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From active users to passive watchers: Profiles of TikTok engagement and mental health predictors

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ABSTRACT

Prior studies suggest that TikTok users vary in their engagement behaviors, including passive viewing, participatory interaction, and content creation, and exhibit varying levels of problematic-use risk. Yet it remains unclear which combinations of these engagement behaviors correspond to higher versus lower risk, and which psychological vulnerabilities contribute to high-risk patterns. In a two-wave study of 715 Chinese young adults, we applied latent profile analysis (LPA) to problematic TikTok use and the frequency of passive viewing, participatory, and contributory behaviors at Time 2. We then used multinomial logistic regression with the three-step method to prospectively examine how Time 1 measures of psychopathology and related affective/cognitive vulnerabilities, including depression, social anxiety, life satisfaction, emotion dysregulation, and boredom proneness, predicted TikTok profile membership. Four profiles emerged: Minimal Users (6.7 %), Passive Watchers with High Problematic Use Tendencies (38.0 %), Moderate Users with Mild Problematic Use Tendencies (42.4 %), and Active Users with Low Problematic Use Tendencies (12.9 %). Greater life satisfaction, lower social anxiety, and lower boredom proneness at baseline predicted membership in the Active rather than Passive, Moderate, or Minimal profiles. Greater emotion dysregulation predicted membership in the Passive rather than Moderate profile. These findings highlight substantial heterogeneity in TikTok use and suggest that higher baseline psychological wellbeing may increase the likelihood of more active and less problematic patterns of engagement. The current study extends prior LPA research by specifying how risk manifests in everyday use, identifying contributors to high-risk profiles, and extending empirical support for the I-PACE theoretical framework of Internet use disorders.

1. Introduction

TikTok, one of the most popular short-video platforms worldwide, had 1.8 billion monthly active users internationally as of February 2023 (Aslam, 2024; Montag et al., 2021). Its algorithm-driven personalized feeds and integration of entertainment, information, social connection, and self-presentation foster diverse use behaviors, including passive viewing, participatory engagement, and contributory content creation (Bucknell Bossen & Kottasz, 2020). At the same time, these design features have raised concerns about problematic use. Despite this concern, research has yet to clarify the heterogeneity of TikTok engagement—-specifically, which combinations of use behaviors correspond to higher versus lower risk of problematic use, and which psychological vulnerabilities contribute to the emergence of high-risk patterns. The present study addressed this gap by applying latent profile analysis (LPA) to identify distinct user profiles that integrated both usage behaviors and problematic-use risk, thereby clarifying how risk manifests in specific usage behaviors. We further examined how baseline psychopathology and related affective and cognitive vulnerabilities predicted high-risk profiles.

While TikTok is a global phenomenon, the current study focused on Chinese users, who constitute one of the largest and most active short-video user groups worldwide. Understanding TikTok's adoption and use patterns in China is therefore crucial for contextualizing our sample and interpreting the latent profiles derived in this study. Specifically, short-video platforms are widely adopted in China, with 1.04 billion

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users by December 2024 (CNNIC, 2025), and TikTok alone attracting more than 600 million daily active users, with young adults aged 18–35 forming its core user base (FAS, 2025). Chinese users commonly engage in passive watching, participatory interaction, and content creation (Wu et al., 2021; Yao et al., 2023; Zhang, 2025), and a considerable proportion demonstrate risk of problematic use (Chao et al., 2023). Compared with U.S. users, Chinese users spend more time on the platform but report fewer follower and influencer connections (Yang, 2022). Moreover, in the Chinese context, content creation is shaped by platform mechanisms that initially provide traffic rewards to encourage contribution, then progressively require creators to meet platform, algorithmic, and advertiser standards, incentivizing engagement while steering production toward commercialization (Y. Huang & Ye, 2024).

Given growing global concern about problematic engagement with TikTok, scholars have increasingly examined its potentially problematic use. However, there is no consensus on problematic TikTok use (PTU) as a distinct diagnostic entity. Prior research has adapted symptom criteria from problematic social media use (PSMU), Internet gaming disorder, and problematic smartphone use (Billieux et al., 2015; Casale & Banchi, 2020; Ding et al., 2024; Elhai et al., 2017; Jiang et al., 2025; Li et al., 2024; Young, 1998), which could all be regarded as specific forms of problematic Internet use (PIU) sharing a common symptom structure (Montag et al., 2015, 2021). In the current study, we specify PTU as a platform-specific manifestation of PSMU (Wegmann & Brand, 2019), reflecting addiction-like symptoms and functional consequences, including preoccupation with TikTok, using TikTok to regulate emotions, increasing engagement to achieve the same effect, distress when use is reduced, interference with daily life, and failed attempts to cut down on use (Andreassen et al., 2016; Smith & Short, 2022).

While PTU captures problematic aspects of TikTok use, it does not account for the fact that most users engage with the platform in non-problematic ways (Smith & Short, 2022). To capture heterogeneity in engagement, it is therefore important to consider daily use behaviors alongside PTU. TikTok use can be meaningfully differentiated into passive viewing (scrolling through recommended videos), participatory behaviors (liking, commenting, sharing), and contributory behaviors (creating content), with passive viewing being the most common. These behaviors are driven by overlapping yet distinct motivational needs (Bucknell Bossen & Kottasz, 2020; Montag et al., 2021). Entertainment and affective needs motivate all three behaviors, but passive viewing is also linked to information-seeking and surveillance, participatory behaviors to relationship-building, and contributory behaviors to self-expression, social recognition, and fame-seeking (Bucknell Bossen & Kottasz, 2020). Empirical work further suggests that these behaviors are differentially associated with well-being: passive viewing is often linked to poorer mental health, whereas participatory or contributory behaviors may have neutral or even protective effects (Verduyn et al., 2021; Wu et al., 2021). Together, these behavioral indicators specify how users interact with the platform and, when included alongside PTU in an LPA framework, enable a more nuanced characterization of engagement by distinguishing profiles that capture both risk levels and associated behavioral patterns.

Beyond characterizing heterogeneity in TikTok engagement, it is important to identify factors that distinguish between usage profiles, particularly those associated with high-risk patterns. The I-PACE theoretical framework (Brand et al., 2016, Brand et al., 2019) provides a basis for such predictions, positing that personal characteristics (P factor), such as psychopathology, influence affective and cognitive processes (A and C factors), which in turn shape specific usage behaviors that may escalate into PIU. Depression and social anxiety are among the most commonly observed psychopathological symptoms associated with PIU, while low life satisfaction often reflects functional impairments linked to these conditions (Elhai et al., 2019; Marino et al., 2018). These conditions may heighten affective and cognitive vulnerabilities, such as boredom proneness (difficulties in sustaining attention and engaging in meaningful activities; Struk et al., 2016, Struk et al., 2017) and emotion dysregulation (difficulties with emotional processes of awareness, clarity, acceptance, goal-directed behavior, impulse control, and regulation strategies; Bjureberg et al., 2016; Gratz & Roemer, 2004). These constructs could undermine self-regulation and contribute to overuse of Internet applications, such as TikTok, as a way to cope with or escape distress, thereby increasing PIU risk (Brand et al., 2016; Kardefelt-Winther, 2014). Incorporating these P and A/C factors, our study could provide a theoretically grounded test of how baseline vulnerabilities differentiate user profiles and identify high-risk users.

Several studies applied LPA to characterize short-video usage patterns and their mental health correlates. Five studies focused on problematic use, deriving three to five profiles and consistently finding that users with higher problematic-use risk exhibited poorer mental health (Ding et al., 2024; Jiang et al., 2025; Li et al., 2024; Y. Liu et al., 2025; Smith & Short, 2022). Two others examined heterogeneity in usage duration: one identified three profiles using short-video time, PSMU, social media usage intensity, and mental health indicators but found no consistent relationship between usage time and mental health (Fortunato et al., 2023), while the other identified four profiles based on short-video time, involvement, and social media engagement metrics, observing that higher usage correlated with poorer mental health (M. Liu et al., 2024).

Despite these efforts, prior LPA research primarily relied on indicators such as general use time or problematic-use risk. General use time reflected the quantity of use but did not clarify how time was allocated across specific daily behaviors, whereas problematic-use indicators captured severity but did not reveal which combinations of behaviors were linked to higher or lower risk. This limits understanding of user heterogeneity. To address this gap, we integrated daily use behaviors and problematic-use risk in a single LPA model, enabling a more precise delineation of both how TikTok usage time was spent and how risk manifested in everyday use. Moreover, prior LPA research was cross-sectional, leaving it unclear whether mental health vulnerabilities predicted usage patterns or merely reflected concurrent associations. By adopting a longitudinal design and testing whether Time 1 vulnerabilities predicted Time 2 profiles, this study examined the prospective differentiation of user profiles and informed identification of high-risk users. In contrast to these LPA studies, prior longitudinal research on problematic short-video use typically treated usage as homogeneous, relying on variable-centered approaches that overlooked how distinct engagement patterns might be shaped by specific psychological mechanisms (Yao et al., 2023). Based on the I-PACE model, we investigated how differentiated user profiles were shaped by personal, affective, and cognitive vulnerability factors. This person-centered approach complements variable-centered work and extends empirical support for the I-PACE framework.

In sum, the current study applied LPA to a web-based sample of Chinese adult TikTok users assessed at two time points. We incorporated indicators of problematic use, as well as frequency of passive viewing, participatory behaviors, and contributory behaviors, to identify distinct user profiles ranging from high-risk to more adaptive. We then examined how baseline psychopathology and affective/cognitive vulnerabilities, including depression, social anxiety, life satisfaction, emotion regulation difficulties, and boredom proneness, predicted profile membership two months later. Although profile classification was exploratory, this approach allowed us to examine how these indicators cluster in real-world data. Based on prior literature (Brand et al., 2016; Chao et al., 2023; Yao et al., 2023), we expected that higher levels of psychopathology and related vulnerabilities would predict membership in higher-risk profiles characterized by elevated problematic use.

2. Methods

2.1. Participants

TikTok users were recruited from an online survey platform (http s://www.credamo.com), which provides services similar to Amazon's Mechanical Turk. It has a large research panel with users of different ages, education levels, and occupations from various regions of China. The following criteria were used for initial recruitment: (1) having a TikTok account; (2) using TikTok at least a few times per week; and (3) identifying TikTok as one's most used short-video platform. Data were collected in two waves. To ensure data quality, three attention-check questions (e.g., "Please select the second option") were included in each assessment. Participants failing any of the attention-check questions were excluded. The final pool for the first assessment had 822 valid participants, and 715 of them completed the follow-up assessment after 2 months. The current analysis focused on these 715 participants with complete data on study variables. Two participants did not provide valid responses for age, which was handled by listwise deletion when conducting covariate analysis. Aside from age, we required responses to questions, so no other missing data were present.

The final sample (N = 715) had an average age of 27.9 (from 18 to 56), and 65.2 % were female (N = 466). The majority of participants had a college education (85.3 %), while 12.2 % held a master's degree or higher, and 2.5 % had a high school education or below. Part of this dataset was published in a prior publication, where additional information can be found (Yao et al., 2023). All participants provided informed consent before taking part in the study. The study was conducted following the Declaration of Helsinki and received approval from the local ethics committee (ID: 2022A21).

2.2. Measures

The current study analyzed mental health data collected at baseline (Time 1) and TikTok usage data collected at follow-up (Time 2; two months later).

The frequency of watching videos on TikTok was assessed by one item (Yao et al., 2023). The frequency of participatory usage was assessed with three items, and frequency of contributory usage was assessed with two items (Bucknell Bossen & Kottasz, 2020). These items were translated into Chinese following a backward translation procedure. The adapted 10-item Smartphone Addiction Scale-Short Version (SAS-SV) measured the tendency of problematic use (Original version: Kwon, Kim, Cho, & Yang, 2013; Chinese version: Chen et al., 2017). The adaptation involves replacing the word "smartphone" in each item with "TikTok". Similar adaptations for social media platforms (e.g., WhatsApp, Facebook, Instagram, Snapchat, TikTok) have consistently demonstrated strong psychometric properties (Chao et al., 2023; Rozgonjuk et al., 2021), thereby supporting validity of the present adaptation. In addition, we asked participants to indicate their daily average TikTok use duration (Q. Huang et al., 2021). They indicated the time on a 10-point Likert-type scale: (1) less than or equal to 10 min, (2) 11–20 min, (3) 21–30 min, (4) 31 min–1 h, (5) 1–1.5 h, (6) 1.5–2 h, (7) 2–3 h, (8) 3–4 h, (9) 4–5 h, and (10) more than 5 h.

The 9-item Patient Health Questionnaire (PHQ-9) was used to assess depression (Original version: Kroenke, Spitzer, & Williams, 2001; Chinese version: Wang et al., 2014). The 17 straightforwardly worded items from the Social Interaction Anxiety Scale (SIAS) were used to assess social anxiety (Original version: Mattick & Clarke, 1998; Rodebaugh, Woods, & Heimberg, 2007; Chinese version: Ye, Qian, Liu, & Chen, 2007). The 5-item Satisfaction with Life Scale (SWLS) was used to assess life satisfaction (Diener, 2009; Diener et al., 1985). The Difficulties in Emotion Regulation Scale–16 (DERS-16) was used to assess emotion dysregulation (Original version: Bjureberg et al., 2016; Chinese version: G. Wang, Guo, & Shen, 2021). The short version of Boredom Proneness Scale was used to access boredom proneness (Original version: Struk et al., 2017; Chinese version: Peng et al., 2019).

All measures were found reliable and valid in prior research. Chinese versions of these measures were used to assess these variables. Sample items and internal consistency estimates are provided in Supplementary Table S1, with all measures demonstrating moderate to high internal consistency.

2.3. Data analysis

LPA was conducted in Mplus 8.1 to identify profiles of TikTok use based on four indicators at Time 2: watching, participating, contributing, and problematic use tendencies. The largest skewness and kurtosis values were −0.93 and 0.73, respectively, both for the watching variable, suggesting normality (Curran et al., 1996). The robust maximum likelihood estimator (MLR) was used, as it provides more reliable estimates when data are not normally distributed and has no disadvantage when data are normally distributed (Bryant & Satorra, 2012). The analysis included a single item for watching, and average scores for participating (3 items), contributing (2 items), and problematic use (10 items). These scores were treated as continuous variables.

Models specifying one to six profiles were estimated. Model fit was evaluated using multiple criteria (Ram & Grimm, 2009), including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), sample-size-adjusted BIC (aBIC), entropy, the Lo-Mendell-Rubin adjusted likelihood ratio test (LMRT), and the bootstrapped likelihood ratio test (BLRT). Lower AIC, BIC, and aBIC values indicate better fit, higher entropy reflects more precise classification, and significant LMRT/BLRT results indicate that a model with k profiles fits better than a model with k-1 profiles.

For the best-fitting model, we first conducted univariate analyses to describe baseline differences between the four user profiles. We compared them on demographics (age, gender, education level), usage duration, and mental health indicators using chi-square tests and ANOVAs in SPSS. Mental health variables that showed significant group differences between profiles were then entered into a multivariate model using LPA in Mplus to assess their unique contributions, with demographic variables showing significant group differences included as control. Specifically, these baseline variables were used to predict Time 2 profile membership using Vermunt's three-step approach in LPA, which accounts for classification uncertainty in mixture models (Collier & Leite, 2017). This approach yielded beta coefficients (unstandardized), odds ratios (ORs), and 95 % confidence intervals (CIs) for each baseline predictor, reflecting their prospective associations with profile membership while controlling for covariates.

3. Results

3.1. Latent profiles of TikTok usage

Fit indices are shown in Table 1. AIC, BIC, and aBIC decreased as more profiles were added, suggesting improving fit. However, the six-profile model did not converge properly, and one profile included only

Table 1
Fit indices for models with 1 to 6 latent profiles.

N	AIC	BIC	aBIC	Entropy	LMRT	BLRT	Classes (%)
1	8132.3	8168.9	8143.5				
2	7907.0	7966.5	7925.2	0.63	0.021	<.001	37.8, 62.2
3	6550.1	6632.4	6575.2	1	0.45	<.001	6.7, 50.9, 42.4
4	**6502.3**	**6607.5**	**6534.5**	**0.88**	**0.003**	**<.001**	**6.7, 38.0, 42.4, 12.9**
5	6392.9	6520.9	6432.0	0.84	0.002	<.001	6.7, 22.0, 20.4, 31.0, 19.9
6	6374.8	6525.7	6420.9	0.85	–	–	22.9, 6.7, 20.1, 17.5, 30.8, 2.0

Note: AIC (Akaike Information Criterion), BIC (Bayesian Information Criterion), aBIC (Sample Size Adjusted BIC), LMRT (LoMendel-Rubin Adjusted Likelihood Ratio Test), and BLRT (Bootstrapped Likelihood Ratio Test). The final selected model (N = 4) was bolded.

about 2 % of the sample, so this solution was not considered further. The three-profile model produced perfect entropy, yet the LMRT was not significant, and closer inspection showed that this classification was driven almost entirely by the passive watching variable, grouping participants into high (score = 5), medium (score = 4), and low (score ≤ 3) categories. This indicated that the model was unstable and did not capture broader engagement patterns. For the four- and five-profile models, LMRT and BLRT tests favored the five-profile solution, but the four-profile model showed better entropy and provided a more parsimonious and interpretable solution. Based on these considerations, the four-profile model was selected as the final solution.

As shown in Fig. 1, the final model identified four distinct profiles of TikTok use. Profile 1, which showed the lowest scores across all indicators, was labeled "Minimal Users" (N = 48, 6.7 %). Profile 2 was marked by high levels of watching, moderate participation, low contribution, and relatively high problematic use, and was labeled "Passive Watchers with High Problematic Use Tendencies" (N = 272, 38.0 %). Profile 3 showed moderate levels across all indicators and was labeled "Moderate Users with Mild Problematic Use Tendencies" (N = 303, 42.4 %). Finally, Profile 4 showed high levels of watching, participation, and contribution, but relatively low problematic use, and was labeled "Active Users with Low Problematic Use Tendencies" (N = 92, 12.9 %).

3.2. Characteristics of profiles

Table 2 summarizes the demographic characteristics. No significant gender differences were found across the four profiles ($\chi^2 = 3.55$, df = 3, $p = 0.31$, $\varphi = 0.07$). Education levels did not differ either ($\chi^2 = 8.93$, df = 6, $p = 0.18$, $\varphi = 0.11$). Age differed significantly ($F(3, 709) = 3.57$, $p = 0.014$, partial $\eta^2 = 0.015$). Post-hoc tests with Bonferroni correction showed that Active Users were older than Passive Watchers ($p = 0.007$). Other group comparisons were not significant (all ps > 0.05).

Group differences in usage duration were significant ($F(3, 711) = 21.84$, $p < 0.001$, partial $\eta^2 = 0.084$), with all pairwise comparisons significant (all ps < 0.01). Active Users reported the longest time spent on TikTok, followed by Passive Watchers, Moderate Users, and Minimal Users.

Significant group differences were found for all mental health measures: depression ($F(3, 711) = 9.84$, $p = 0.006$, partial $\eta^2 = 0.04$), anxiety ($F(3, 711) = 21.44$, $p < 0.001$, partial $\eta^2 = 0.083$), life satisfaction ($F(3, 711) = 28.94$, $p < 0.001$, partial $\eta^2 = 0.11$), emotion dysregulation ($F(3, 711) = 25.17$, $p < 0.001$, partial $\eta^2 = 0.096$), and boredom proneness ($F(3, 711) = 28.77$, $p < 0.001$, partial $\eta^2 = 0.11$). Across all measures, Active Users showed the most favorable mental health conditions. In contrast, Passive Users reported poorer outcomes, including higher emotion dysregulation compared with Moderate Users. All significant pairwise comparisons (Bonferroni corrected) are indicated in Fig. 2.

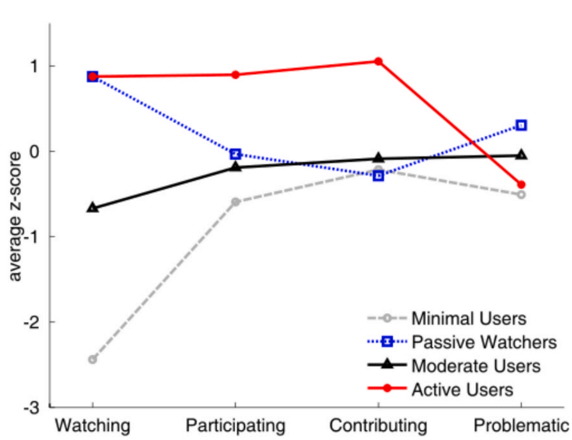

Fig. 1. Average z-scores in each usage dimension for the 4 profiles.

3.3. Predicting user profiles at T2 from baseline mental health

Given that age showed significant group differences in the univariate analysis, we included age as a control variable in the multivariate analysis with Vermunt's three-step approach. Results are shown in Table 3. When comparing Active Users with Passive Users, lower social anxiety, greater life satisfaction and lower boredom proneness were associated with a greater likelihood of being in the Active group. A similar pattern emerged when comparing Active Users with Moderate Users: individuals with lower social anxiety, greater life satisfaction and lower boredom proneness were more likely to belong to the Active group. Comparisons between Passive and Moderate Users indicated that higher levels of emotion dysregulation significantly predicted membership in the Passive group. Comparisons with the Minimal User group are reported in Table S3. These results showed that users with greater life satisfaction and lower boredom proneness were more likely to be Active than Minimal. No significant mental health predictors were found when comparing Passive/Moderate Users with Minimal Users. Given the small size of the Minimal User group (N = 48, 6.7 %) and the substantial within-group variability (see Fig. 2), these null effects should be interpreted with caution, as they may reflect limited statistical power rather than true absence of associations.

4. Discussion

This study employed a person-centered approach to examine TikTok usage patterns and identified four distinct user profiles: Active Users with Low Problematic Use, Passive Watchers with High Problematic Use, Moderate Users with Mild Problematic Use, and Minimal Users. These profiles captured both everyday engagement behaviors and different levels of problematic use, thereby providing a refined picture of how different levels of risk are associated with distinct everyday usage patterns. Baseline psychopathology and related affective/cognitive vulnerabilities prospectively predicted membership in these profiles, clarifying which vulnerabilities differentiated user groups, particularly those at higher risk.

4.1. TikTok user profiles

Both Passive Watchers and Active Users showed high levels of passive viewing but differed in other behaviors: Passive Watchers reported only moderate participation and low contribution, whereas Active Users reported high participation and contribution. These results highlight that even the most active users spend substantial time passively watching, while those who are largely passive may still engage in other activities occasionally. Notably, neither passive viewing nor overall time spent on TikTok was directly linked to problematic use. Despite engaging in similar levels of passive watching and spending even more time on the platform than Passive Watchers, Active Users reported much lower problematic use. This pattern is consistent with work in the gaming context, where high engagement does not necessarily indicate addiction or distress (Katz et al., 2024). Together, these results suggest that users who primarily engage in passive watching are most likely to demonstrate problematic use risk, whereas those adopting a more balanced mix of passive, participatory, and contributory behaviors are less likely to show such risk.

Prior latent profile studies of short-video use have typically distinguished users based on general use time or severity of problematic use (Ding et al., 2024; Fortunato et al., 2023; Jiang et al., 2025; Li et al., 2024; Liu et al., 2024; Liu et al., 2025; Smith & Short, 2022). Beyond short-video platforms, person-centered studies of broader social media use have similarly identified heterogeneous user profiles, often reflecting differences in use intensity or problematic use (Keum et al., 2023; Russell et al., 2022; Stănculescu & Griffiths, 2022). The present findings

Table 2
Demographic characteristics of each profile.

	GenderN (percentage)		Education LevelN (percentage)			AgeM (SD)
	Male	Female	High school education or below	College Education	Master's degree or above	
Minimal Users (N = 48)	14 (29.2 %)	34 (70.8 %)	0	39 (81.3 %)	19 (18.8 %)	28.1 (5.6)
Passive Watchers (N = 272)	106 (39.0 %)	166 (61.0 %)	8 (2.9 %)	235 (86.4 %)	29 (10.7 %)	27.3 (6.4)
Moderate Users (N = 303)	99 (32.7 %)	204 (67.3 %)	9 (3.0 %)	251 (82.8 %)	43 (14.2 %)	27.9 (6.2)
Active Users (N = 92)	30 (32.6 %)	62 (67.4 %)	1 (1.1 %)	85 (92.4 %)	6 (6.5 %)	29.7 (4.1)

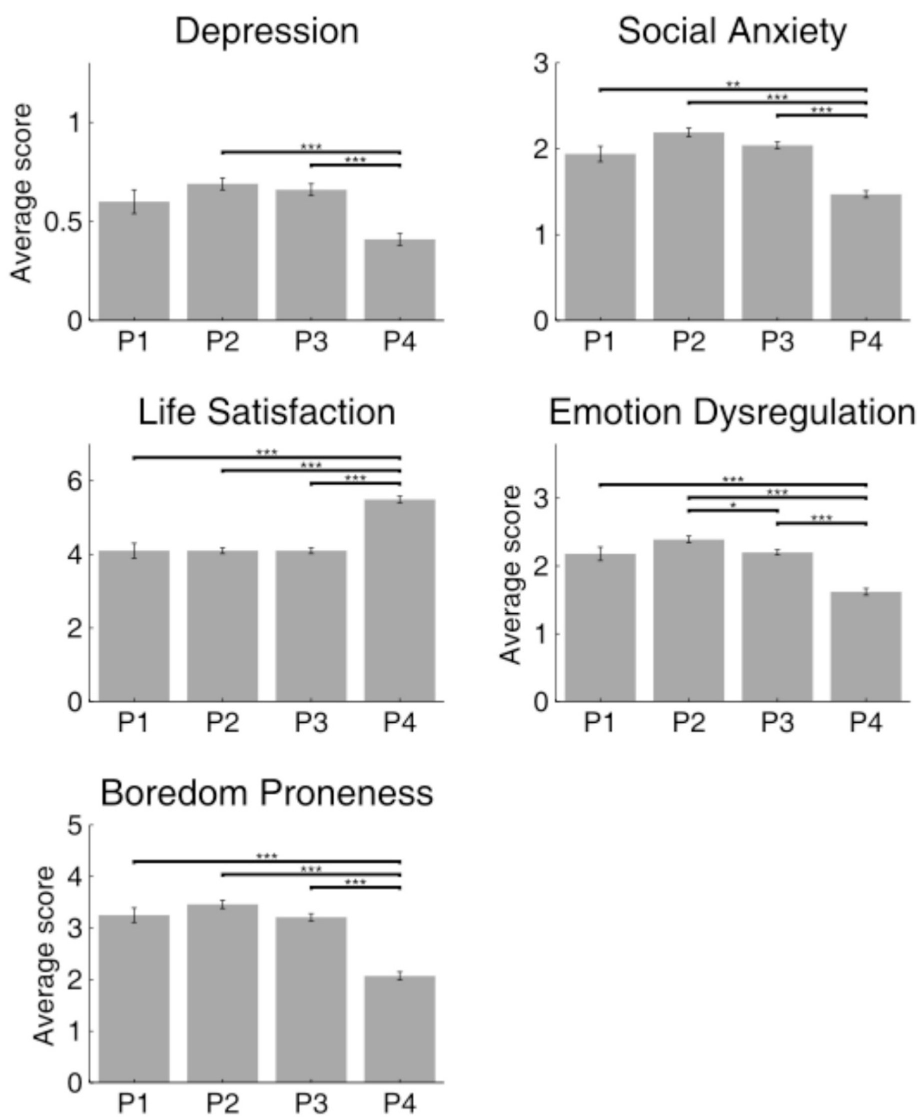

Fig. 2. Baseline mental health (Time 1) across the four user profiles. P1: minimal users; P2: passive watchers; P3: moderate users; P4: active users. * $p < 0.05$, ** $p < 0.01$ ***: $p < 0.001$.

extend this literature by showing not only differences in overall engagement or risk, but also how specific engagement behaviors and their particular combinations relate to problematic use. By identifying distinct constellations of everyday behaviors that map onto diverse risk levels, this study provides a refined understanding of heterogeneity in short-video engagement.

4.2. Predicting TikTok user profiles

In univariate analyses, all baseline psychopathology and affective/ cognitive vulnerabilities differed significantly across the four profiles, indicating robust associations between these characteristics and TikTok use. In the multivariate prediction model, however, only certain vulnerabilities independently predicted profile membership. Passive Watchers, the highest-risk group, were characterized by greater emotion

Table 3
Associations between user profiles and covariates.

Covariate	B (SE)	z-score	p	Odds Ratio (95 % CI)
Active (vs Passive)				
Age	−0.06(0.03)	−1.83	0.068	0.94 ([0.88 1.01])
Depression	2.04(1.27)	1.61	0.11	7.70 ([0.64 92.4])
Anxiety	**−1.39 (0.69)**	**−2.00**	**0.046**	**0.25 ([0.06 0.97])**
Life Satisfaction	**1.28(0.59)**	**2.16**	**0.031**	**3.58 ([1.13 11.4])**
Emotion Dysregulation	−1.06(0.68)	−1.56	0.12	0.35 ([0.09 1.31])
Boredom Proneness	**−1.14 (0.32)**	**−3.55**	**<0.001**	**0.32 ([0.17 0.60])**
Active (vs Moderate)				
Age	**−0.07 (0.03)**	**−2.16**	**0.031**	**0.94 ([0.88 0.99])**
Depression	1.57(1.17)	1.34	0.18	4.78 ([0.48 47.48])
Anxiety	**−1.26 (0.64)**	**−1.98**	**0.048**	**0.28 ([0.08 0.99])**
Life Satisfaction	**1.34(0.57)**	**2.35**	**0.019**	**3.82 ([1.25 11.72])**
Emotion Dysregulation	−0.68(0.63)	−1.08	0.28	0.51 ([0.15 1.75])
Boredom Proneness	**−0.97 (0.30)**	**−3.23**	**0.001**	**0.38 ([0.21 0.69])**
Passive (vs Moderate)				
Age	−0.00(0.02)	−0.11	0.91	1.00 ([0.97 1.03])
Depression	−0.48(0.29)	−1.63	0.10	0.62 ([0.35 1.10])
Anxiety	0.13(0.19)	0.68	0.50	1.13 ([0.79 1.63])
Life Satisfaction	0.07(0.08)	0.77	0.44	1.07 ([0.91 1.26])
Emotion Dysregulation	**0.38(0.19)**	**2.03**	**0.042**	**1.47 ([1.01 2.13])**
Boredom Proneness	0.18(0.11)	1.55	0.12	1.19 ([0.95 1.50])

Note. Significant effects are shown in bold. Reference profiles are indicated in parentheses in the column on the left.

dysregulation compared with Moderate Users, as well as higher social anxiety, lower life satisfaction, and higher boredom proneness compared with Active Users. Within the I-PACE framework, these results highlight Personal (increased anxiety and reduced life satisfaction), Affective (emotion dysregulation), and Cognitive (boredom proneness) factors as key predictors of high-risk TikTok engagement. Difficulties in emotion regulation may increase the likelihood of high-risk use rather than more controlled use (as in Moderate Users), potentially reflecting an increasing reliance on TikTok for mood regulation. Additionally, individuals with lower life satisfaction, higher anxiety, and greater boredom may also use TikTok in a compensatory way, either to cope with distress or to seek cognitive stimulation, which may reinforce maladaptive patterns and elevate risk of problematic use. Interestingly, although depression was elevated in Passive Watchers in the univariate analyses (Fig. 2), it was no longer significant in the multivariate model, suggesting that its effect may operate indirectly through affective and/or cognitive vulnerabilities. Taken together, these findings shed light on potential mechanisms within the I-PACE framework that may predispose individuals to a high-risk profile characterized by greater problematic TikTok use severity, complementing prior variable-centered research.

Active Users, by contrast, displayed the most favorable baseline mental health conditions and were prospectively predicted by lower social anxiety, higher life satisfaction and lower boredom proneness. These individuals may exhibit better overall psychological functioning and, in turn, use TikTok in more adaptive ways that sustain or enhance positive affect and social connection without elevating risk. Notably, they engaged in as much passive viewing and spent more total time on TikTok than Passive Watchers. Their higher levels of participatory and contributory use may buffer risk by supporting social connection, self-expression, and a sense of achievement, particularly when content creation is positively reinforced. Consistent with prior research, actively engaged, socially oriented use of smartphones appears more adaptive than non-social use (Elhai et al., 2020; Rozgonjuk et al., 2019), with active engagement on social media often linked to well-being through expanded social networks and meaningful interactions (Verduyn et al., 2017, 2021).

While previous LPA studies on short video use have been cross-sectional, the present study contributes to this literature by employing a longitudinal design to identify baseline psychological vulnerabilities that can be associated with subsequent profile membership after two months. Moreover, as prior research has mainly examined associations between psychopathology and problematic short video use from a variable-centered perspective (Chao et al., 2023; Yao et al., 2023), the present study complements this work by adopting a person-centered perspective. In doing so, it demonstrates how psychological vulnerabilities and wellbeing manifest in everyday patterns of short video use and extends empirical support for the I-PACE framework in the context of short video use profiles.

4.3. Limitations and further directions

This study has several limitations. First, while the study focused on key dimensions of TikTok usage, other potentially relevant factors, such as public versus private use (Manago et al., 2012), social versus non-social use (Alfasi, 2019; S. Chen et al., 2019), were not examined and should be explored in future research. Second, the current study established short-term links between psychological vulnerabilities and usage patterns over two-month intervals, leaving the long-term effect unclear. Generalization to longer time intervals awaits further investigation. Third, it remains to be tested in future studies whether these findings generalize to other platforms with different usage dynamics. Finally, this study's sample consisted of adult users, limiting its relevance to children/adolescents. Future studies could prioritize examining younger users.

5. Conclusion

This study identified four distinct TikTok user profiles and demonstrated that baseline mental health predicts later profile membership after two months. Specifically, higher social anxiety, lower life satisfaction, greater boredom proneness, and higher emotion dysregulation predicted Passive rather than Active or Moderate use, while lower social anxiety, higher life satisfaction, and lower boredom proneness predicted Active rather than Passive, Moderate or Minimal use. These findings classify TikTok use into patterns ranging from high-risk to more adaptive, clarify which psychological variables may be associated with these patterns of use, and thus identify who may be at risk in the short term, extending prior LPA-based research and offering further empirical support for the I-PACE framework.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors used generative AI (ChatGPT-4, OpenAI Inc., https://openai.com/) to enhance the readability and language of this article. Following the use of the tool, the authors carefully reviewed and edited the content to ensure its accuracy and quality, and they take full responsibility for the final published material.

CRediT authorship contribution statement

Jing Chen: Writing – review & editing, Writing – original draft, Formal analysis, Conceptualization. **Nisha Yao:** Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Jon D. Elhai:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The authors declare that they have no competing interests to declare. For reasons of transparency, Jon Elhai notes that he receives royalties for several books published on posttraumatic stress disorder (PTSD); is a paid, full-time faculty member at University of Toledo; occasionally serves as a paid, expert witness on PTSD legal cases; and recently received grant research funding from the U.S. National Institutes of Health.

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None.

Data statement

Data and code supporting the present study are available in the online supplementary materials.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.addbeh.2025.108552.

Data availability

Data have been included in this submission - an archive/zipped file containing data (SPSS and Mplus formats), along with Mplus input files.

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