.91–0.93; McDonald's ω = 0.91–0.94).

Microsystem predictors (T1) and mental health outcomes (T1-T3). In addition to the primary measures of PUI, this study included assessments of microsystem predictors at T1 (i.e., harsh parenting, teacher-student conflict, and bullying victimization) and mental health outcomes at T1 to T3 (i.e., depression, anxiety, and suicidality). More information on these instruments is provided in the Supplementary Materials. All study measures demonstrated adequate model fit in confirmatory factor analyses (see Table S1).

Procedure

Prior to data collection, this study received ethical approval from the Human Research Ethics Committee of the first author's university. Following the acquisition of parental consent and student assent, data were collected from participants across three waves. At each wave, students filled out online surveys in the school computer labs during regular school hours, with assistance from trained graduate research assistants. All items were required to be completed before submission. To ensure consistency, participants received identical verbal and written instructions at each administration. They were assured of confidentiality, reminded that participation was voluntary, and encouraged to answer honestly. Longitudinal data were linked using unique participant IDs assigned at the first wave. To protect participant anonymity, the key file connecting personal identities to these IDs was stored separately from the anonymized dataset used for statistical analysis.

Data analysis

Descriptive statistics and bivariate correlations for all study variables were examined using SPSS 29.0. The longitudinal measurement invariance and primary longitudinal analyses were conducted in Mplus 8.3. All analyses used robust maximum likelihood (MLR) estimation. Missing data were handled using full information maximum likelihood (FIML) procedure, which utilizes all available participant data.

Latent class growth modeling (LCGM) with a parallel process framework was employed to identify distinct, heterogeneous co-developmental trajectories of the three forms of PUI simultaneously. A series of models with an increasing number of latent classes, from two to six, were estimated. The selection of the optimal number of classes was guided by a comprehensive evaluation of statistical indices and theoretical considerations. We jointly evaluated: (1) information criteria, specifically lower values of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the Sample-Size Adjusted BIC (A-BIC); (2) the results of likelihood ratio tests that compare a k-class model to a k-1 class model (i.e., the Lo-Mendell-Rubin Likelihood Ratio Test, or LMR-LRT, and the Bootstrap Likelihood Ratio Test, or BLRT); (3) classification certainty, as indicated by higher entropy values; and (4) the principle of parsimony, ensuring that each class was of a sufficient size to be practically meaningful (e.g., >5% of the total sample) (Wickrama, Lee, O'Neal, & Lorenz, 2021). Most importantly, trajectory classes were required to be theoretically interpretable and substantively meaningful.

Upon determining the optimal class solution, the associations between trajectory membership and both baseline predictors and distal outcomes were examined. To investigate the predictors, baseline microsystem factors (harsh parenting, teacher-student conflict, and bullying victimization) were entered as covariates in a multinomial logistic regression using the three-step (R3STEP) auxiliary function in Mplus, which accounts for classification uncertainty when predicting latent class membership (Asparouhov & Muthén, 2014). Subsequently, the relations between latent class membership and distal mental health outcomes were examined using the auxiliary (BCH) function. This procedure was utilized to test differences in the mean scores of depression, anxiety, and suicidality across the identified trajectory classes. The BCH method is appropriate for examining distal outcomes as it estimates these associations without allowing the outcome variables themselves to influence the formation of the latent classes, thereby preserving the integrity of the class solution (Asparouhov & Muthén, 2014).

Ethics

The present study was approved by the School of Psychology Research Ethics Committee, South China Normal University. All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. Informed consent was obtained from all individual participants included in the study.

RESULTS

Descriptive statistics

Table 1 presents the descriptive statistics and bivariate correlations for the study variables. The results indicated a pattern of significant positive associations among the variables, both concurrently (i.e., within the same time point) and longitudinally (i.e., across different time points).

Longitudinal measurement invariance

As detailed in Table S2, longitudinal measurement invariance analyses established scalar invariance for all PUI measures and mental health variables, indicating that observed changes over time reflect true change rather than measurement artifacts.

Parallel-process latent class growth model (PP-LCGM)

To determine the optimal number of latent classes representing distinct co-developmental trajectories, a series of PP-LCGM models ranging from two to six classes were specified and compared (see Table 2 for fit indices). The AIC, BIC, and A-BIC all demonstrated a consistent decrease without a clear elbow as the number of classes increased. The LMR-LRT was not statistically significant for the five-class solution ($p = 0.58$), suggesting that, from this specific statistical standpoint, the four-class solution fit the data better than the five-class solution. However, we prioritized the BLRT, which is the most consistent and accurate indicator for class enumeration compared to LMR-LRT and Information Criteria (Nylund, Asparouhov, & Muthén, 2007) and which remained significant for each class solution. The six-class solution was rejected because it generated two classes that each contained less than 5% of the sample. Such small class sizes are a strong indication of model overfitting and suggest these emergent groups may not be stable or practically meaningful, thus offering no significant interpretive gain. Consequently, the selection between the four- and five-class solutions balanced statistical evidence with theoretical interpretability. While the four-class model was a viable parsimonious alternative, the five-class solution identified a meaningful and theoretically critical class (Moderate-Increasing Social Media). This class captured a unique group of adolescents whose risk was specifically escalating in one domain, a vital nuance that was lost in the more parsimonious model. In addition, the strong entropy value of 0.89 for the five-class solution suggested clear and exact class separation, indicating a high degree of confidence in the model's classification of individuals into the distinct trajectory groups. Therefore, based on the BLRT results and theoretical utility, the five-class solution was selected.

Table 3 and Fig. 1 show the estimated growth parameters and plots for each of the five classes, respectively. The first

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Table 1. Descriptive statistics and correlations among variables of interest

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1. T1 PIGU	1.71	0.78	–																			
2. T2 PIGU	1.67	0.80	0.58***	–																		
3. T3 PIGU	1.59	0.77	0.56***	0.59***	–																	
4. T1 PSVU	1.77	0.81	0.58***	0.40***	0.39***	–																
5. T2 PSVU	1.70	0.82	0.35***	0.59***	0.42***	0.56***	–															
6. T3 PSVU	1.61	0.77	0.34***	0.40***	0.56***	0.53***	0.62***	–														
7. T1 PSMU	1.67	0.82	0.41***	0.34***	0.30***	0.66***	0.49***	0.46***	–													
8. T2 PSMU	1.61	0.83	0.25***	0.41***	0.32***	0.43***	0.69***	0.50***	0.52***	–												
9. T3 PSMU	1.51	0.78	0.29***	0.31***	0.44***	0.44***	0.49***	0.67***	0.51***	0.53***	–											
10. T1 Bullying victimization	1.24	0.39	0.30***	0.24***	0.25***	0.32***	0.21***	0.20***	0.35***	0.19***	0.23***	–										
11. T1 Teacher-student conflict	1.27	0.56	0.37***	0.26***	0.26***	0.36***	0.24***	0.24***	0.38***	0.22***	0.20***	0.51***	–									
12. T1 Harsh parenting	1.26	0.42	0.23***	0.17***	0.17***	0.24***	0.18***	0.18***	0.28***	0.20***	0.24***	0.40***	0.31***	–								
13. T1 Depression	1.43	0.53	0.31***	0.28***	0.27***	0.48***	0.37***	0.33***	0.53***	0.40***	0.38***	0.49***	0.42***	0.41***	–							
14. T2 Depression	1.42	0.54	0.24***	0.34***	0.30***	0.36***	0.50***	0.41***	0.37***	0.56***	0.42***	0.29***	0.23***	0.24***	0.58***	–						
15. T3 Depression	1.39	0.52	0.22***	0.25***	0.33***	0.34***	0.39***	0.47***	0.37***	0.43***	0.56***	0.31***	0.23***	0.27***	0.57***	0.66***	–					
16. T1 Anxiety	1.43	0.6	0.28***	0.27***	0.24***	0.43***	0.34***	0.31***	0.46***	0.37***	0.35***	0.47***	0.35***	0.36***	0.84***	0.53***	0.53***	–				
17. T2 Anxiety	1.42	0.58	0.21***	0.30***	0.27***	0.32***	0.43***	0.36***	0.33***	0.49***	0.39***	0.29***	0.22***	0.23***	0.54***	0.83***	0.63***	0.58***	–			
18. T3 Anxiety	1.40	0.56	0.21***	0.25***	0.33***	0.31***	0.36***	0.44***	0.32***	0.38***	0.51***	0.31***	0.23***	0.25***	0.51***	0.60***	0.85***	0.54***	0.64***	–		
19. T1 Suicidality	1.30	0.74	0.28***	0.25***	0.24***	0.37***	0.31***	0.27***	0.38***	0.31***	0.31***	0.45***	0.37***	0.40***	0.65***	0.47***	0.47***	0.61***	0.45***	0.44***	–	
20. T2 Suicidality	1.28	0.73	0.24***	0.28***	0.28***	0.29***	0.34***	0.32***	0.26***	0.37***	0.30***	0.32***	0.26***	0.28***	0.47***	0.63***	0.52***	0.45***	0.62***	0.49***	0.62***	–
21. T3 Suicidality	1.26	0.73	0.21***	0.22***	0.31***	0.28***	0.30***	0.35***	0.27***	0.31***	0.40***	0.31***	0.24***	0.29***	0.44***	0.50***	0.64***	0.42***	0.47***	0.61***	0.59***	0.68***

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; PIGU = Problematic internet game use; PSVU = Problematic short video use; PSMU = Problematic social media use; T1 = Time 1; T2 = Time 2; T3 = Time 3.

Table 2. Model fit indices for parallel process latent class growth models

Classes	AIC	BIC	A-BIC	Entropy	LMR-LRT	BLRT	Smallest group
2	41034.278	41207.516	41109.028	0.893	0.0546	< 0.001	22.3%
3	39814.093	40026.449	39905.722	0.899	< 0.001	< 0.001	9.4%
4	39164.748	39416.223	39273.256	0.883	0.0062	< 0.001	10.0%
5	38824.885	39115.478	38950.272	0.892	0.5827	< 0.001	6.9%
6	38461.336	38791.048	38603.602	0.906	0.2492	< 0.001	3.2%

Note: AIC Akaike information criteria, BIC Bayesian information criteria, A-BIC sample size adjusted BIC, LMR-LRT Lo–Mendell–Rubin likelihood ratio test, BLRT bootstrap likelihood ratio test.

Table 3. Parallel-process latent class growth model parameter estimates

	Parameters	Class 1	Class 2	Class 3	Class 4	Class 5
PIGU	Intercept	−0.41 (0.10)***	1.45 (0.14)***	0.96 (0.14)***	−0.38 (0.07)***	0.05 (0.23)
	Slope	−0.05 (0.05)	0.18 (0.09)	0.02 (0.21)	0.02 (0.05)	0.10 (0.08)
PSVU	Intercept	−0.45 (0.07)***	1.25 (0.12)***	0.56 (0.10)***	1.22 (0.16)***	−0.00 (0.11)
	Slope	−0.04 (0.04)	0.24 (0.07)**	−0.13 (0.12)	0.09 (0.07)	0.18 (0.07)**
PSMU	Intercept	−0.39 (0.05)***	1.12 (0.13)***	0.29 (0.10)**	1.08 (0.15)***	0.30 (0.14)*
	Slope	−0.05 (0.03)	0.39 (0.08)***	−0.30 (0.06)***	0.06 (0.06)	0.50 (0.10)***

Note: Class 1 Low-Stable, class 2 High-Increasing, class 3 High-Stable Gaming and Moderate-Decreasing Social Media, class 4 High-Stable Social Media and Short Video, class 5 Moderate-Increasing Social Media; PIGU = Problematic internet game use; PSVU = Problematic short video use; PSMU = Problematic social media use; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

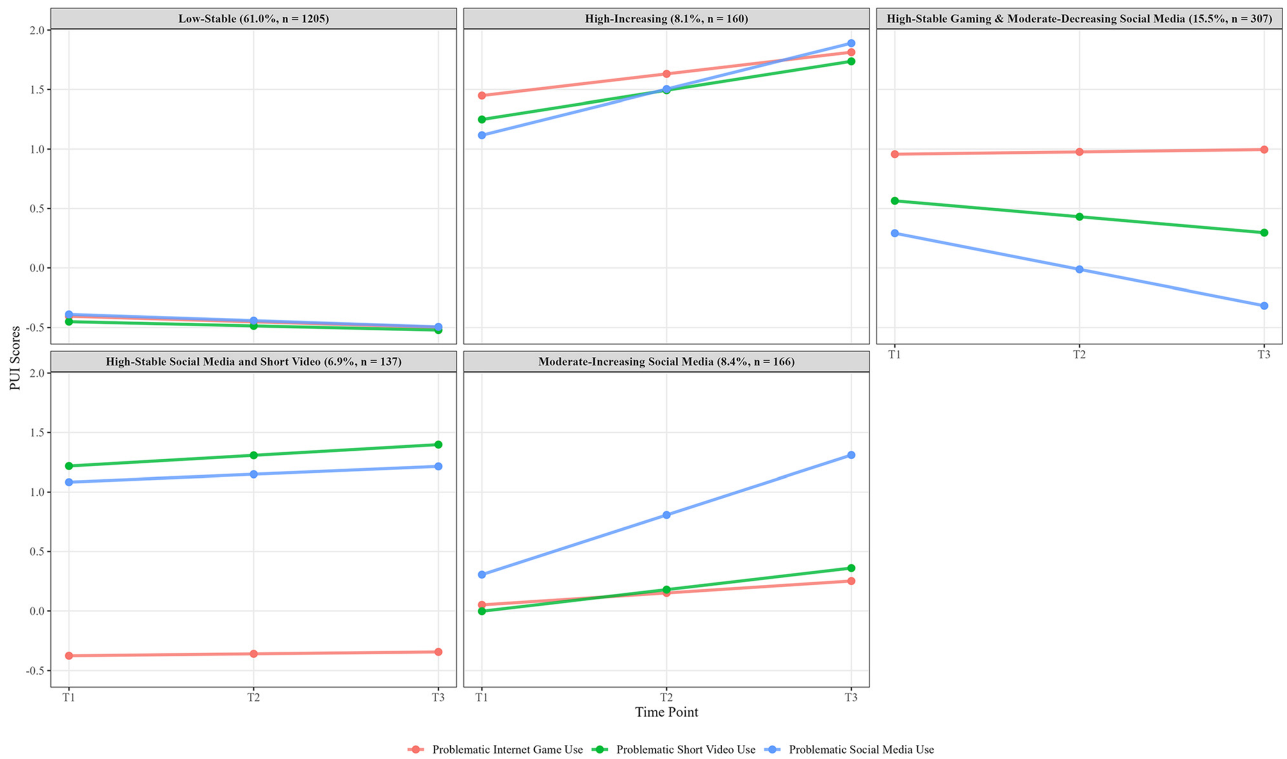

Fig. 1. Estimated means of problematic usage of the internet of the five latent classes in parallel process Latent Class Growth Model *Y*-axis indicates the z-scores of problematic usage of the internet; *X*-axis indicates the measurement times. T1-T3 represents Time 1-Time 3 respectively.

and largest class (61.0%, n = 1,205), labelled Low-Stable, was characterized by consistently low and stable trajectories across all three problematic online behaviors. In contrast, the second class, High-Increasing (8.1%, n = 160), exhibited initially high levels for all behaviors, with subsequent significant increases in PSVU and PSMU while PIGU remained persistently high. A third class, High-Stable Gaming and Moderate-Decreasing Social Media (15.5%, n = 307), was distinguished by a high and stable trajectory for PIGU, alongside a moderate, stable trajectory for PSVU and a significantly decreasing trajectory for PSMU. The fourth group, High-Stable Social Media and Short Video (6.9%, $n = 137$), showed a low and stable trajectory for PIGU but displayed high, stable trajectories for both PSVU and PSMU. Finally, the fifth class (8.4%, $n = 166$), labelled Moderate-Increasing Social Media, began with low to moderate levels across the behaviors but was defined by significant increasing trends over time for both PSVU and, most notably, PSMU, while PIGU remained stable.

Predictors of PUI trajectories

The multinomial logistic regression results predicting trajectory class membership are presented in Table 4. Harsh parenting was found to significantly differentiate several trajectories. When the Low-Stable class was the reference group, higher levels of harsh parenting increased the likelihood of adolescents belonging to the High-Increasing, High-Stable Social Media and Short Video, and Moderate-Increasing Social Media classes. Its effect was not significant for distinguishing the High-Stable Gaming and Moderate-Decreasing Social Media class from the Low-Stable group. Further comparisons revealed that adolescents experiencing more harsh parenting were also significantly less likely to be in the High-Stable Gaming and Moderate-Decreasing Social Media class compared to the High-Increasing class. No other significant effects for harsh parenting were found when distinguishing between the various high-risk classes. Regarding teacher-student conflict, this factor served as a robust predictor differentiating the Low-Stable class from all other higher-risk groups. Poorer teacher-student relationships consistently and significantly increased the odds of membership in the High-Increasing, High-Stable Gaming and Moderate-Decreasing Social Media, High-Stable Social Media and Short Video, and Moderate-Increasing Social Media classes. Additionally, this factor distinguished between some of the high-risk classes; adolescents with teacher-student conflict were significantly less likely to be in the High-Stable Social Media and Short Video class compared to both the High-Increasing and the High-Stable Gaming and Moderate-Decreasing Social Media classes. The predictive role of bullying victimization revealed a more nuanced pattern of associations. Compared to the Low-Stable class, greater exposure to bullying victimization significantly increased the likelihood of an adolescent being in the High-Increasing and High-Stable Gaming and Moderate-Decreasing Social Media classes. Notably, bullying victimization did not significantly differentiate the High-Stable Social Media and Short Video or the Moderate-Increasing Social Media classes from the Low-Stable group. Among the high-risk classes, bullying victimization also played a significant role. Adolescents with higher victimization were significantly less likely to belong to the High-Stable Gaming and Moderate-Decreasing Social Media and the Moderate-Increasing Social Media classes when compared to the High-Increasing class. Furthermore, they were significantly less likely to be in the Moderate-Increasing Social Media class compared to the High-Stable Gaming and Moderate-Decreasing Social Media class.

Mental health outcomes across classes

Based on the five-class parallel-process latent class growth model, the relationships between the PUI trajectories and mental health outcomes were examined. Results from the comparisons of depression, anxiety, and suicidality across classes are reported in Table 5. The mental health outcomes varied significantly across the five co-developmental trajectories across all three time points. Longitudinally, the adolescents in the Low-Stable class consistently reported the

Table 4. Multinomial logistic regression of predictors on PUI trajectories

Predictor	Class 2		Class 3		Class 4		Class 5	
	OR (SE)	*p* value	OR (SE)	*p* value	OR (SE)	*p* value	OR (SE)	*p* value
Class 1 (Ref)								
Teacher-student conflict	**3.45 (0.71)**	0.001	**3.04 (0.62)**	0.001	**1.98 (0.45)**	0.029	**2.13 (0.51)**	0.026
Bullying victimization	**3.32 (0.87)**	0.007	**2.16 (0.53)**	0.030	1.97 (0.55)	0.079	1.16 (0.35)	0.642
Harsh parenting	**2.42 (0.56)**	0.012	1.55 (0.39)	0.159	**2.39 (0.60)**	0.020	**2.52 (0.65)**	0.019
Class 2 (Ref)								
Teacher-student conflict			0.88 (0.14)	0.401	**0.57 (0.13)**	0.001	**0.62 (0.14)**	0.006
Bullying victimization			**0.65 (0.17)**	0.036	**0.59 (0.18)**	0.019	**0.35 (0.11)**	< 0.001
Harsh parenting			**0.64 (0.14)**	0.009	0.99 (0.23)	0.963	1.04 (0.24)	0.866
Class 3 (Ref)								
Teacher-student conflict					**0.65 (0.14)**	0.010	**0.70 (0.17)**	0.042
Bullying victimization					0.91 (0.25)	0.726	**0.54 (0.17)**	0.005
Harsh parenting					1.55 (0.38)	0.146	1.63 (0.41)	0.125
Class 4 (Ref)								
Teacher-student conflict							1.08 (0.28)	0.791
Bullying victimization							0.59 (0.21)	0.050
Harsh parenting							1.05 (0.29)	0.855

Note: Class 1 Low-Stable, class 2 High-Increasing, class 3 High-Stable Gaming and Moderate-Decreasing Social Media, class 4 High-Stable Social Media and Short Video, class 5 Moderate-Increasing Social Media, ref reference class; Significant coefficients ($p < 0.05$) are shown in bold.

Table 5. Comparisons of mental health outcomes across classes

	Time points	Class 1 *M (SE)*	Class 2 *M (SE)*	Class 3 *M (SE)*	Class 4 *M (SE)*	Class 5 *M (SE)*	Summary of significant differences
Depression	T1	1.27 (0.01)	2.01 (0.06)	1.54 (0.04)	1.76 (0.06)	1.59 (0.04)	1 < 2/3/4/5; 2 > 3/4/5; 3 < 4, 3 = 5; 4 > 5
	T2	1.24 (0.01)	2.00 (0.06)	1.53 (0.04)	1.83 (0.06)	1.68 (0.05)	1 < 2/3/4/5; 2 > 3/5,2 = 4; 3 < 4/5; 4 = 5
	T3	1.21 (0.01)	2.05 (0.06)	1.39 (0.03)	1.80 (0.05)	1.77 (0.05)	1 < 2/3/4/5; 2 > 3/4/5; 3 < 4/5; 4 = 5
Anxiety	T1	1.25 (0.01)	2.03 (0.07)	1.52 (0.04)	1.81 (0.07)	1.60 (0.06)	1 < 2/3/4/5; 2 > 3/4/5; 3 < 4, 3 = 5; 4 > 5
	T2	1.24 (0.01)	1.96 (0.07)	1.52 (0.04)	1.89 (0.07)	1.68 (0.06)	1 < 2/3/4/5; 2 > 3/5,2 = 4; 3 < 4/5; 4 > 5
	T3	1.20 (0.01)	2.01 (0.06)	1.43 (0.03)	1.80 (0.06)	1.80 (0.06)	1 < 2/3/4/5; 2 > 3/4/5; 3 < 4/5; 4 = 5
Suicidality	T1	1.11 (0.02)	1.98 (0.08)	1.43 (0.05)	1.64 (0.08)	1.45 (0.07)	1 < 2/3/4/5; 2 > 3/4/5; 3 < 4, 3 = 5; 4 = 5
	T2	1.21 (0.01)	2.05 (0.06)	1.50 (0.05)	1.60 (0.08)	1.46 (0.08)	1 < 2/3/4/5; 2 > 3/4/5; 3 = 4 = 5
	T3	1.06 (0.02)	2.02 (0.09)	1.32 (0.04)	1.65 (0.09)	1.53 (0.08)	1 < 2/3/4/5; 2 > 3/4/5; 3 < 4/5; 4 = 5

Note: Class 1 Low-Stable, class 2 High-Increasing, class 3 High-Stable Gaming and Moderate-Decreasing Social Media, class 4 High-Stable Social Media and Short Video, class 5 Moderate-Increasing Social Media, ref reference class. " = " represents that the difference between the two groups has not reached statistical significance. The ">" and "<" represent that the difference between the two groups has reached statistical significance at .05 level.

most favorable mental health status, maintaining the lowest levels of depression, anxiety, and suicidality throughout T1 to T3. The next-best mental health status was experienced by the adolescents in the High-Stable Gaming and Moderate-Decreasing Social Media class. While demonstrating better outcomes than the remaining high-risk classes, adolescents in this class still reported significantly higher levels of depression, anxiety, and suicidality when compared to the Low-Stable class.

By contrast, adolescents in the High-Increasing, High-Stable Social Media and Short Video, and Moderate-Increasing Social Media classes reported poorer mental health outcomes. Most notably, the High-Increasing class consistently showed the most severe outcomes, reporting the highest levels across all three indicators at all time points. Interestingly, the High-Stable Social Media and Short Video class and the Moderate-Increasing Social Media class, despite showing different initial levels, converged over time to show no statistically significant differences by T3 on depression ($p = 0.71$), anxiety ($p = 0.98$), or suicidality ($p = 0.36$). The mental health of adolescents in these two classes was significantly worse than that of the Low-Stable and High-Stable Gaming and Moderate-Decreasing Social Media classes, but generally significantly better than the High-Increasing class on all three indicators.

DISCUSSION

The Spectrum Hypothesis posits that various forms of PUI represent related but distinguishable phenomena (Baggio et al., 2018; Starcevic & Aboujaoude, 2017). However, prior empirical tests of this hypothesis have primarily relied on cross-sectional network analyses or examined specific problematic behaviors in isolation, without investigating whether these behaviors follow divergent developmental trajectories over time—a critical test that would provide stronger evidence for their distinctness. Addressing this limitation, the present study utilized a longitudinal design combined with a person-centered approach to identify the co-developmental trajectories of PIGU, PSMU, and PSVU during adolescence. The findings revealed five trajectory patterns (i.e., Low-Stable, High-Increasing, High-Stable Gaming and Moderate-Decreasing Social Media, High-Stable Social Media and Short Video, and Moderate-Increasing Social Media), providing empirical support for the Spectrum Hypothesis by demonstrating that these behaviors develop along unique pathways. Furthermore, by investigating how these trajectories are predicted by key microsystem factors and, in turn, predict critical mental health outcomes, this study offers a comprehensive, ecologically-valid perspective on the complex interplay between adolescents' digital lives and their psychological well-being. The findings provide a robust empirical foundation for developing more targeted and effective prevention and intervention strategies.

Heterogeneous trajectories of PUI

A primary aim of this study was to challenge the assumption of developmental homogeneity by identifying distinct subgroups of adolescents following different longitudinal pathways of PUI. Consistent with our central hypothesis and the core tenets of developmental contextualism, which posits that development is characterized by profound individual differences rather than a single normative trajectory (Lerner, 2018), our latent class growth analysis successfully identified five distinct trajectory classes. The largest of these was the Low-Stable class, comprising nearly two-thirds of the sample (61.0%). This group was characterized by consistently low levels of engagement across all three platforms throughout the study period. This pattern is consistent with prior large-scale longitudinal research showing that the majority of adolescents successfully integrate digital media into their lives as a form of normative entertainment and social connection without developing problematic patterns (Peng et al., 2025; Xiao et al., 2025). However, a substantial minority of adolescents, representing nearly 40% of the sample, followed one of four higher-risk trajectories. This finding underscores the limitations of mean-level analyses and highlights the critical importance of a person-centered approach for identifying vulnerable subgroups who might otherwise be obscured within population averages (Howard & Hoffman, 2018).

A key discovery of this study was the emergence of classes defined by platform specialization, namely the High-Stable Gaming and Moderate-Decreasing Social Media class and the High-Stable Social Media and Short Video class. Specifically, the High-Stable Gaming and Moderate-Decreasing Social Media class was distinguished by a high and stable trajectory for PIGU, coupled with a moderate, stable trajectory for PSVU and a significantly decreasing trajectory for PSMU. In contrast, the High-Stable Social Media and Short Video class displayed high, stable trajectories for both PSVU and PSMU, while PIGU remained low and stable. This finding lends strong empirical support to the Spectrum Hypothesis from a developmental perspective (Baggio et al., 2022; Starcevic & Aboujaoude, 2017), which argues that various forms of PUI, while potentially co-occurring, are phenomenologically and etiologically distinct. The motivations underlying these specialized patterns are likely to differ substantially. For instance, adolescents in the gaming-dominant class may reflect behaviors primarily driven by intrinsic needs for competence, autonomy, and achievement within structured, immersive virtual worlds (Brown et al., 2024). In contrast, the pathway characterized by high PSMU and PSVU appears driven by extrinsic, peer-related motivations—including social validation, fear of missing out, and the instant gratification of algorithm-curated content (Brailovskaia & Margraf, 2024; Zhang et al., 2023). This perspective offers a lens for interpreting the complex nature of adolescent digital engagement, underscoring the necessity of intervention approaches tailored to different developmental trajectories.

Perhaps the most concerning finding was the identification of two trajectories characterized by escalating symptomatology: the High-Increasing class and the Moderate-Increasing Social Media class. The High-Increasing class exhibited initially high levels across all three behaviors, with subsequent significant increases in PSVU and PSMU while PIGU remained persistently high. In contrast, the Moderate-Increasing Social Media class began with low to moderate levels across the behaviors but was defined by a significant increasing trend over time for PSMU, which became its defining feature. The escalating nature of their problematic engagement suggests deficits in the development of self-regulatory skills during a critical neurodevelopmental window (Pyeon et al., 2021; Qiu et al., 2022). For these adolescents, online platforms increasingly serve as a primary, yet ultimately maladaptive, coping strategy for managing the mounting academic and social stressors of adolescence. This pattern is particularly worrying as it indicates that these problematic behaviors are not a transient phase but are becoming more deeply entrenched over time, likely leading to an accumulation of negative consequences, as borne out by our analysis of their mental health outcomes.

Microsystem predictors of developmental trajectories

A central goal of this study, grounded in Bronfenbrenner's (1979) ecological systems theory, was to identify early contextual factors within adolescents' immediate microsystems (family, school, and peers) that predict membership in these distinct developmental trajectories. Our findings reveal that specific risks within these domains are differentially associated with the various pathways of PUI, providing valuable insights for targeted prevention. At the family level, and consistent with compensatory internet use theory (Kardefelt-Winther, 2014), harsh parenting emerged as a powerful predictor for three of the four high-risk trajectories. When home life is characterized by conflict, criticism, and a lack of warmth, the digital world can become a crucial sanctuary. It may offer an escape from aversive family interactions, providing a domain where adolescents can experience a sense of control, autonomy, or social validation that is profoundly lacking in their offline lives (Wang et al., 2023). This finding highlights the spillover of negative family dynamics into adolescents' digital coping strategies. Intriguingly, harsh parenting did not significantly predict membership in the High-Stable Gaming and Moderate-Decreasing Social Media class when compared to the Low-Stable group. This non-significant finding is itself informative, suggesting that the pathway to problematic gaming behavior may be less influenced by aversive family dynamics and perhaps more strongly linked to individual temperamental factors (e.g., sensation-seeking, poor effortful control) or the powerful influence of peer-group norms surrounding gaming, a distinction that warrants dedicated future research.

Within the school context, teacher-student conflict was found to be a robust predictor, significantly increasing the odds of membership in all four high-risk trajectories compared to the Low-Stable group. This result highlights the school environment as a developmental context for PUI. According to self-determination theory, positive and supportive relationships with teachers are fundamental to satisfying adolescents' basic psychological needs for competence and relatedness within the academic sphere (Ryan & Deci, 2023; Tan et al., 2024). When these needs are thwarted by conflictual teacher relationships, adolescents are likely to experience feelings of alienation and incompetence. This leads them to disengage from the school environment and seek fulfillment elsewhere (Díaz-Aguado, Martín-Babarro, & Falcón, 2018; Giardina et al., 2024). Online platforms, offering immediate feedback, a sense of mastery, and boundless social arenas, present a readily accessible and highly rewarding alternative, thereby elevating the risk of problematic engagement across all forms (Canale et al., 2025; Cruz, Hanus, & Fox, 2017; Díaz-Aguado et al., 2018; Liu et al., 2024; Nesi, Choukas-Bradley, & Prinstein, 2018).

The predictive role of bullying victimization revealed a more complex pattern of associations, highlighting the importance of considering the functions and affordances of different online platforms. Consistent with the compensatory framework (Kardefelt-Winther, 2014), victimized adolescents were more likely to belong to the High-Increasing and High-Stable Gaming and Moderate-Decreasing Social Media classes. The immersive, often empowering nature of many internet games may provide a particularly potent psychological escape, allowing victimized adolescents to construct identities of power, competence, and high status that are cruelly denied to them in their offline peer context (Brown et al., 2024; Giardina et al., 2024; Király, Koncz, Griffiths, & Demetrovics, 2023). However, bullying victimization did not significantly differentiate the classes dominated by social media use from the Low-Stable group. It suggests that for adolescents already suffering from negative peer interactions, social media platforms may not be a refuge. Given that these platforms are often an extension of the offline peer environment (Reich, Subrahmanyam, & Espinoza, 2012), they can amplify exclusion and peer-related stress, potentially representing a further source of distress rather than an escape from it. This finding illustrates that not all screen time is equal; its function is highly dependent on the interplay between an individual's specific vulnerabilities and the unique characteristics of the platform itself.

Developmental outcomes of PUI trajectories

A crucial component of this study was to establish the significance of these trajectories by examining their associations with adolescents' mental health across three time points. By incorporating longitudinal data on psychological outcomes, we were able to move beyond a static snapshot and test how behavioral trajectories predicted mental health outcomes over time. As hypothesized, membership in the different trajectory classes was strongly and differentially associated with not only the levels but also the changes in depression, anxiety, and suicidality. This finding supports the central tenet of life course theory, which posits that the negative effects of chronic risk exposure—in this case, PUI—accumulate over time, leading to increasingly detrimental developmental outcomes (Hertzman, Power, Matthews, & Manor, 2001). These results revealed a dynamic and concerning picture of this cumulative risk.

We observed clear evidence of diverging mental health outcomes across different trajectory groups over time. Specifically, adolescents in the High-Increasing class, who exhibited pervasive and worsening symptoms across all platforms, consistently demonstrated the most severe levels of depression, anxiety, and suicidal ideation at all three time points, showing a chronically poor profile of psychological well-being. This highlights the profound psychological toll associated with a generalized failure to regulate online engagement.

The comparison of other high-risk groups provides additional critical insights into risk accumulation dynamics. While the High-Stable Social Media and Short Video class initially showed higher psychological distress, the Moderate-Increasing Social Media class experienced marked deterioration in well-being from a better starting point, with both classes ultimately converging at similarly poor mental health levels. This convergence pattern illustrates that the rate of change of PUI development is a risk factor as potent as its initial severity. This suggests that a rapidly escalating pattern of online engagement represents a particularly acute threat to adolescent mental health. These findings are highly consistent with the I-PACE model (Brand et al., 2016, 2019), which theorizes that as problematic use becomes entrenched, its initial function as a source of gratification diminishes, and it increasingly becomes a necessary, albeit maladaptive, mechanism for coping with pre-existing or escalating negative emotions. This creates a vicious cycle wherein distress drives problematic use, while problematic use generates further distress through its negative consequences such as sleep interference and social conflict (Bender et al., 2020; Jiang & Yoo, 2024; Männikkö et al., 2015; Oberst et al., 2017; Zamani et al., 2009).

An interesting pattern emerged when comparing trajectories with different directions of change. For instance, the High-Stable Gaming and Moderate-Decreasing Social Media class was uniquely defined by high, stable PIGU alongside a significant decrease in PSMU. Despite their high gaming engagement, this group reported significantly better mental health outcomes compared to other high-risk classes, though still worse than the Low-Stable group. This finding suggests a potential trade-off between platforms' distinct functions. While their high engagement in gaming, likely sustained by its capacity to satisfy needs for competence and autonomy (Zhou, Lv, Wang, Li, & Gao, 2023), still conferred risk, their simultaneous disengagement from social media may have acted as a protective buffer. This could shield them from digital stressors, such as anxiety over social approval and the fear of missing out, which are central to the social media experience (Hall, Steele, Christofferson, & Mihailova, 2021).

In stark contrast, the Low-Stable group not only began with the most favorable mental health profile but also maintained this low-risk status across all three waves. This underscores the importance of fostering and maintaining a balanced relationship with digital media as a key component of adolescent well-being and resilience. Overall, these results demonstrate the complex interplay between different forms of online engagement and adolescent mental health. The clear dose-response relationship observed provides strong evidence for the detrimental impact of PUI on adolescent development.

Limitations and future directions

The study's limitations must be acknowledged and used to guide future research. First, this study relied exclusively on adolescent self-report measures over a one-year period. While essential for capturing subjective experiences and developmental dynamics, this approach is susceptible to common method variance and may not fully capture longer-term developmental trajectories. Future research would benefit from extended follow-up durations and adopting a multi-informant approach, incorporating reports from parents and teachers to provide a more objective and comprehensive assessment. Second, our analysis explored the independent, additive effects of microsystem predictors. The reality of development is likely more complex, involving interactive effects as proposed by bioecological theory (Bronfenbrenner & Ceci, 1994). For instance, future studies should investigate whether positive teacher-student relationships can buffer the negative impact of harsh parenting or bullying victimization on an adolescent's trajectory membership. Third, while our selection of predictors was theory-driven, other influential variables were not included. Individual temperamental differences (e.g., impulsivity, effortful control, sensation-seeking) and pre-existing psychopathology (e.g., ADHD, anxiety disorders) are known to be powerful predictors of PUI (Brand et al., 2016, 2019). Integrating such individual-level factors is a critical next step for refining our understanding of who is most at risk. Fourth, this study was conducted with a sample of Chinese adolescents. While this adds valuable data from a non-Western cultural context, the specific form, prevalence, and social meaning of these trajectories may differ across cultures. Cross-cultural replications are needed to establish the universality of these findings and to explore how cultural values may shape the relationship between online behavior and well-being. Finally, while gaming was assessed using DSM-5 criteria, measures for PSMU and PSVU relied on adapted instruments based on established theoretical frameworks due to the absence of formal diagnostic standards. Although these adapted tools are widely used, they may not fully reflect current developments in diagnostic conceptualization, necessitating future validation using standardized, platform-specific instruments.

CONCLUSION

The present study challenges a monolithic view of PUI by empirically demonstrating the existence of five co-developmental pathways of social media, gaming, and short video use during adolescence. These trajectories were differentially predicted by specific risk factors within the family, school, and peer domains, and were associated with varying mental health outcomes. The results suggest that prevention and intervention strategies must be tailored and nuanced rather than one-size-fits-all. By identifying such usage patterns and the contextual factors that sustain them, clinicians, educators, and parents can develop more targeted strategies to support adolescent well-being.

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Data availability: The datasets generated and/or analyzed during the current study are not publicly available but are available from the corresponding author on reasonable request.

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SUPPLEMENTARY MATERIAL

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