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Identifying Generative AI Use Profiles Among College Students Using Latent Profile Analysis: Associations with Depression and Anxiety

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Abstract:	Background: Generative artificial intelligence (GenAI) has become widely adopted among college students, yet its relationship with mental health remains poorly understood. Most existing studies treat AI users as a homogeneous group, failing to capture considerable heterogeneity in usage patterns. This study aimed to identify latent profiles of GenAI use among Chinese college students and examine their differential associations with depression and anxiety. Methods: A cross-sectional survey was conducted with 5,748 Chinese college students. Participants completed measures of AI usage behaviors, motivations, AI literacy, dependency, depression (BDI-II), and anxiety (BAI). Latent profile analysis identified distinct usage patterns, and random forest classification with SHAP analysis validated the profiles and identified key distinguishing features. Results: Four distinct profiles emerged: Rational-Instrumental, Adaptive-Compensatory, Problematic-Dependent, and Light-Exploratory. The Problematic-Dependent profile (15%) was characterized by high escapism motivation, low AI literacy, and high dependency, and was associated with significantly elevated depression and anxiety. In contrast, the Rational-Instrumental profile, marked by high AI literacy and instrumental motivation, showed the most favorable mental health outcomes. The random forest classifier achieved good performance (accuracy=.81; mean AUC=.894). SHAP analysis identified depression, smartphone addiction, and executive function deficits as key features of the Problematic-Dependent profile, whereas conscientiousness was most strongly associated with the Rational-Instrumental profile. Conclusions: These findings reveal that GenAI usage patterns among college students vary considerably in their associations with depressive and anxiety symptoms. Interventions should target usage motivations and AI literacy rather than usage frequency alone, underscoring the importance of person-centered approaches for understanding technology use and psychological well-being.
Opposed Reviewers:	

Highlights

- Four distinct GenAI usage profiles were identified among Chinese college students.
- The Problematic-Dependent profile exhibited the highest levels of depression and anxiety.
- Escapism motivation was most strongly associated with depression and anxiety.
- AI literacy may serve as a protective factor for psychological well-being.
- Usage patterns, rather than frequency alone, differentiated mental health outcomes.

Abstract

Background: Generative artificial intelligence (GenAI) has become widely adopted among college students, yet its relationship with mental health remains poorly understood. Most existing studies treat AI users as a homogeneous group, failing to capture considerable heterogeneity in usage patterns. This study aimed to identify latent profiles of GenAI use among Chinese college students and examine their differential associations with depression and anxiety.

Methods: A cross-sectional survey was conducted with 5,748 Chinese college students. Participants completed measures of AI usage behaviors, motivations, AI literacy, dependency, depression (BDI-II), and anxiety (BAI). Latent profile analysis identified distinct usage patterns, and random forest classification with SHAP analysis validated the profiles and identified key distinguishing features.

Results: Four distinct profiles emerged: Rational-Instrumental, Adaptive-Compensatory, Problematic-Dependent, and Light-Exploratory. The Problematic-Dependent profile (15%) was characterized by high escapism motivation, low AI literacy, and high dependency, and was associated with significantly elevated depression and anxiety. In contrast, the Rational-Instrumental profile, marked by high AI literacy and instrumental motivation, showed the most favorable mental health outcomes. The random forest classifier achieved good performance (accuracy=.81; mean AUC=.894). SHAP analysis identified depression, smartphone addiction, and executive function deficits as key features of the Problematic-Dependent profile, whereas conscientiousness was most strongly associated with the Rational-Instrumental profile.

Conclusions: These findings reveal that GenAI usage patterns among college students vary considerably in their associations with depressive and anxiety symptoms. Interventions should target usage motivations and AI literacy rather than usage frequency alone, underscoring the importance of person-centered approaches for understanding technology use and psychological well-being.

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Identifying Generative AI Use Profiles Among College Students Using Latent Profile Analysis: Associations with Depression and Anxiety

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Author Notes

CRediT authorship contribution statement. Haoyang Shi: Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft. **Tongyi Zhang**: Data curation, Formal analysis, Methodology, Writing – original draft. **Zihao Wang**: Data curation, Investigation, Methodology. **Xiaolong Yang**: Funding acquisition, Resources, Writing – review & editing. **Zixuan Shao**: Writing – review & editing. **Xiaofeng Ma**: Conceptualization, Project administration, Supervision, Writing – review & editing.

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Declaration of interests

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

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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Dear Editor, *Journal of Affective Disorders*

We are pleased to submit our manuscript entitled "**Identifying Generative AI Use Profiles Among College Students Using Latent Profile Analysis: Associations with Depression and Anxiety**" for consideration as an original research article in the *Journal of Affective Disorders*. This manuscript has not been published previously and is not under consideration elsewhere. All authors have reviewed and approved this final version, and the research adheres to the ethical standards required by your journal. The authors declare no conflicts of interest.

Generative artificial intelligence has rapidly become part of the daily lives of college students, yet its relationship with mental health remains poorly understood. Existing research has produced mixed findings, with some studies highlighting therapeutic benefits and others raising concerns about dependency and social displacement. A key limitation of this literature is its reliance on variable-centered approaches that treat AI users as a homogeneous group, thereby obscuring considerable heterogeneity in how young people engage with these technologies. To address this gap, we conducted a cross-sectional survey of 5,748 Chinese college students and employed latent profile analysis to identify distinct patterns of generative AI use based on multiple dimensions, including usage behaviors, motivations, AI literacy, and dependency. We further validated the identified profiles using random forest classification with SHAP analysis.

Our analysis revealed four distinct profiles: *Rational-Instrumental* (27.99%), *Adaptive-Compensatory* (33.99%), *Problematic-Dependent* (15.00%), and *Light-Exploratory* (23.02%). These profiles showed clear differences in mental health outcomes. The *Problematic-Dependent* profile, characterized by high escapism motivation, low AI literacy, and high dependency, was associated with significantly elevated levels of depression and anxiety. In contrast, the *Rational-Instrumental* profile, marked by high AI literacy and instrumental motivation, showed the most favorable mental health outcomes. Machine learning analysis identified depression, smartphone addiction, and executive function deficits as key features of the *Problematic-Dependent* profile, whereas conscientiousness was most strongly associated with the *Rational-Instrumental* profile.

These findings have important implications for both research and practice. At the theoretical level, our results demonstrate the value of person-centered approaches in revealing heterogeneous effects that variable-centered methods cannot capture. At the practical level, the findings suggest that interventions should target usage motivations and AI literacy rather than usage frequency alone, and that prevention efforts for problematic AI use should be integrated within broader digital health frameworks. We believe this work is well-suited for the *Journal*

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of Affective Disorders given its focus on mental health implications of emerging technologies and its contribution to understanding risk and protective factors for depression and anxiety among young adults.

Thank you for considering our manuscript.

Sincerely,

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Identifying Generative AI Use Profiles Among College Students Using Latent Profile Analysis: Associations with Depression and Anxiety

1. Introduction

Generative artificial intelligence (GenAI) has become increasingly integrated into the daily lives of young people. Text-based conversational agents and image generation systems are reshaping how people access information, acquire knowledge, and engage in social interactions. By 2024, the global user base of generative AI had reached hundreds of millions, with young people representing the majority and college students showing particularly high adoption rates (Liu et al., 2024; Strzelecki, 2024). This rapid uptake raises important questions about how GenAI use may relate to psychological well-being, particularly among college students who are navigating a critical developmental period.

The college years coincide with what Arnett (2000) termed "emerging adulthood"—a transitional period characterized by identity exploration, shifting social roles, and the development of autonomy. This developmental stage is also associated with heightened vulnerability to mental health difficulties (Arnett et al., 2014; Tanner & Arnett, 2016). Depression and anxiety are especially prevalent in this population, with approximately 31% of college students worldwide screening positive for one or both conditions (Auerbach et al., 2018). In China, a large-scale survey of over 40,000 students across 106 universities found prevalence rates of 9.8% for depression, 15.5% for anxiety, and 6.5% for comorbid presentations (Han et al., 2025). Given the well-documented associations between these conditions and impaired academic performance (Eisenberg et al., 2009), reduced quality of life, and suicidal ideation (Mortier et al., 2018), understanding how emerging technologies such as GenAI may influence mental health outcomes in this population is both timely and important. However, because GenAI is a relatively new technology, the nature of its relationship with mental health remains unclear.

1.1. Generative AI Use and Mental Health: Benefits and Risks

Research on the mental health implications of GenAI use is growing rapidly, revealing a complex picture of both potential benefits and risks. On the positive side, GenAI has shown promise as a tool for mental health support. In a qualitative study by Siddals et al. (2024), users who engaged with GenAI chatbots for mental health purposes reported positive experiences, including a sense of emotional refuge, insightful guidance, and meaningful connection. More recently, a clinical trial by Heinz et al. (2025) found that patients with major depressive disorder who used a purpose-built GenAI therapeutic chatbot experienced an average symptom reduction of 51%, while those with generalized anxiety disorder showed a 31% reduction. Although these findings pertain to AI systems specifically designed for therapeutic purposes rather than general-purpose conversational agents, they suggest that GenAI may serve as a supplementary channel for emotional support, particularly for individuals who face barriers to professional mental health services due to stigma or limited resources (Wang et al., 2025).

At the same time, a growing body of research has highlighted potential negative effects. Regarding social functioning, Yang et al. (2024) found that increased engagement with AI chatbots was associated with psychological dependence. When students rely on AI chatbots as their primary source of social support, they may reduce genuine interpersonal interactions, potentially leading to social isolation and weakened interpersonal skills (Chaudhry & Debi, 2024). Similarly, Crawford et al. (2024) surveyed 387 college students and found that AI use was associated with reduced sense of belonging and increased loneliness. Other researchers have begun to conceptualize excessive GenAI use as a form of behavioral addiction. Yankouskaya et al. (2025) proposed that ChatGPT may foster user dependency through its capacity for instant gratification, personalized responses, and round-the-clock availability, potentially creating "parasocial bonds" that substitute for real interpersonal relationships. Sun et al. (2025) reported that high-frequency GenAI users exhibited more indicators of problematic use, including immersion, withdrawal symptoms, loss of control, and difficulties with emotional regulation. Yu et al. (2024) further found that AI use motivated by a desire to escape real-world stress was positively correlated with depression and anxiety symptoms, suggesting that usage motivation may be a key factor shaping mental health outcomes.

These mixed findings—with some studies demonstrating benefits and others highlighting risks—suggest that the relationship between GenAI use and mental health is not uniform across users. Notably, GenAI differs from traditional digital technologies in several important ways: it can generate human-like conversational content, provide immediate emotional responses, and simulate social interaction to a degree not previously possible. Prior research has established that excessive social media use is associated with increased depressive and anxiety symptoms (Twenge et al., 2018), and that smartphone addiction predicts higher levels of depression and anxiety (Elhai et al., 2017). The unique interactive capabilities of GenAI may produce different patterns of association with mental health than those observed with other digital technologies. To make sense of the contradictory findings in the literature, a more systematic theoretical framework is needed to understand how different usage patterns may lead to different mental health outcomes.

1.2. Theoretical Framework for Understanding Generative AI Use and Mental Health

The heterogeneous findings reviewed above suggest that the relationship between GenAI use and mental health cannot be adequately characterized by examining usage frequency or duration in isolation. Rather, a comprehensive understanding requires consideration of why individuals use GenAI (motivations), how they engage with it (competencies), and who is most vulnerable to adverse outcomes (individual differences). To address these distinct but interrelated questions, we integrate three complementary theoretical frameworks.

Uses and Gratifications Theory (Katz et al., 1973) posits that individuals are active media users who select and use specific technologies to satisfy diverse psychological and social needs, including cognitive, affective, social integrative, and tension release needs (Ruggiero, 2000). In the context of GenAI, research has identified differential associations between various usage motivations and mental health outcomes. For example, a latent profile study by Ling et al. (2025) on TikTok users identified four motivation profiles, with users in the "escapist addiction and novelty motivation" profile showing the poorest mental health outcomes. Similarly, social media use primarily motivated by escapism has been associated with higher addiction risk and poorer mental health (Kardefelt-Winther, 2014). Drawing on this framework, we distinguish among four dimensions of usage motivation—instrumental, entertainment, social, and escapism—to capture how different need-satisfaction patterns may lead to different mental health outcomes.

Beyond motivations, individual cognitive resources also shape the quality of technology engagement. The extended Technology Acceptance Model (Venkatesh et al., 2003) emphasizes the role of individual cognitive factors in shaping technology use patterns. Accordingly, we incorporate AI literacy as a key variable. AI literacy has been defined as "the competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool" (Long & Magerko, 2020). Ng et al. (2021) proposed a multidimensional framework for AI literacy encompassing understanding and using AI, evaluating and creating AI, and AI ethics. Research has found that higher levels of AI literacy are associated with greater self-efficacy in AI use (Laupichler et al., 2022), while lower digital literacy is associated with increased psychological burden during technology use (Bansal & Choudhary, 2024). These findings suggest that AI literacy may serve a protective function in the relationship between AI use and mental health.

Finally, stable individual characteristics may predispose certain users toward adaptive or maladaptive usage patterns. Person-Environment Fit Theory (Edwards, 1991) proposes that the degree of match between individual characteristics and the environment determines adaptive outcomes. Applied to GenAI use, individuals with different personality traits and emotion regulation strategies may develop different usage patterns. A meta-analysis by Andreassen et al. (2012) found that neuroticism was positively correlated with social media addiction, while conscientiousness showed a negative correlation. Wilson et al. (2010) similarly demonstrated that conscientiousness was negatively associated with social media use and addiction tendencies. Additionally, Pentina et al. (2023) found that among AI chatbot users, individuals high in neuroticism were more likely to develop emotional dependency over time. Research has also established that sleep quality is closely linked to both technology use behaviors and mental health: poor sleep is associated with increased problematic technology use (Scott & Woods, 2018) and is both a risk factor for and consequence of depression and anxiety (Alvaro et al., 2013). Executive function deficits have likewise been implicated in the development of problematic technology use patterns (Oh et al., 2021). Taken together, these findings suggest that highly conscientious individuals may be more likely to develop rational, goal-directed usage patterns, while highly neurotic individuals or those with self-regulation difficulties may be more prone to escapist or problematic use.

These three theoretical frameworks can be integrated to provide a comprehensive understanding of GenAI use and mental health. Uses and Gratifications Theory explains why individuals use GenAI (motivations); the Technology Acceptance Model addresses how cognitive resources such as AI literacy shape the quality of technology engagement; and Person-Environment Fit Theory illuminates which individual characteristics predispose users toward adaptive versus maladaptive usage patterns. Importantly, these frameworks may operate interactively: individuals with low AI literacy may be more likely to use GenAI for escapism rather than instrumental purposes, and personality traits such as conscientiousness may influence both usage motivations and the capacity to maintain controlled use. By integrating these perspectives, we construct a multidimensional framework that captures behavioral, motivational, cognitive, and individual difference factors in GenAI use.

1.3. Variable-Centered versus Person-Centered Research Perspectives

As noted above, the relationship between GenAI use and mental health is complex and characterized by inconsistent findings. A key limitation of existing research lies in its methodological approach. Most studies have employed variable-centered analytical strategies that treat AI users as a homogeneous group, estimating "average effects" by calculating correlations between usage frequency or duration and mental health indicators. This approach implicitly assumes that all individuals follow the same use-outcome pattern, thereby overlooking inter-individual heterogeneity (Laursen & Hoff, 2006). Moreover, existing research has typically examined single dimensions of AI use—such as frequency or duration—without considering how multiple dimensions including usage motivations, AI literacy, and dependency may combine to form distinct usage patterns. In reality, individuals may develop distinctly different AI usage patterns based on their characteristics, needs, and contextual factors, and the associations between these patterns and mental health may differ substantially.

Latent Profile Analysis (LPA), as a person-centered analytical approach, can identify latent subgroups with similar characteristics based on multiple observed indicators, thereby revealing heterogeneous structures within populations (Nylund et al., 2007). This method has been widely applied in research on technology use and mental health. For example, Bányai et al. (2017) used LPA to analyze social media addiction among 5,961 European adolescents, identifying three groups: high-risk, low-risk, and no-risk. Similarly, Cheng et al. (2025) employed LPA to identify low-risk, medium-risk, and high-risk latent classes of social media addiction, finding significant differences in comorbidity patterns with depression and anxiety across classes. Wang et al. (2024) analyzed data from 7,422 adolescents using LPA to identify four internet addiction profiles and found significant differences in their prediction of depression and anxiety. Collectively, these studies demonstrate that person-centered approaches can more precisely reveal the heterogeneous effects of technology use. However, no study to date has applied this approach to GenAI use specifically. Identifying different user subgroups based on multidimensional characteristics of AI use and examining the differential associations of each subgroup with anxiety and depression is therefore an important next step for understanding the heterogeneous effects of GenAI use.

1.4. The Present Study

In summary, GenAI use has become prevalent among young people, and research focus has gradually shifted from "whether AI affects mental health" to "*how AI use can be more beneficial for mental health*." However, the relationship between GenAI use and mental health appears to be heterogeneous, and the methodological limitations of existing research make it difficult to fully characterize the mental health implications of different AI usage patterns. To address these gaps, the present study aimed to: (1) employ latent profile analysis to identify heterogeneous subgroups of GenAI use among college students based on multidimensional AI use characteristics (i.e., usage motivation, AI literacy, and usage behavior); (2) examine differences in depression and anxiety levels across profiles; and (3) validate the identified profiles using machine learning classification and identify key features associated with profile membership based on demographic characteristics, personality traits, emotion regulation strategies, and sleep quality. These findings are intended to contribute to a deeper understanding of the heterogeneous effects of GenAI use and to provide empirical evidence for the development of targeted prevention and intervention strategies.

2. Methods

2.1. Participants

This study employed a combination of stratified random sampling and convenience sampling to recruit participants from four universities in western China, including comprehensive universities, science and technology institutions, and normal universities. The target population consisted of undergraduate and graduate students enrolled in mainland Chinese universities. Inclusion criteria were as follows: (1) current enrollment in a full-time undergraduate or graduate program; (2) use of generative AI tools within the past three months; (3) ability to independently understand and complete the questionnaire; and (4) voluntary participation with provision of informed consent. Exclusion criteria were: (1) currently receiving psychotherapy or taking psychiatric medication; (2) presence of a serious physical illness affecting daily academic or personal functioning; and (3) experience of a major life event within the past six months.

Initial recruitment yielded 5,923 students who expressed willingness to participate. Following eligibility screening, 142 responses were excluded for not meeting the inclusion criteria, and an additional 33 questionnaires were removed due to excessively short completion times or obvious response patterns indicative of careless responding. The final analytic sample comprised 5,748 valid responses, yielding an effective response rate of 97.05%. Sample size determination was guided by recommendations from Nylund et al. (2007), who suggested a minimum of 50–100 observations per latent class. Given that the present study anticipated identifying four to six latent profiles, the obtained sample size was deemed sufficient for latent profile analysis. This study was conducted in accordance with the ethical principles of the Declaration of Helsinki and received approval from the Ethics Review Committee of **[For Blind Review]**.

2.2. Measures

2.2.1. Demographic Information

Demographic information was collected using a researcher-developed questionnaire that assessed age, gender, academic discipline, place of origin (urban vs. rural), only-child status, and body mass index (BMI). Family socioeconomic status (SES) was assessed using a scale developed by Zhao et al. (2022), which includes four dimensions: material wealth, monthly household income per capita, parental education level, and parental occupational status. Total scores range from 4 to 20. Cronbach's α for this scale in the present study was .87.

2.2.2. Generative AI Use Assessment

Generative AI use was assessed across multiple dimensions.

AI use behaviors. Usage behaviors were measured using a researcher-developed questionnaire that assessed usage frequency (on a 5-point scale) and average daily usage duration (measured continuously in hours).

AI usage motivation. Motivation for AI use was assessed using the AI Usage Motivation Scale revised by Huang et al. (2024). Based on the Uses and Gratifications framework, this scale comprises 12 items across four dimensions: instrumental motivation, entertainment motivation, social motivation, and escapism motivation. Items are rated on a 4-point Likert scale. In the present study, Cronbach's α was .88, and confirmatory factor analysis indicated good structural validity.

AI literacy. AI literacy was measured using the Artificial Intelligence Literacy Scale for Chinese College Students (AILS-CCS) developed by Ma and Chen (2024). This scale consists of 15 items across four dimensions: cognitive, usage, evaluative, and ethical. Items are rated on a 5-point Likert scale. Cronbach's α was .91, and confirmatory factor analysis supported the four-factor structure.

AI dependency. AI dependency was measured using a researcher-developed scale based on the theoretical frameworks of internet addiction and smartphone dependency research. The scale comprises five items rated on a 5-point Likert scale, with a Cronbach's α of .89.

2.2.3. Depression, Anxiety, and Sleep Quality Assessment

Depressive symptoms were assessed using the Chinese version of the Beck Depression Inventory–Second Edition (BDI-II; Wang et al., 2011). This scale consists of 21 items with total scores ranging from 0 to 63. Cronbach's α was .92. Anxiety symptoms were assessed using the Chinese version of the Beck Anxiety Inventory (BAI; Liang et al., 2018). This scale comprises 21 items with total scores ranging from 0 to 63. Cronbach's α was .93. Sleep quality was assessed using the Chinese version of the Pittsburgh Sleep Quality Index (PSQI; Liu et al., 2005). Total scores range from 0 to 21, with higher scores indicating poorer sleep quality. Cronbach's α was .83.

2.2.4. Other Psychological Measures

Emotion regulation. Emotion regulation strategies were assessed using the Chinese version of the Emotion Regulation Questionnaire (ERQ; Gross & John, 2003). This scale consists of 10 items measuring two dimensions: cognitive reappraisal and expressive suppression. Items are rated on a 7-point Likert scale. Cronbach's α coefficients were .86 and .79 for the two subscales, respectively.

Executive function. Executive function deficits were assessed using the Chinese version of the Executive Function Index–Short Form (EFI-S; Spinella, 2005). This scale comprises 14 items rated on a 5-point scale, with higher scores indicating greater executive function deficits. Cronbach's α was .88.

Smartphone addiction. Smartphone addiction was assessed using the Chinese version of the Mobile Phone Addiction Index (MPAI; Leung, 2008). This scale consists of 17 items rated on a 5-point Likert scale. Cronbach's α was .90.

Personality traits. Personality traits were assessed using the Chinese version of the Big Five Inventory–Short Form (BFI-S; Zhang et al., 2019). This scale comprises 15 items measuring five dimensions: extraversion, agreeableness, conscientiousness, neuroticism, and openness. Items are rated on a 5-point Likert scale. Cronbach's α coefficients for the five subscales ranged from .74 to .82.

2.3. Procedure

Data collection was conducted between September and November 2025. The survey was administered on a class-by-class basis using standardized procedures with uniform instructions. Students who agreed to participate signed an electronic informed consent form and then completed the online questionnaire in a computer laboratory. Data collection was overseen by graduate students in psychology who had received standardized training. The questionnaire took approximately 30 minutes to complete. Upon completion, participants received a small gift as compensation.

2.4. Data Analysis

2.4.1. Preliminary Analyses

Missing value analysis indicated that the missing rate for all variables was below 5%. Missing data were handled using full information maximum likelihood (FIML) estimation. Pearson correlation coefficients were computed to examine bivariate associations among study variables, with the Benjamini–Hochberg method applied to control the false discovery rate (FDR). Preliminary analyses were performed using SPSS version 27.0 and R version 4.3.2.

2.4.2. Latent Profile Analysis

Latent profile analysis (LPA) was conducted using the tidyLPA package in R (version 4.3.2) to identify heterogeneous patterns of generative AI use among college students. Based on theoretical considerations and prior literature, eight variables were selected as profile indicators: AI usage frequency, daily usage duration, four types of usage motivation (instrumental, entertainment, social, and escapism), total AI literacy score, and AI dependency level. Together, these indicators capture the behavioral, motivational, competency, and dependency dimensions of AI use. Prior to analysis, all profile indicators were standardized (z-score transformation) to ensure comparability across different measurement scales (Li et al., 2026).

Model estimation began with a single-profile model and proceeded sequentially up to six-profile models. Parameter estimation was conducted using the mclust package (Scrucca et al., 2016), with equal variance–covariance matrices assumed across profiles (EEI model). The optimal number of profiles was determined based on the following criteria: (1) *Information criteria*: The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-adjusted BIC (aBIC) were examined, with lower values indicating better model fit. The BIC is considered the most reliable indicator (Nylund et al., 2007). (2) *Classification accuracy*: Classification accuracy was evaluated using entropy, which ranges from 0 to 1, with values exceeding 0.80 generally indicating reliable classification. (3) *Likelihood ratio tests*: The Lo–Mendell–Rubin adjusted likelihood ratio test (LMR-LRT) and the bootstrap likelihood ratio test (BLRT) were used to compare nested models. A significant p-value (< .05) indicates that a k-profile model fits better than a $k - 1$ profile model. (4) *Practical considerations*: Each profile was required to contain at least 5% of the total sample (Lubke & Muthén, 2005). (5) *Interpretability*: The final model was required to be theoretically meaningful and practically interpretable.

Once the optimal number of profiles was established, one-way analysis of variance (ANOVA) was used to examine differences across profiles on continuous variables, and chi-square tests (χ^2) were used to examine differences in the distribution of categorical variables. Post-hoc pairwise comparisons were conducted using Tukey's HSD test, with correction for multiple comparisons using the Benjamini–Hochberg method (Benjamini et al., 2001).

2.4.3. Machine Learning Classification

To examine the robustness of the latent profile solution and identify key predictive features, a random forest classification model was constructed (Breiman, 2001). Model development was performed using the scikit-learn library in Python (Pedregosa et al., 2011). The identified AI usage profiles served as classification targets, with mental health indicators, executive function, smartphone addiction, emotion regulation strategies, personality traits, and family SES serving as predictive features. The sample was split into training (n = 4,024) and testing (n = 1,724) sets at a 70:30 ratio. Hyperparameter optimization was conducted using 5 × 3 nested cross-validation combined with the Optuna framework (Akiba et al., 2019). To enhance model interpretability, feature importance was analyzed using SHAP values (Lundberg et al., 2020) to quantify the contribution of each feature to classification outcomes.

3. Results

3.1. Sociodemographic Characteristics and Correlation Analysis

The final analytic sample comprised 5,748 Chinese college students. Sociodemographic characteristics and descriptive statistics for all study variables are presented in Table 1. The mean age of participants was 20.73 years (SD = 2.51), with females comprising the majority (67.86%). Regarding mental health indicators, 15.41% of students reported moderate or greater depressive symptoms, and 17.30% exhibited moderate or greater anxiety.

Correlation analysis results are presented in Table 2. With respect to associations among AI use variables, AI usage frequency was moderately positively correlated with daily usage duration ($r = .54$, $p_{FDR} < .001$), and both were significantly positively correlated with all usage motivations, with the strongest associations observed for escapism motivation. AI literacy was moderately positively correlated with instrumental motivation ($r = .39$, $p_{FDR} < .001$) but significantly negatively correlated with escapism motivation ($r = -.21$, $p_{FDR} < .001$), suggesting that individuals with higher AI literacy tend to use AI primarily as a productivity tool. AI dependency showed the strongest correlation with escapism motivation ($r = .58$, $p_{FDR} < .001$) and was negatively correlated with AI literacy ($r = -.24$, $p_{FDR} < .001$).

Regarding associations between AI use variables and mental health indicators, daily usage duration showed stronger correlations with depression ($r = .28$, $p_{FDR} < .001$) and anxiety ($r = .24$, $p_{FDR} < .001$) than did usage frequency, suggesting that daily usage duration is more closely linked to mental health outcomes than is usage frequency. Among the four usage motivations, escapism motivation showed the most pronounced correlations with depression ($r = .41$, $p_{FDR} < .001$) and anxiety ($r = .36$, $p_{FDR} < .001$), whereas instrumental motivation showed weak negative or nonsignificant correlations with both outcomes. AI literacy was negatively correlated with depression ($r = -.19$, $p_{FDR} < .001$) and anxiety ($r = -.16$, $p_{FDR} < .001$), suggesting that it may serve as a protective factor for mental health. Additionally, AI dependency was moderately positively correlated with depression, anxiety, and smartphone addiction, indicating that problematic AI use may be associated with broader patterns of technology dependence.

3.2. Latent Profile Analysis Results

3.2.1. Model Fit and Determination of the Optimal Number of Profiles

Latent profile analysis was conducted using eight profile indicators: AI usage frequency, daily usage duration, four types of usage motivation (instrumental, social, entertainment, and escapism), total AI literacy score, and dependency level. Models specifying one to six profiles were fitted sequentially, and fit indices for each solution are presented in Table 3.

The four-profile model demonstrated optimal fit characteristics across multiple criteria. First, the BIC value reached its minimum at the four-profile solution (BIC = 102,970.17), representing a substantial improvement over the three-profile model (ΔBIC = 835.06). Although AIC continued to decrease with additional profiles, BIC increased for the five-profile solution (BIC = 103,147.91), indicating diminishing returns in model parsimony. Second, entropy for the four-profile model was .81, reflecting good classification precision. Third, both the LMR-LRT and BLRT were significant ($p < .01$), supporting the superiority of the four-profile solution over the three-profile alternative. In contrast, neither the five- nor the six-profile model demonstrated significant improvement on these likelihood ratio tests. Finally, from a practical standpoint, the sample distribution across the four profiles was well-balanced, with the smallest profile (Problematic-Dependent) comprising 15.0% of the total sample—well above the commonly recommended 5% threshold for profile viability. Based on statistical fit indices, practical distributional criteria, and theoretical interpretability, the four-profile model was selected as the optimal solution.

3.2.2. Characteristics of the Four AI User Profiles

Based on the classification results of the four-profile model, the 5,748 college students were categorized into four distinct AI use profiles. Standardized score patterns on the eight profile indicators for each profile are displayed in Figure 1A, with specific values and between-group differences presented in Table 4.

Profile 1: Rational-Instrumental (n = 1,609, 27.99%) exhibited a "high literacy–low dependency–tool-oriented" usage pattern. This profile showed moderately low usage frequency and daily duration, the highest instrumental motivation scores among all four profiles, and the lowest scores on all other motivations. This profile also demonstrated the highest AI literacy and the lowest dependency levels.

Profile 2: Adaptive-Compensatory (n = 1,954, 33.99%) represented the largest group, characterized by a "moderate frequency–affect-oriented–gradual dependency" pattern. This profile showed moderate levels of usage frequency, daily duration, AI literacy, and dependency. The distinguishing feature of this profile was relatively elevated entertainment and social motivation.

Profile 3: Problematic-Dependent (n = 862, 15.00%) comprised the smallest proportion but represented the high-risk group warranting the most attention. This profile exhibited a "high frequency–high dependency–low literacy–escapism-oriented" problematic usage pattern. Specifically, this profile showed the highest usage frequency, daily duration, and escapism motivation among all four profiles, while demonstrating the lowest instrumental motivation and AI literacy. AI dependency levels were markedly elevated.

Profile 4: Light-Exploratory (n = 1,323, 23.02%) represented individuals with minimal engagement with generative AI, characterized by a "low frequency–low engagement–low dependency" pattern. This profile showed the lowest usage frequency and daily duration among all profiles, with all motivation types and dependency at relatively low levels.

3.2.3. Between-Group Differences Among the Four AI User Profiles

Table 4 presents between-group differences in sociodemographic characteristics, mental health indicators, and other psychological variables across the four AI use profiles.

Sociodemographic characteristics. Rational-Instrumental users were the oldest, significantly older than Problematic-Dependent users (F = 7.84, p < .001). Gender distribution differed significantly across profiles (χ^2 = 31.24, p < .001), with females comprising the highest proportion in the Problematic-Dependent profile (75.68%). Family socioeconomic status also differed significantly (F = 38.92, p < .001), with Rational-Instrumental users reporting the highest levels and Problematic-Dependent users reporting the lowest levels.

Mental health indicators. As shown in Figures 1B and 1C, significant between-group differences were observed for depressive symptoms (F = 142.67, p < .001, η^2 = .07), with Problematic-Dependent users scoring highest (mild to moderate range) and Rational-Instrumental users scoring lowest (minimal range). Anxiety symptoms (F = 124.58, p < .001, η^2 = .06) and sleep quality (F = 108.34, p < .001, η^2 = .05) showed similar patterns.

Executive function and behavioral addiction. Problematic-Dependent users showed the highest scores on executive function deficits (F = 134.21, p < .001, η^2 = .07) and smartphone addiction (F = 156.78, p < .001, η^2 = .08), whereas Rational-Instrumental users showed the lowest scores on both measures.

Emotion regulation and personality traits. Cognitive reappraisal scores (F = 87.45, p < .001, η^2 = .04) followed the pattern: Rational-Instrumental > Light-Exploratory > Adaptive-Compensatory > Problematic-Dependent, with expressive suppression showing the reverse pattern. Neuroticism (F = 124.87, p < .001, η^2 = .06) and conscientiousness (F = 118.47, p < .001, η^2 = .06) showed the most pronounced between-group differences, with Problematic-Dependent users exhibiting the highest neuroticism and lowest conscientiousness, and Rational-Instrumental users showing the opposite pattern.

3.3 Machine Learning Classification Model

To examine the robustness of the latent profile analysis results and identify key features distinguishing different AI usage patterns, a random forest classification model was constructed. The classifier achieved an overall accuracy of 81.0% on the test set, with a macro-average AUC of .894 (Figure 2). Classification performance varied across profiles: Problematic-Dependent users were identified most accurately (AUC = .938), followed by Rational-Instrumental users (AUC = .893), whereas Adaptive-Compensatory (AUC = .873) and Light-Exploratory (AUC = .872) users showed relatively lower but still acceptable classification accuracy.

SHAP analysis was subsequently conducted to examine the contribution of each feature to classification prediction (Figure 3). For Rational-Instrumental users, conscientiousness was the most important predictive feature, followed by executive function and smartphone addiction (negative association). For Adaptive-Compensatory users, smartphone addiction was the most important predictive feature, followed by depression and anxiety. For Problematic-Dependent users, depression emerged as the most important predictive feature, followed by smartphone addiction and executive function deficits, indicating that problematic AI use is closely associated with depressive symptoms, broader technology dependence patterns, and executive function impairment. For Light-Exploratory users, conscientiousness was the most important predictive feature, followed by smartphone addiction (negative association) and depression (negative association).

4. Discussion

This study identified four distinct patterns of generative AI use among 5,748 Chinese college students and systematically examined their associations with depression and anxiety. The findings revealed significant heterogeneity in AI use, with the four profiles showing marked differences in usage motivation, AI literacy, and dependency levels. The Problematic-Dependent profile exhibited significantly higher levels of depression and anxiety compared to the other profiles, whereas the Rational-Instrumental profile demonstrated the most favorable mental health outcomes. The machine learning classification model validated the reliability of the latent profiles and identified depression, smartphone addiction, and executive function deficits as key features associated with the Problematic-Dependent profile, while conscientiousness was closely associated with the Rational-Instrumental profile.

4.1. Heterogeneous Patterns of Generative AI Use

The identification of four distinct generative AI use profiles extends previous research on the heterogeneity of digital technology use to the emerging domain of generative AI. Prior studies have demonstrated significant individual differences in internet use among young people (Wang et al., 2024), smartphone use (Yang et al., 2022), and social media use (Akbari et al., 2023), yet traditional variable-centered approaches have difficulty capturing such within-group heterogeneity (Spurk et al., 2020). The present findings demonstrate that college students' AI use patterns differ significantly across multiple dimensions, including usage motivation, AI literacy, and dependency levels, suggesting that assessing the adaptiveness of AI use based solely on single indicators such as usage duration or frequency is insufficient. These results support the Differential Susceptibility to Media Effects Model (Valkenburg & Peter, 2013), which posits that the impact of technology use on mental health depends on the interaction among user characteristics, usage patterns, and environmental factors rather than on inherent properties of the technology itself.

Regarding the number of profiles, different studies have yielded varying results due to differences in sample characteristics and measurement instruments. The findings of the present study are consistent with those of Xie et al. (2024) and Daniilidou and Antoniadou (2025), although Kim and Song (2022) and Wu et al. (2025) each identified three profiles. This discrepancy may reflect the present study's simultaneous inclusion of usage motivation, AI literacy, and dependency as analytical dimensions, whereas previous studies have often focused on single-dimension addiction symptom measures. Furthermore, college students are at a critical stage of identity exploration and career preparation (Arnett, 2000), and their AI usage motivations may be more diverse than those of other age groups.

Each of the four profiles exhibited unique usage characteristics. The Rational-Instrumental profile was characterized by high AI literacy, high instrumental motivation, and low dependency. This group primarily views AI as a tool for enhancing efficiency and is capable of critically evaluating AI-generated content. From the perspective of Uses and Gratifications Theory, this pattern primarily satisfies cognitive needs and reflects a clear goal orientation (Katz et al., 1973). The Adaptive-Compensatory profile represented the largest group (33.99%), showing diverse usage motivations including instrumental, entertainment, and social needs. This pattern may reflect attempts by some individuals to compensate for unmet needs in real-world interpersonal interactions by turning to AI (Kardefelt-Winther, 2014). Although smallest in proportion (15.00%), the Problematic-Dependent profile represented the highest-risk group, exhibiting high usage frequency, high dependency, low AI literacy, and strong escapism motivation. Notably, escapism motivation is considered a key predictor of technology addiction (Chang et al., 2018), and longitudinal studies have demonstrated its strong within-person effects on excessive gaming and internet use (Zhou et al., 2020). The characteristics of this group align with perspectives that conceptualize excessive AI use as a novel behavioral addiction (Yankouskaya et al., 2025). The Light-Exploratory profile represented individuals with minimal engagement with generative AI (23.02%), showing the lowest usage frequency and duration among all groups. Previous research has also identified similar "low engagement" groups, whose mental health outcomes typically fall between those of problematic users and healthy users (Moreno et al., 2022).

4.2. Associations Between Generative AI Use Patterns and Depression and Anxiety

The four profiles demonstrated significant gradient differences in depression and anxiety, with the Problematic-Dependent profile showing the highest symptom levels and the Rational-Instrumental profile showing the lowest. Depression scores in the Problematic-Dependent profile reached clinically significant levels (mild to moderate range), whereas scores in the Rational-Instrumental profile fell within the minimal range. This gradient pattern is consistent with findings from studies of adolescent internet addiction (Wang et al., 2024) and smartphone addiction (Kim et al., 2023).

The social displacement hypothesis (Kraut et al., 1998) provides one possible explanation for these results. Individuals who spend substantial time in digital interactions may spend less time in face-to-face communication, and the resulting lack of social support may contribute to depressive symptoms. Although recent research has questioned the universal applicability of this hypothesis (Beyens et al., 2020), displacement effects may be more pronounced for technology use motivated by escapism (Meier & Reinecke, 2020). Individuals in the Problematic-Dependent profile may immerse themselves in AI interaction to temporarily avoid real-world stress, but this avoidance behavior neither effectively addresses underlying problems nor facilitates the development of adaptive coping strategies.

For anxiety, the four profiles showed a similar gradient pattern. From the perspective of behavioral addiction, problematic AI use can be viewed as a maladaptive coping strategy in which individuals attempt to alleviate anxiety through AI interaction (Stavropoulos et al., 2017). However, individuals highly dependent on AI may experience anxiety resembling withdrawal effects when unable to access AI (Yankouskaya et al., 2025). Prior longitudinal research on technology use has demonstrated bidirectional relationships between mental health problems and technology dependency, with psychological distress predicting increased dependency, which in turn exacerbates subsequent mental health difficulties (Coyne et al., 2020; Houghton et al., 2018). Although direct longitudinal evidence for generative AI remains limited given its recent emergence, similar reciprocal patterns are likely to characterize the relationship between AI dependency and mental health.

Correlation analysis revealed that among the four usage motivations, escapism motivation showed the strongest associations with depression and anxiety, whereas instrumental motivation showed weak or negative associations with these outcomes. This pattern is consistent with prior research demonstrating that escapism-motivated social media use more strongly predicts mental health problems than does instrumental use (Bányai et al., 2017). From a theoretical perspective, escapism motivation reflects a maladaptive coping style. Escape theory (Baumeister, 1990) proposes that when self-awareness becomes aversive, individuals seek relief from this state, and technology use provides a convenient avenue for such escape—yet this strategy provides only temporary relief rather than lasting improvement.

The executive function deficits observed in the Problematic-Dependent profile also warrant attention. Executive function represents the core cognitive foundation of self-regulation (Hofmann et al., 2012), and deficits in this area may make it difficult for individuals to control AI use behavior, flexibly switch between activities, and inhibit impulses toward AI dependence. Neurobiological research provides mechanistic explanations: internet gaming disorder is associated with reduced prefrontal cortex function and decreased functional connectivity in cognitive control networks (Dong & Potenza, 2014). The I-PACE model (Brand et al., 2019) suggests that executive function deficits may impair individuals' ability to monitor and regulate their technology use behavior. However, the cross-sectional nature of our data precludes causal inference regarding whether executive function deficits precede or follow problematic AI use patterns.

4.3. Features Associated with Different AI Use Profiles

The machine learning classification model achieved good predictive accuracy (AUC = 0.81), and SHAP analysis revealed distinct feature importance patterns across the four profiles. Depression emerged as the most important feature associated with the Problematic-Dependent profile, indicating a close association between psychological distress and problematic AI use patterns. Individuals experiencing depression may be more inclined to seek temporary emotional comfort or escape from negative emotions through AI interaction.

However, a complex bidirectional relationship likely exists between AI use and depression. Compensatory internet use theory posits that people go online to escape real-world problems or alleviate negative emotions, but this may ultimately contribute to problematic technology use (Kardefelt-Winther, 2014). Problematic AI use may not only be associated with depression but may also exacerbate depressive symptoms through pathways such as reduced real-world social interaction and sleep disruption. Of note, the unique characteristics of generative AI may amplify this risk. Unlike traditional social media, AI chatbots can provide highly personalized, instantly responsive "conversation partners," which may hold particular appeal for individuals who feel lonely or depressed. De Freitas et al. (2024) found that users described AI chatbots as an "emotional refuge," while Yankouskaya et al. (2025) identified multiple features of ChatGPT addiction, including instant gratification, parasocial bonding, loss of control, and withdrawal symptoms—all characteristics similar to those of traditional behavioral addictions.

Smartphone addiction emerged as the second most important feature associated with the Problematic-Dependent profile, suggesting that problematic AI use may be embedded within a broader pattern of technology dependence behaviors. This finding is consistent with the comorbidity of multiple technology addiction behaviors observed in previous research (Hussain et al., 2020; Toklu Baloglu & Caferoglu Akin, 2024). From a neurobiological perspective, different forms of technology dependence may share similar neural circuits and psychological mechanisms, particularly those related to reward processing, impulse control, and habit formation (Brand et al., 2019).

With respect to personality traits, the associations of neuroticism and conscientiousness with profile membership were consistent with expectations from Person-Environment Fit Theory. Individuals high in neuroticism have lower emotional stability and higher stress sensitivity, making them more likely to adopt avoidant coping strategies when facing challenges. Multiple meta-analyses have found that neuroticism shows the strongest positive correlation with technology addiction among the Big Five personality traits (Marciano et al., 2022). Conversely, conscientiousness was associated with the Rational-Instrumental profile, consistent with the view of conscientiousness as a protective factor against problematic technology use (Marciano et al., 2022). Individuals high in conscientiousness typically demonstrate stronger self-control and higher self-discipline, which may help maintain healthy technology use boundaries.

Differences in emotion regulation strategies across profiles further illuminate the psychological mechanisms underlying problematic AI use. The Problematic-Dependent profile used cognitive reappraisal—an adaptive emotion regulation strategy—less frequently while relying more heavily on expressive suppression—a maladaptive strategy (Gross & John, 2003). Research by Liang et al. (2021) among Chinese adolescents found that cognitive reappraisal had a significant direct negative effect on internet addiction, and negative emotions mediated the relationship between expressive suppression and internet addiction. A lack of effective emotion regulation strategies may lead individuals to rely more heavily on AI as an external tool for emotion regulation, thereby forming a maladaptive pattern of substituting technology for self-regulation. This finding suggests that cultivating emotion regulation skills may be an important intervention target for preventing problematic AI use.

4.4. Implications

At the theoretical level, the findings demonstrate the value of adopting person-centered approaches when examining AI use among college students. Traditional variable-centered approaches focus on average associations between variables and have difficulty revealing within-group heterogeneity, whereas latent profile analysis can identify subgroups with similar characteristic combinations, providing a more nuanced perspective for understanding the complexity of the relationship between AI use and mental health. The present study integrated multiple theoretical frameworks, including Uses and Gratifications Theory, Person-Environment Fit Theory, and behavioral addiction theory, to construct a multidimensional analytical framework encompassing usage motivation, AI literacy, and dependency levels. In addition, machine learning methods validated the robustness of the latent profile analysis results and provided empirical evidence for identifying high-risk individuals.

At the practical level, the findings highlight the necessity of differentiated interventions. Different AI use patterns are underlain by different psychological mechanisms, making uniform educational or intervention strategies unlikely to achieve optimal results. For the Problematic-Dependent profile, intervention efforts might focus on cultivating adaptive emotion regulation strategies, enhancing AI literacy, and improving executive function, while also attending to elevated levels of depression and anxiety and referring individuals to professional mental health services when necessary. For the Adaptive-Compensatory profile, interventions might emphasize guiding individuals to develop diversified sources of social support and strengthening real-world interpersonal connections. For the Light-Exploratory profile, appropriate education and guidance on AI use could help individuals better leverage the positive functions of AI.

Furthermore, the present study found that AI literacy was negatively correlated with mental health problems and that the Rational-Instrumental profile scored highest across all dimensions of AI literacy, providing empirical support for the importance of AI literacy education. Universities and educational institutions might consider incorporating AI literacy into curricula to help students understand the basic principles and limitations of AI technology, develop the ability to critically evaluate AI-generated content, and establish awareness and boundaries for appropriate AI use. Naamati-Schneider and Alt (2025) found that distrust and ethical concerns about generative AI were common among medical students, suggesting that AI literacy education should encompass not only technical skills but also ethical discussion and critical thinking training. Finally, the finding that problematic AI use was highly correlated with smartphone addiction suggests that prevention and intervention efforts need to be conducted within a broader digital health framework, helping college students establish healthy technology use habits and lifestyles.

4.5. Limitations and Future Directions

Several limitations should be acknowledged. First, the cross-sectional design precludes causal inference. Although we found associations between the Problematic-Dependent profile and poorer mental health outcomes, the temporal direction of these relationships cannot be determined. Future research should employ longitudinal designs, such as latent transition analysis, to explore dynamic changes in profiles over time and examine temporal relationships between usage patterns and mental health outcomes. Second, the exclusion of students currently receiving psychotherapy or psychiatric medication may have resulted in underrepresentation of individuals with severe mental health problems. Additionally, the sample was drawn from four universities in western China, which may limit generalizability to other regions or educational contexts. Future research should expand geographic coverage and include more diverse institutional types to enhance external validity. Third, this study relied primarily on self-report measures, which may be subject to social desirability bias and recall bias. Future research could incorporate objective behavioral data, such as app usage logs, and combine neurocognitive testing to enhance measurement objectivity. Qualitative methods could also provide deeper understanding of the subjective experiences underlying different usage patterns. Fourth, this study did not differentiate among specific types of AI applications. Generative AI encompasses multiple application types, including text generation, image generation, and AI companions, which may have different implications for mental health. Future research could examine heterogeneous patterns across different AI application types.

5. Conclusions

This study identified four distinct generative AI use profiles among Chinese college students: Rational-Instrumental, Adaptive-Compensatory, Problematic-Dependent, and Light-Exploratory. These profiles showed gradient differences in mental health indicators, with the Problematic-Dependent profile exhibiting the highest levels of depression and anxiety symptoms and the Rational-Instrumental profile demonstrating the most favorable mental health outcomes. Machine learning analysis identified key features associated with different usage patterns: depression, smartphone addiction, and executive function deficits were closely associated with the Problematic-Dependent profile, while conscientiousness and higher AI literacy were associated with the Rational-Instrumental profile. Taken together, these findings suggest that the association between AI use and mental health depends more on usage patterns and individual characteristics than on usage frequency alone. These findings provide empirical evidence for identifying high-risk individuals and developing differentiated intervention strategies.

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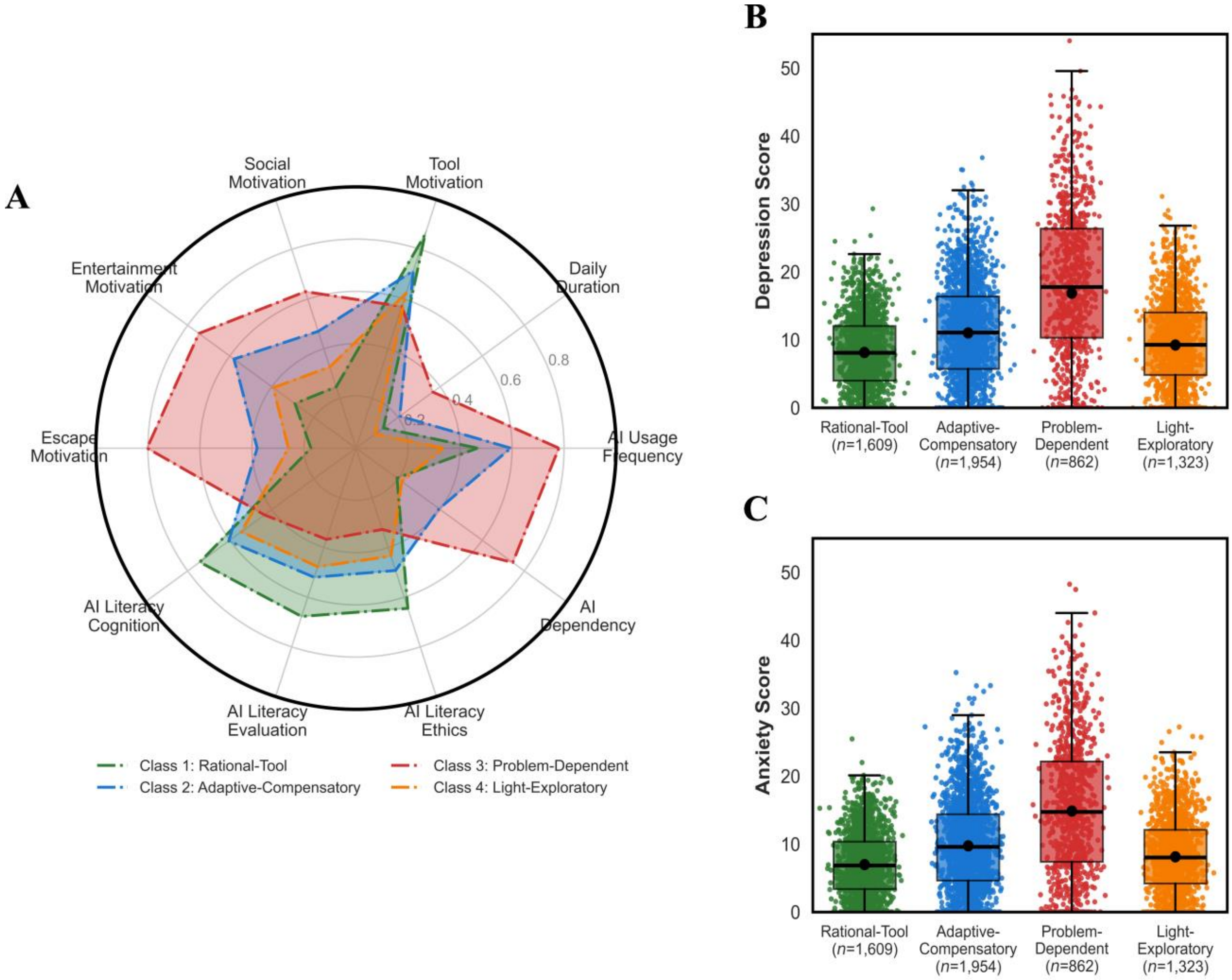
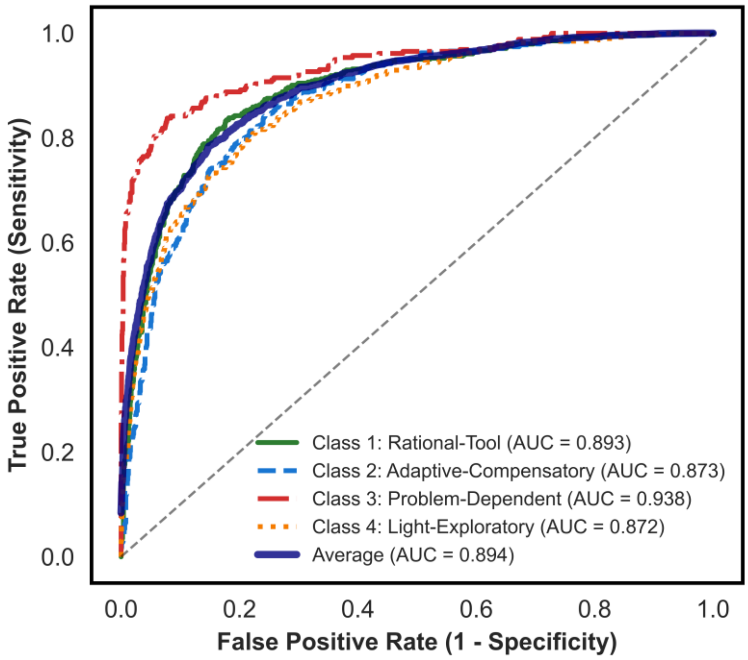
Figure 1. Latent Profiles of Generative AI Use and Mental Health Comparisons Across Profiles



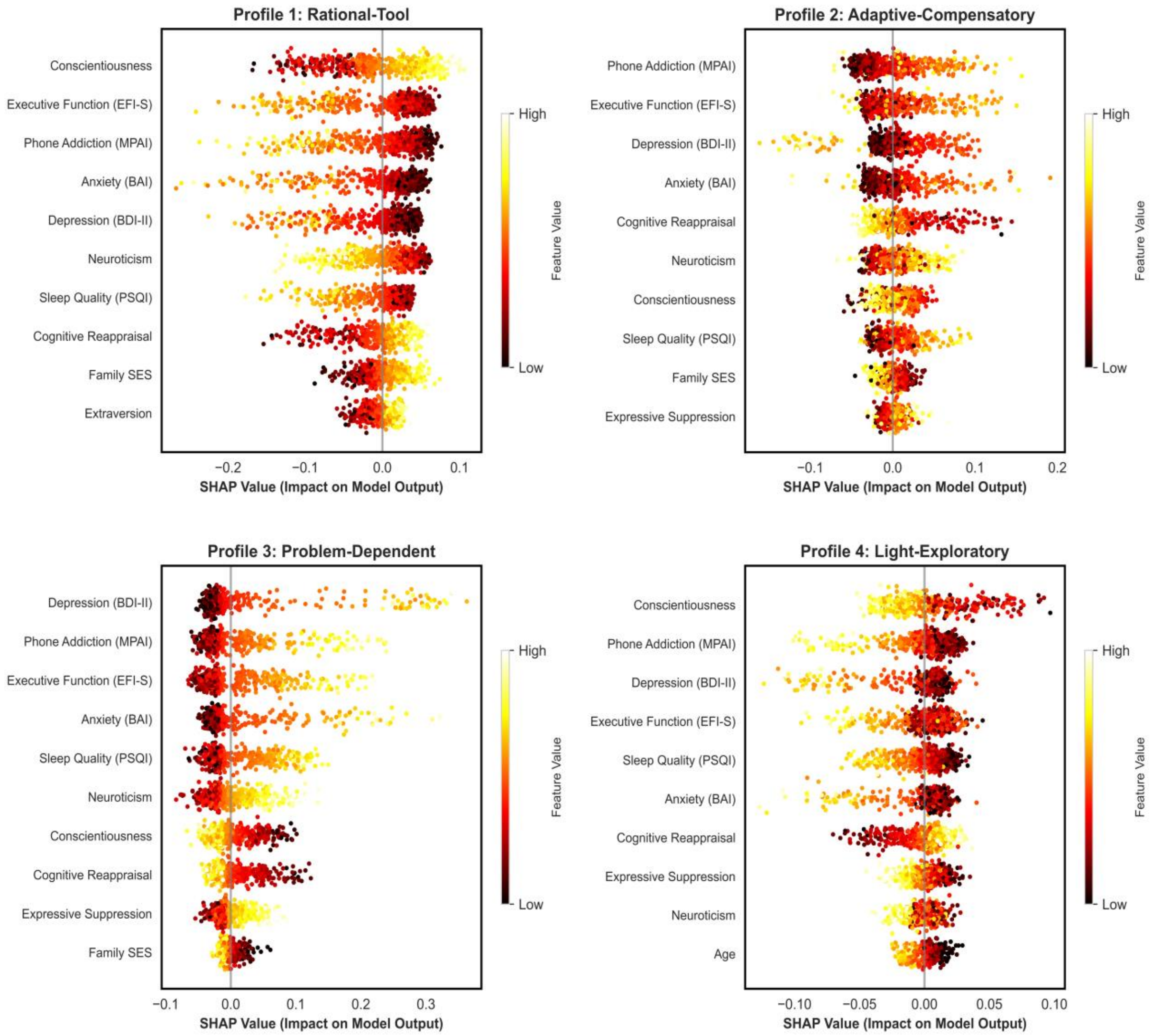
Note. (A) Standardized scores (z-scores) on eight profile indicators across the four latent profiles of AI use. (B) Distribution of depression severity (BDI-II) across the four profiles. (C) Distribution of anxiety severity (BAI) across the four profiles.

Figure 2. Random Forest Classification Performance for Four AI User Profiles



Note. Receiver operating characteristic (ROC) curves and area under the curve (AUC) values for each AI user profile. The diagonal dashed line represents chance-level classification (AUC = 0.50).

Figure 3. SHAP Feature Importance for AI User Profile Classification



Note. SHAP summary plots displaying the contribution of each feature to profile classification. Bar length represents the mean absolute SHAP value. Features are ranked by importance within each profile.

Table 1. Sociodemographic Characteristics and Descriptive Statistics for Study Variables

Variable	*n* (%) / M ± SD	Range
Demographic Characteristics		
Age (years)	20.73 ± 2.51	17–35
Gender		
Male	1,847 (32.14%)	
Female	3,901 (67.86%)	
Academic Discipline		
Humanities	1,724 (29.99%)	
Engineering	1,983 (34.50%)	
Science	2,041 (35.51%)	
Only Child		
Yes	2,156 (37.51%)	
No	3,592 (62.49%)	
Place of Origin		
Urban	3,967 (69.01%)	
Rural	1,781 (30.99%)	
Family Socioeconomic Status (SES)	11.08 ± 3.74	4–20
BMI (kg/m²)	21.42 ± 3.27	14.8–41.2
AI Use Characteristics		
Usage Frequency (1–5)	3.14 ± 1.18	1–5
Daily Usage Duration (hours)	1.79 ± 1.61	0–9.5
AI Usage Motivation		
Instrumental Motivation	3.11 ± 0.74	1–4
Social Motivation	2.24 ± 0.91	1–4
Entertainment Motivation	2.58 ± 0.87	1–4
Escapism Motivation	2.07 ± 0.96	1–4
AI Literacy		
Cognitive Dimension	3.38 ± 0.86	1–5
Usage Dimension	3.26 ± 0.91	1–5
Evaluative Dimension	3.04 ± 0.89	1–5
Ethical Dimension	2.91 ± 1.04	1–5
AI Literacy Total Score	3.15 ± 0.78	1–5
AI Dependency Level	2.41 ± 1.07	1–5
Mental Health Indicators		
Depression (BDI-II)	10.84 ± 8.76	0–54
Minimal (0–13)	3,856 (67.09%)	
Mild (14–19)	1,006 (17.50%)	
Moderate (20–28)	598 (10.40%)	
Severe (29–63)	288 (5.01%)	
Anxiety (BAI)	9.47 ± 7.89	0–53
Minimal (0–7)	2,978 (51.81%)	
Mild (8–15)	1,776 (30.90%)	
Moderate (16–25)	701 (12.20%)	
Severe (26–63)	293 (5.10%)	
Sleep Quality (PSQI)	6.67 ± 3.44	0–19
Other Psychological Variables		
Executive Function Total Score	35.21 ± 10.84	14–71
Smartphone Addiction	41.23 ± 13.58	17–85
Emotion Regulation Strategies		
Cognitive Reappraisal	4.48 ± 1.27	1–7
Expressive Suppression	4.11 ± 1.29	1–7
Personality Traits		

Extraversion	3.18 ± 0.94	1–5
Agreeableness	3.61 ± 0.78	1–5
Conscientiousness	3.28 ± 0.89	1–5
Neuroticism	2.97 ± 0.91	1–5
Openness	3.39 ± 0.81	1–5

Note: BMI = body mass index; SES = socioeconomic status; BDI-II = Beck Depression Inventory–Second Edition; BAI = Beck Anxiety Inventory; PSQI = Pittsburgh Sleep Quality Index. Depression severity was categorized according to BDI-II clinical cutoffs: minimal (0–13), mild (14–19), moderate (20–28), and severe (29–63). Anxiety severity was categorized according to BAI clinical cutoffs: minimal (0–7), mild (8–15), moderate (16–25), and severe (26–63).

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Table 2. Pearson Correlation Matrix of AI Use Variables and Mental Health Indicators

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Usage Frequency	—														
2. Daily Usage Duration	.54***	—													
3. Instrumental Motivation	.29***	.21***	—												
4. Entertainment Motivation	.35***	.41***	.08*	—											
5. Social Motivation	.31***	.36***	.11**	.49***	—										
6. Escapism Motivation	.38***	.44***	−.04	.53***	.45***	—									
7. AI Literacy	.18***	.06	.39***	−.11**	−.07*	−.21***	—								
8. Dependency Level	.49***	.55***	.08*	.46***	.41***	.58***	−.24***	—							
9. Depression	.21***	.28***	−.08*	.32***	.27***	.41***	−.19***	.38***	—						
10. Anxiety	.18***	.24***	−.05	.29***	.24***	.36***	−.16***	.34***	.62***	—					
11. Sleep Quality	.16***	.23***	−.04	.24***	.19***	.31***	−.13***	.28***	.46***	.42***	—				
12. Executive Function	.15***	.21***	−.11**	.22***	.18***	.27***	−.18***	.26***	.39***	.34***	.32***	—			
13. Smartphone Addiction	.36***	.43***	.02	.38***	.33***	.45***	−.15***	.49***	.36***	.32***	.28***	.31***	—		
14. Cognitive Reappraisal	−.09**	−.12***	.19***	−.14***	−.11**	−.21***	.26***	−.18***	−.26***	−.22***	−.18***	−.14***	−.12***	—	
15. Expressive Suppression	.11**	.15***	−.01	.18***	.16***	.22***	−.08*	.21***	.22***	.18***	.15***	.13***	.17***	−.06	—

*Note:*p < .05, **p < .01, ***p < .001*; All p-values were corrected using the Benjamini–Hochberg method.

Table 3. Model Fit Indices for Latent Profile Analysis of Generative AI Use Patterns

Number of Profiles	LL	AIC	BIC	aBIC	Entropy	LMR-LRT	BLRT
1	−54,123.47	108,278.94	108,385.21	108,325.87	—	—	—
2	−52,487.63	105,031.26	105,218.73	105,115.42	.71	3,241.18***	3,271.68***
3	−51,734.28	103,536.56	103,805.23	103,658.95	.74	1,486.92***	1,506.70***
4	**−51,267.15**	**102,620.30**	**102,970.17**	**102,780.92**	**.81**	**921.34*****	**934.26*****
5	−51,089.42	102,272.84	103,147.91	102,871.69	.76	347.82	355.46*
6	−50,978.31	102,058.62	103,258.89	102,895.70	.73	216.54	222.22

Note: :$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$; LL = log-likelihood; AIC = Akaike information criterion; BIC = Bayesian information criterion; aBIC = sample-adjusted BIC; LMR-LRT = Lo–Mendell–Rubin adjusted likelihood ratio test; BLRT = bootstrap likelihood ratio test (5,000 resamples). The bolded row indicates the selected model. Although AIC continued to decrease with additional profiles, BIC reached its minimum at the four-profile solution. The four-profile model also demonstrated adequate entropy (.81), significant LMR-LRT and BLRT ($p < .01$), and all profile proportions exceeded 5%, supporting its selection as the optimal solution.

Table 4. Comparisons of Sociodemographic, AI Use, and Psychological Variables Across Four AI User Profiles

Variable	Rational-Instrumental (n=1,609)	Adaptive-Compensatory (n=1,954)	Problematic-Dependent (n=862)	Light-Exploratory (n=1,323)	F/χ^2	η^2/V	Post-hoc
Sociodemographics							
Age (years)	21.02 ± 2.47	20.81 ± 2.53	20.34 ± 2.71	20.58 ± 2.44	7.84***	.004	1 > 3
Gender					31.24***	.07	—
Male	36.22%	30.87%	24.32%	33.41%			
Female	63.78%	69.13%	75.68%	66.59%			
Academic discipline					19.87**	.04	—
Humanities	27.18%	31.54%	34.12%	29.21%			
Engineering	37.86%	33.19%	30.58%	35.67%			
Science	34.96%	35.27%	35.30%	35.12%			
Only child					14.67**	.05	—
Yes	40.14%	37.23%	31.64%	38.08%			
No	59.86%	62.77%	68.36%	61.92%			
Place of origin					22.41***	.06	—
Urban	73.51%	68.04%	61.28%	69.78%			
Rural	26.49%	31.96%	38.72%	30.22%			
Family SES	12.04 ± 3.56	10.97 ± 3.71	9.84 ± 3.98	11.21 ± 3.61	38.92***	.02	1 > 2, 4 > 3
BMI (kg/m²)	21.34 ± 3.18	21.47 ± 3.29	21.58 ± 3.41	21.38 ± 3.24	0.89	<.001	—
AI Use Characteristics[a]							
Usage frequency (1–5)	2.87 ± 0.81	3.38 ± 0.87	4.12 ± 0.64	2.34 ± 0.76	487.24***	.20	3 > 2 > 1 > 4
Daily duration (hours)	1.24 ± 0.71	1.98 ± 1.14	3.47 ± 1.68	0.87 ± 0.54	521.38***	.21	3 > 2 > 1 > 4
Usage Motivation							
Instrumental (1–4)	3.58 ± 0.52	3.14 ± 0.68	2.71 ± 0.84	2.87 ± 0.74	142.18***	.07	1 > 2 > 4, 3
Entertainment (1–4)	1.87 ± 0.72	2.74 ± 0.81	3.24 ± 0.71	2.18 ± 0.84	298.56***	.13	3 > 2 > 4 > 1
Social (1–4)	1.74 ± 0.68	2.41 ± 0.87	2.89 ± 0.82	1.98 ± 0.81	198.42***	.09	3 > 2 > 4 > 1
Escapism (1–4)	1.52 ± 0.64	2.14 ± 0.81	3.41 ± 0.67	1.78 ± 0.74	512.34***	.21	3 > 2 > 4 > 1
AI Literacy							
Cognitive	3.97 ± 0.68	3.42 ± 0.81	2.74 ± 0.94	3.18 ± 0.87	201.45***	.10	1 > 2 > 4 > 3
Usage	3.84 ± 0.71	3.31 ± 0.88	2.58 ± 0.97	3.08 ± 0.91	187.32***	.09	1 > 2 > 4 > 3
Evaluative	3.71 ± 0.74	3.08 ± 0.86	2.47 ± 0.92	2.91 ± 0.88	178.56***	.09	1 > 2 > 4 > 3

Ethical	3.58 ± 0.84	2.97 ± 0.98	2.31 ± 1.02	2.74 ± 0.97	154.23***	.07	1 > 2 > 4 > 3
Total score (1–5)	3.78 ± 0.62	3.20 ± 0.76	2.53 ± 0.87	2.98 ± 0.82	267.89***	.12	1 > 2 > 4 > 3
Dependency (1–5)	1.78 ± 0.71	2.58 ± 0.87	3.98 ± 0.74	1.87 ± 0.78	578.42***	.23	3 > 2 > 1, 4
Mental Health							
Depression (BDI-II)	8.14 ± 5.87	11.02 ± 8.14	16.87 ± 11.54	9.24 ± 6.78	142.67***	.07	3 > 2 > 4, 1
Anxiety (BAI)	6.98 ± 5.12	9.74 ± 7.21	14.87 ± 10.24	8.12 ± 5.89	124.58***	.06	3 > 2 > 4, 1
Sleep quality (PSQI)	5.54 ± 2.81	6.87 ± 3.42	9.18 ± 4.14	6.14 ± 3.21	108.34***	.05	3 > 2 > 4, 1
Other Psychological Variables							
Executive function (EFI-S)	31.24 ± 8.14	35.47 ± 10.24	43.87 ± 13.47	33.18 ± 9.24	134.21***	.07	3 > 2 > 4 > 1
Smartphone addiction (MPAI)	35.14 ± 10.87	42.18 ± 13.14	52.47 ± 16.87	38.24 ± 11.87	156.78***	.08	3 > 2 > 4 > 1
Emotion Regulation (ERQ)							
Cognitive reappraisal	4.91 ± 1.18	4.42 ± 1.31	3.58 ± 1.47	4.67 ± 1.24	87.45***	.04	1 > 4 > 2 > 3
Expressive suppression	3.78 ± 1.21	4.14 ± 1.28	4.87 ± 1.41	3.91 ± 1.24	64.32***	.03	3 > 2, 4 > 1
Personality (BFI-S)							
Extraversion	3.41 ± 0.87	3.14 ± 0.94	2.78 ± 1.04	3.24 ± 0.91	42.18***	.02	1 > 4, 2 > 3
Agreeableness	3.71 ± 0.74	3.58 ± 0.78	3.47 ± 0.84	3.64 ± 0.77	8.42***	.004	1 > 3
Conscientiousness	3.74 ± 0.78	3.28 ± 0.87	2.71 ± 0.98	3.24 ± 0.89	118.47***	.06	1 > 2, 4 > 3
Neuroticism	2.68 ± 0.84	3.04 ± 0.91	3.71 ± 0.97	2.84 ± 0.88	124.87***	.06	3 > 2 > 4, 1
Openness	3.54 ± 0.78	3.37 ± 0.82	3.24 ± 0.87	3.41 ± 0.79	12.47***	.006	1 > 3

*Note: :*p < .05, **p < .01, ***p < .001*. PPost-hoc comparisons were conducted using Tukey's HSD test ($p < .05$). ANOVA (F) was used for continuous variables; chi-square tests (χ^2) were used for categorical variables. Profile 1 = Rational-Instrumental; Profile 2 = Adaptive-Compensatory; Profile 3 = Problematic-Dependent; Profile 4 = Light-Exploratory. SES = socioeconomic status; BDI-II = Beck Depression Inventory–Second Edition; BAI = Beck Anxiety Inventory; PSQI = Pittsburgh Sleep Quality Index; EFI-S = Executive Function Index–Short Form; MPAI = Mobile Phone Addiction Index; ERQ = Emotion Regulation Questionnaire; BFI-S = Big Five Inventory–Short Form.

[a] Variables under "AI Use Characteristics" served as profile indicators in the latent profile analysis. Large effect sizes for these variables are expected, as between-group differences on profile indicators are maximized by design in LPA.

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