International Journal of
Mental Health Promotion

Tech Science Press

http://doi.org/10.32604/ijmhp.2026.077564

ARTICLE

The Relationship between Big Five Personality Traits and Smartphone Addiction among University Students: Mindfulness as a Self-Regulatory Mediating Mechanism

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Received: 11 December 2025; Accepted: 11 March 2026; Published: 28 April 2026

ABSTRACT: Objectives: Smartphone addiction has become a salient mental health concern among university students. Although the Big Five personality traits are associated with problematic smartphone use, less is known about the psychological mechanisms linking personality to addictive smartphone behavior. This study examined whether mindfulness functions as a self-regulatory mechanism linking personality traits to smartphone addiction. **Method:** A cross-sectional survey was administered to Taiwanese university students (N = 665). Partial least squares structural equation modeling with bootstrapping was used to test direct and indirect associations among the Big Five traits, mindfulness, and smartphone addiction. **Results:** Mindfulness was negatively associated with smartphone addiction ($\beta = -0.305$, $p < 0.001$). Neuroticism showed a positive direct association with smartphone addiction ($\beta = 0.278$, $p < 0.001$) and a negative association with mindfulness ($\beta = -0.372$, $p < 0.001$), yielding a significant indirect effect via mindfulness ($\beta = 0.113$, $p < 0.001$). Openness also showed a positive direct association with smartphone addiction ($\beta = 0.163$, $p = 0.003$). Conscientiousness was positively associated with mindfulness ($\beta = 0.224$, $p < 0.001$). It exerted a significant indirect effect on smartphone addiction through mindfulness ($\beta = -0.068$, $p < 0.001$), while its direct path to smartphone addiction was not supported. **Conclusions:** Mindfulness appears to be a key self-regulatory mechanism linking personality traits to smartphone addiction. These findings support the practical value of mindfulness-based approaches for promoting healthier digital habits and improving student digital well-being.

KEYWORDS: Smartphone addiction; Big Five personality traits; mindfulness; university students

1 Introduction

In today's digitized society, smartphones are deeply embedded in university students' daily lives, supporting learning, socialization, entertainment, and emotion regulation [1,2]. Alongside these benefits, escalating use has been accompanied by growing concerns about smartphone addiction, which has emerged as a widespread psychological and social issue [1]. Evidence from Taiwan further suggests that under demanding academic contexts, students may rely on smartphones to cope with stress and negative affect, potentially increasing the risk of excessive and dysregulated use [3,4].

Prior work highlights close links between problematic smartphone use and mental health-related outcomes, including associations with stress, depression, and loneliness [5]. In addition, evidence comparing self-reported and logged digital behavior suggests that behavioral indicators may complement traditional questionnaires and support early identification of risk patterns [6,7].

Problematic Smartphone Use (PSU) is often accompanied by deficits in emotional competence and fear of missing out (FoMO), and adolescents' strong need for belonging, combined with limited inhibitory control, may further intensify overuse and its negative consequences [8]. These findings indicate that focusing solely on behavioral indicators or self-report symptom severity may be insufficient. A more integrative perspective is needed to explain why some individuals are more vulnerable to addictive patterns of smartphone use than others.

The Big Five personality traits provide a foundational framework for understanding stable individual differences in behavior. Accumulating evidence suggests that these traits are related to smartphone addiction, yet findings remain mixed across studies. Neuroticism is often associated with higher risk, whereas conscientiousness tends to be associated with a protective effect [4,9]. Extraversion and low neuroticism have also been linked to emotion-regulation tendencies, such as greater cognitive reappraisal and lower expressive suppression, which may support psychological adjustment [10]. However, the roles of openness and agreeableness appear less consistent across the literature [1,10]. Such variability suggests that personality may not operate as a simple direct predictor of addictive smartphone use; instead, intervening psychological mechanisms may be necessary to clarify how personality translates into risk or protection.

Mindfulness has been proposed as one such mechanism. As a relatively stable psychological resource, mindfulness emphasizes attending to present-moment experiences with nonjudgmental acceptance [11]. Empirical work indicates that mindfulness is associated with reduced automatic and compulsive tendencies and with enhanced emotion regulation and self-control [12,13]. At the same time, meta-analytic evidence has reported relatively small overall effect sizes, underscoring the need for large samples and rigorous designs to clarify when and how mindfulness exerts protective effects [14]. Accordingly, mindfulness may be relevant for explaining personality-related differences in smartphone addiction, but its role as a mediator requires more explicit testing.

Although prior studies have linked the Big Five traits to problematic smartphone use, evidence of mediation remains fragmented. For example, recent studies have examined psychosocial mechanisms (e.g., stress and self-regulation) that mediate associations between personality traits and problematic smartphone use in student populations [3,9].

To address these gaps, the present study tests mindfulness as a mediator linking each Big Five trait to smartphone addiction within a single unified model. Specifically, this study aims to: (i) examine associations between the Big Five personality traits and smartphone addiction; (ii) test whether mindfulness mediates the relationships between personality and smartphone addiction; and (iii) validate an integrated model with personality as antecedents, mindfulness as a mediator, and smartphone addiction as the outcome. The findings are expected to strengthen theoretical connections between personality psychology and technology-related addiction and to provide empirical implications for campus-based mindfulness education and preventive interventions [2,15].

2 Literature Review

2.1 Big Five Personality Traits

The Big Five Personality Traits constitute one of the most explanatory frameworks in contemporary personality psychology, widely used to predict behavioral tendencies and mental health [16]. The model includes Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness, which correspond to relatively stable characteristics such as sociability, self-discipline, emotional stability, and cognitive flexibility [16].

Evidence shows that neuroticism is positively associated with anxiety and depression and demonstrates predictive utility for mental disorders [17,18]. In contrast, conscientiousness is positively associated with self-control, mindfulness, and behavioral regularity, which help mitigate digital addiction [19,20]. Further empirical findings indicate that extraversion and emotional stability are positively associated with cognitive reappraisal and negatively associated with expressive suppression, highlighting their central role in emotion regulation; by comparison, the associations of conscientiousness, agreeableness, and openness with emotion regulation are inconsistent [10]. Moreover, extraversion and emotional stability are core predictors of adolescent adaptive emotion regulation, facilitating healthy interpersonal interactions and reducing psychopathological symptoms [10].

Overall, neuroticism shows the strongest negative association with trait mindfulness, whereas conscientiousness shows the strongest positive association, underscoring the role of personality in cultivating mindfulness and regulating digital behaviors [12,21,22]. Accordingly, the Big Five provides a crucial theoretical framework for understanding the processes linking smartphone addiction and mindfulness [5,23].

2.2 Smartphone Addiction

Smartphone addiction (SA) is a form of behavioral addiction that involves excessive and compulsive phone use, leading to impairment in emotion regulation, interpersonal relationships, and academic or workplace performance [24]. Core symptoms include tolerance, withdrawal, loss of control, and functional impairment, which parallel the features observed in substance addictions [25]. From a motivational perspective, excessive smartphone use may arise from attempts to avoid stress, to obtain immediate gratification, or to regulate emotions [21,26].

Recent large-scale evidence also indicates that smartphone addiction remains prevalent among adolescents and is associated with identifiable patterns of smartphone use and risk factors in everyday settings [27]. Recent studies further describe Problematic Smartphone Use (PSU) as frequent overuse accompanied by regulatory difficulties, resulting in adverse consequences in daily life [8]. Adolescents and university students, given strong belonging needs and limited inhibitory control, are particularly vulnerable [8]. In addition, FoMO is positively associated with PSU, whereas emotional intelligence is negatively associated, suggesting that deficits in psychological regulation are important risk factors for addiction [8]. Beyond smartphone use alone, adjacent digital addictions may further compound daily impairment; for example, short-form video overuse has been linked to addictive tendencies and reduced attention control among adolescents [4], and social media addiction has been associated with poorer sleep quality [28]. Moreover, evidence comparing self-reports with logged behavior suggests that objective smartphone-use indicators can complement traditional questionnaires [6,7]. These findings highlight the tight interweaving between PSU and mental health and support the development of diverse approaches to early identification and intervention.

From a theoretical standpoint, self-regulation theory posits that addictive behaviors stem from difficulty delaying gratification and sustaining goal-directed action [29]; the compensatory internet use model proposes that smartphone use often serves as a compensatory strategy in response to negative emotions and real-world stress [30]. Consistent with these perspectives, recent evidence suggests that mental distress is linked to problematic smartphone and social media use through stress-related cognitive and affective processes [31]. Research further suggests that individuals high in neuroticism, due to emotional instability and anxiety proneness, are more likely to rely on smartphones to alleviate stress [9,32]. In contrast, mindfulness and self-control can effectively reduce the risk of overuse [13,33]. Intervention evidence also supports the broader psychological benefits of mindfulness in adolescents [34], and meta-analytic findings indicate that mindfulness is associated with lower learning burnout among university students [35], aligning with its proposed role in self-regulation. Understanding PSU, therefore, requires attention to both behavioral manifestations and the integration of personality with psychological processes, thereby enabling the construction of more explanatory models.

2.3 Mindfulness

Mindfulness is a psychological process of attending to present-moment internal and external experiences with an open and nonjudgmental attitude; it can also be conceptualized as a dispositional tendency to sustain such awareness [36,37]. In empirical research, trait mindfulness is assessed using self-report measures that emphasize mindful attention and awareness (e.g., the Mindful Attention Awareness Scale, MAAS) or broader multi-component conceptualizations (e.g., the Five Facet Mindfulness Questionnaire, FFMQ) [36,38]. In the present study, mindfulness was operationalized as mindful attention and awareness in daily life and measured using the five-item MAAS short form (MAAS-5) [36,39].

Mindfulness is considered beneficial for stress adaptation and behavioral control and shows protective effects against dependency-like digital behaviors such as smartphone addiction [12,21]. In theoretical terms, mindfulness is commonly defined as paying deliberate attention to present-moment experience rather than operating on “autopilot” [11,36]. Empirical work indicates that individuals with higher trait mindfulness are less likely to engage in avoidant or compulsive smartphone use when experiencing stress or emotional distress and display stronger self-control [14,40]. From an attention-regulation perspective, mindful awareness helps individuals notice habitual checking and mind-wandering, thereby reducing attentional impulsivity and supporting behavioral restraint in smartphone use [2,14]. Nevertheless, meta-analytic syntheses report small effect sizes, indicating a need for more rigorous research designs and larger sample sizes for validation [14,41]. It is also important to note that mindfulness is not a universal remedy; researchers should distinguish active ingredients from commercialized or popularized elements that lack substance [11]. This perspective aligns with the present study’s aim of examining how personality traits influence smartphone addiction through mindfulness, clarifying the underlying psychological processes, and offering theoretical and practical implications.

2.4 Hypotheses Development

2.4.1 Relationships between the Big Five Personality Traits and Smartphone Addiction

Given the observed prevalence of smartphone addiction and its links with distress-related processes in young populations [27,31], individual differences such as the Big Five personality traits have been widely examined as potential predictors of compulsive smartphone use.

Within individual-differences research on smartphone addiction, Openness has received growing attention. Openness reflects the degree to which individuals embrace new experiences, including curiosity, creativity, and exploratory tendencies [17]. Some studies report no significant association between openness and smartphone addiction [1,32]. In contrast, others argue that individuals high in openness, due to their enthusiasm for new knowledge and technologies, may use smartphones more frequently [42] and be more susceptible to problematic smartphone engagement [43]. Accordingly, this study proposes the following hypothesis:

H1a: *Openness is positively associated with smartphone addiction.*

Among predictors of smartphone addiction, Agreeableness often shows relatively weak predictive power, yet it remains theoretically meaningful. Agreeableness reflects tendencies toward cooperation, consideration, and interpersonal harmony and is typically negatively associated with impulsive control failures and addictive behaviors [19]. Although many studies report no significant association between agreeableness and smartphone addiction [1,32], some argue that individuals high in agreeableness, who seek to avoid conflict and please others, may increase smartphone use under interpersonal stress. However, evidence remains mixed [32,44]. Although findings are mixed, some studies that control for confounders have observed a small negative association between agreeableness and technology addiction [43,44]. Therefore, this study hypothesizes:

H1b: *Agreeableness is negatively associated with smartphone addiction.*

In the Big Five framework, Conscientiousness represents self-discipline, planning, goal orientation, and self-control [17]. Evidence shows that highly conscientious individuals manage time effectively, remain task-focused, and inhibit impulses, which reduces the likelihood of excessive smartphone use [19,45]. Marengo et al. [43] found that greater conscientiousness is associated with stronger emotional and behavioral regulation, which reduces addictive tendencies. Other work emphasizes the close links between conscientiousness and mindfulness or self-regulation, which enhance self-monitoring and inhibit compulsive smartphone use [15,21]. In contrast, those low in conscientiousness often lack self-discipline and goal focus, leading to uncontrolled use [43,44]. Ran [20] also indicates that via improved self-control, conscientiousness can indirectly alleviate smartphone addiction. Hence, this study proposes:

H1c: *Conscientiousness is negatively associated with smartphone addiction.*

Within the psychological mechanisms of smartphone addiction, Neuroticism is widely considered one of the strongest personality predictors. Individuals high in neuroticism often display emotional instability, anxiety, and impulsive behavior, and tend to use smartphones to escape reality and regulate negative emotions [9,32,46]. This trait can also weaken self-control, further increasing reliance on smartphones [4]. Doménech et al. [10] also report that neuroticism is associated with poorer emotion regulation, suggesting an indirect reinforcement of phone dependence. In line with compensatory accounts, stress and distress-related processes appear closely intertwined with problematic smartphone use [31]. Based on this evidence, it is hypothesized that:

H1d: *Neuroticism is positively associated with smartphone addiction.*

Many studies indicate that Extraversion may be unrelated or weakly protective regarding smartphone addiction. Bhayangkara et al. [1] found a significant negative association between extraversion and smartphone addiction, suggesting that extraverts, who prefer face-to-face interaction to satisfy social needs, rely less on virtual socializing [1,47]. Kayiş et al. [45] likewise reported that frequent engagement in social activities reduces the likelihood of smartphone overuse among extraverts. Recent evidence syntheses further suggest that extraversion is not a robust risk factor for smartphone addiction compared with traits such as neuroticism and conscientiousness [5]. Doménech et al. [10] add that extraversion correlates with stronger emotion regulation, such as cognitive reappraisal, which may indirectly lower addiction risk. In short, real-world social engagement may substitute for digital reliance among extraverts, thereby reducing addiction risk. Thus, it is hypothesized that:

H1e: *Extraversion is negatively associated with smartphone addiction.*

2.4.2 Relationship between Mindfulness and Smartphone Addiction

Mindfulness functions as a crucial protective factor against smartphone addiction, involving present-moment awareness and enhanced self-regulation. Individuals with high trait mindfulness can better detect internal cues and habitual impulses, thereby reducing engagement in compulsive behaviors such as excessive smartphone use [14,40]. Guided by conservation of resources theory, trait mindfulness can be conceptualized as a personal resource that supports emotion regulation and psychological well-being under stress [48,49]. Consistent with this view, evidence from randomized controlled trials indicates that mindfulness-based programs can improve psychological resources and stress-related outcomes [34,41]. Importantly, when mindfulness is operationalized as mindful attention and awareness (as in the MAAS-5), it is expected to reduce automatic or mindless smartphone checking by strengthening awareness of ongoing behavior [14,36]. Meta-analytic evidence indicates that the effects of mindfulness are generally small, underscoring the need for rigorous designs and large samples [14]. Mindfulness is not a panacea, and its active ingredients must be distinguished from popularized elements that lack substance [11].

Recent evidence nonetheless supports a significant risk-reducing role of mindfulness for smartphone addiction, achieved through enhanced self-control and emotion regulation that curb compulsive and avoidant use [14,50,51]. In addition, evidence synthesized across university samples indicates that mindfulness is associated with lower learning burnout [35], which is theoretically compatible with the view that mindfulness protects self-regulatory capacity under sustained demands. Therefore, this study hypothesizes:

H2: *Trait mindfulness is negatively associated with smartphone addiction.*

2.4.3 Relationships between the Big Five Traits and Mindfulness

Openness, characterized by receptivity to new experiences and cognitive flexibility, may relate to mindful awareness through curiosity and flexible attention. Prior research reports a small positive association between openness and trait mindfulness, especially for attention/awareness components [15]. Measurement also matters; attention/awareness measures (e.g., the MAAS) and multi-facet measures (e.g., the FFMQ) can yield different patterns of association with personality traits [19,52]. The introspection, self-exploration, and flexible thinking inherent in openness may support the cultivation of an attentive stance in daily life [15,19]. Although the overall correlation may be weaker than for other traits, openness remains meaningful for reflective engagement with experience and cognitive flexibility [53]. Errasti-Pérez et al. [11] further note that, although the effects of mindfulness are minor, mindful awareness remains theoretically relevant for self-regulation. Hence, this study proposes:

H3a: *Openness is positively associated with trait mindfulness.*

Agreeableness encompasses empathy, trust, and cooperation. These characteristics may facilitate mindful attention by reducing interpersonal conflict and promoting prosocial coping under stress, thereby supporting the maintenance of present-moment awareness [12,54]. Meta-analytic evidence indicates a small but reliable positive association between agreeableness and trait mindfulness [19]. In addition, mindfulness-related attitudes such as self-acceptance and an observational stance toward internal experience have been linked to psychological adjustment beyond the Big Five, suggesting possible pathways through which agreeableness may support mindful awareness [22]. Prior work also suggests that the supportive qualities of agreeableness may indirectly strengthen mindfulness-related self-regulation processes [53]. Doménech et al. [10] caution that associations between agreeableness and emotion regulation are not always consistent, which implies possible contextual moderation of their relationship with mindfulness. Thus, it is hypothesized that:

H3b: *Agreeableness is positively associated with trait mindfulness.*

Among the Big Five, Conscientiousness aligns closely with mindfulness, as reflected in self-discipline, responsibility, and planning. It is often the strongest predictor of personality tendencies in mindfulness. Individuals high in self-discipline and organization are better able to maintain steady mindfulness practice and sustained present-moment awareness [12], and meta-analytic work confirms a strong link [19]. Zhao [54] further notes that responsibility and personal standards bolster goal-directed action and awareness within mindfulness processes. Even when neuroticism is negatively associated with mindfulness, conscientiousness can compensate by helping individuals maintain mindfulness under stress [15]. Although mindfulness can be trained, conscientiousness provides stable behavioral persistence and motivational regulation that support long-term practice [53]. Therefore, this study hypothesizes:

H3c: *Conscientiousness is positively associated with trait mindfulness.*

Neuroticism shows a stable, significant negative association with mindfulness; its hallmarks of emotional instability, anxiety, and rumination conflict with present-moment awareness and nonjudgmental acceptance [12,15]. Meta-analytic evidence indicates that weaker self-regulation and emotional stability among individuals high in neuroticism hinder sustained mindfulness practice [19]. Avoidant and reactive modes in response to negative emotions impede entry into the nonreactive, accepting states required for mindfulness. Zhao [54] adds that intense affective lability under stress undermines the benefits of mindfulness for emotion regulation and mental health among those high in neuroticism. Doménech et al. [10] likewise link neuroticism to difficulties in emotion regulation, supporting its role as a negative predictor of mindfulness. Hence, this study proposes:

H3d: *Neuroticism is negatively associated with trait mindfulness.*

Extraversion reflects sociability, energetic engagement, and positive affectivity; however, its association with mindfulness is typically small and less consistent than that of neuroticism and conscientiousness [15,19]. Meta-analytic findings suggest that extraversion has limited predictive power for mindfulness outcomes, possibly because outward engagement can compete with sustained attentional monitoring in daily life [15]. Moreover, associations between extraversion and mindfulness can vary by measurement approach; attention/awareness measures, such as the MAAS, may yield different patterns than multi-facet measures, such as the FFMQ [52]. Doménech et al. [10] report a positive association between extraversion and cognitive reappraisal, suggesting a potential supportive role for extraversion in mindfulness-related regulation processes. Thus, it is hypothesized that:

H3e: *Extraversion is positively associated with trait mindfulness, although the association is weaker than for other personality dimensions.*

2.4.4 The Mediating Effect of Mindfulness between Big Five Personality Traits and Smartphone Addiction

Openness represents cognitive flexibility and a tendency to explore novel and complex experiences and is considered relevant to technology-use behaviors. Although some studies find no significant association with smartphone addiction [1,32], others argue that high-openness individuals, who prefer novel stimulation and technological media, may be more susceptible to problematic engagement with smartphones [42]. Mindfulness is a key protective factor that reduces avoidant and addictive tendencies via emotion regulation and self-control [12,36]. Studies also report a positive association between mindfulness and openness, especially for cognitive acceptance and experiential receptivity [15,53]. In addition, mindfulness can significantly lower smartphone addiction risk and may serve as a mediator between openness and addictive behaviors [3,55]. Among adolescents, mindfulness improves self-control and emotion regulation and reduces overuse driven by negative emotion or fear [8,21]. Errasti-Pérez et al. [11] add that, although mindfulness is not universally effective, it targets specific cognitive processes that may mediate the relationship between openness and smartphone addiction. Therefore, this study hypothesizes:

H4a: *Mindfulness mediates the relationship between openness and smartphone addiction.*

Individuals high in agreeableness typically display interpersonal harmony and cooperative coping under stress. These characteristics may support mindful attention by reducing conflict-related rumination and facilitating awareness of present-moment experience [12,54]. Mindfulness, operationalized as present-moment attention and awareness, can inhibit impulsive and avoidant behaviors, increase awareness and restraint in phone use, and reduce tendencies toward smartphone addiction [21,36]. Thus, mindfulness is expected to mediate the link between agreeableness and smartphone addiction, such that higher agreeableness is associated with higher mindfulness and, in turn, lower addiction risk [41,48,49]. Therefore, this study hypothesizes:

H4b: *Mindfulness mediates the relationship between agreeableness and smartphone addiction.*

Conscientiousness is a robust protective factor encompassing self-discipline, goal orientation, and behavioral control, and is closely associated with mindfulness tendencies [19]. Hanley and Garland [12] indicate that higher conscientiousness supports sustained present-moment awareness and nonjudgmental attitudes, thereby strengthening the self-monitoring and emotion-regulation components of mindfulness. Mindfulness is also a negative predictor of smartphone addiction, lowering impulsive and avoidant use [21]. Lan et al. [51] found that individuals high in mindfulness show greater awareness during phone use, thereby reducing compulsive and automatic behavior. Consistent with Doménech et al. [10], conscientiousness is associated with adaptive emotion regulation, which, in turn, further reduces addiction risk through mindfulness. Therefore, this study posits a mediating role for mindfulness in the relationship between conscientiousness and smartphone addiction, such that higher conscientiousness indirectly reduces addiction risk by increasing mindfulness, consistent with conservation of resources theory regarding the protection and conversion of self-regulatory resources [41,48,49,56]. Hence, this study proposes:

H4c: *Mindfulness mediates the relationship between conscientiousness and smartphone addiction.*

Neuroticism has long been viewed as a key risk factor for smartphone addiction and shows a stable negative relationship with mindfulness [12,15]. Due to emotional instability, anxiety, and rumination, individuals high in neuroticism are prone to avoidant strategies under stress, which can undermine sustained present-moment attention and increase mind-wandering. Such individuals may rely on smartphones to cope with distress and the risk of dependence [54]. Mindfulness, in contrast, strengthens awareness of thoughts and urges and supports self-control, thereby reducing compulsive smartphone use and technology-related addictions [14,21]. Individuals can better manage emotions and impulses by cultivating mindful attention, thereby mitigating neuroticism-driven smartphones [13]. Consistent with conservation of resources theory, mindfulness operates as a psychological resource that helps individuals high in neuroticism rely less on smartphones when facing anxiety and stress [41,48,49]. Prior work comparing self-reported and logged digital behavior indicates that self-reports may be insufficient for fully capturing relevant usage patterns, and that integrating behavioral indicators can improve measurement and inference [6,7].

H4d: *Mindfulness mediates the relationship between neuroticism and smartphone addiction.*

Although some evidence suggests that extraversion is a relatively weak and heterogeneous correlate of smartphone addiction [5,45], its association with trait mindfulness is also typically small and measure-dependent [15,19,52]. Frequent social engagement and positive affect among extraverts may support adaptive emotion regulation strategies (e.g., cognitive reappraisal), which could indirectly facilitate mindful awareness [10]. Since mindfulness promotes self-control and present-moment attention, reduces compulsive smartphone use [14,21], and can be conceptualized as a psychological resource within conservation of resources theory [41,48,49], a mediating role of mindfulness between extraversion and smartphone addiction is inferred [2,12]. Thus, it is hypothesized that:

H4e: *Mindfulness mediates the relationship between extraversion and smartphone addiction.*

3 Methods

3.1 Participants and Procedures

To reduce the risks of Type I and Type II errors, an a priori power analysis was conducted [57]. Using G*Power 3.1.9.7, we conducted a power analysis for multiple regression (fixed model, R^2 deviation from zero), alpha set at 0.05, power set at 0.80, and an effect size of 0.15. The maximum number of predictors pointing to an endogenous construct in the proposed model was six. The minimum required sample size was estimated at 98 [58].

The survey was conducted in December 2023 using convenience sampling, which relies on voluntary participation and high accessibility and is commonly employed in studies focused on specific populations [59]. The questionnaire was distributed via Instagram, Facebook, LINE groups managed by university instructors, and digital learning platforms. Because the survey link was distributed via open online channels, the number of individuals who viewed the invitation could not be precisely determined; therefore, the response rate was unavailable. Before starting the questionnaire, participants read an information sheet and provided electronic informed consent.

All items were mandatory, and automatic validation checks were implemented to ensure accuracy and completeness. Invalid responses were identified and excluded based on duplicate submissions, extremely short completion times, and clear straightlining patterns (e.g., invariant responses across long item blocks).

After screening and excluding 24 invalid responses, the final sample comprised 665 valid cases. Participants' demographic characteristics are summarized in Table 1.

Sampling planning also referenced the minimum sample guideline of at least 100 participants proposed by Comrey and Lee [60] and the rule of five participants per scale item recommended by Gorsuch [61]. Regarding sample composition, 64.7% were female, and 35.3% were male. Most participants were under 30, with a mean age of 21.9 years, and the largest group was aged 21–30. By grade level, juniors accounted for 28.6% and seniors for 29%. By field of study, education-related majors accounted for the largest share at 61.5%.

Table 1: Demographic information of the sample.

Demographic Variables	Category	N	Percentage
Gender	1. Male	235	35.30%
	2. Female	430	64.70%
Grade	1. Freshman	117	17.60%
	2. Sophomore	143	21.50%
	3. Junior	190	28.60%
	4. Senior	193	29.00%
	5. Master's Program	22	3.30%
Age	1. ≤20 years	299	44.96%
	2. 21–30 years	341	51.28%
	3. 31–40 years	8	1.20%
	4. 41–50 years	5	0.75%
	5. ≥51 years	12	1.80%
Major	A. Humanities, Social Sciences, and Business Management	125	18.80%
	B. Education	409	61.50%
	C. Natural Sciences and Engineering	40	6.00%
	D. Medical, Biological, and Agricultural Fields	46	6.90%
	E. Other Fields	45	6.80%

3.2 Measures

All instruments used in this study were adapted from previously published questionnaires in international academic journals. Except for the Chinese Shortened Big Five Inventory, which used an existing Chinese version, the English versions of all other instruments were translated into Chinese by a professor proficient in English using the back-translation method [62]. After translation, five professors reviewed and refined the items to ensure consistency with the present research context and minimize potential bias in the scales.

3.2.1 Chinese Shortened Big Five Inventory (CBF-PI-15)

The Big Five personality traits were assessed using the Chinese Big Five Personality Inventory-15 (CBF-PI-15) [63]. The CBF-PI-15 is a 15-item shortened version derived from the Chinese Big Five Personality Inventory Brief Version (CBF-PI-B), consisting of five subscales: Neuroticism, Conscientiousness, Agreeableness, Openness, and Extraversion, with three items per trait.

In the scale development study, the CBF-PI-15 demonstrated acceptable internal consistency given its brevity, with Cronbach's α ranging from 0.611 to 0.803 in Sample 1 (N = 10,738) and from 0.612 to 0.811 in Sample 2 (N = 256). Good model supported factorial validity fit in confirmatory factor analysis (MLRχ^2 = 918.882, df = 80, CFI = 0.946, TLI = 0.929, RMSEA = 0.044, SRMR = 0.040), and measurement invariance was further supported across gender and age groups.

3.2.2 Mindful Attention Awareness Scale (MAAS)

The Mindful Attention Awareness Scale (MAAS) was originally developed as a 15-item measure of dispositional mindfulness (present-moment attention and awareness) [36]. In this study, we adopted a five-item short form (MAAS-5) adapted from the original MAAS to reduce respondent burden, drawing on prior cross-cultural validation of the MAAS-5 [39].

Items describe day-to-day lapses in attention and awareness (e.g., "I do jobs or tasks automatically, without being aware of what I'm doing") and were rated on a 6-point frequency scale from 1 (almost always) to 6 (almost never). Scores were coded such that higher values indicate higher mindfulness. In the present sample, confirmatory factor analysis supported the adequacy of the five-item MAAS, with all item loadings exceeding 0.700 (CFI = 0.941, GFI = 0.948, NFI = 0.918, RMR = 0.039, RMSEA = 0.043). Composite reliability was 0.888, and Cronbach's alpha was 0.844.

3.2.3 Smartphone Addiction Scale-Short Version (SAS-SV)

The Smartphone Addiction Scale-Short Version (SAS-SV), developed by Kwon et al. [64], was administered to assess smartphone addiction among university students. The original scale comprises 10 items, each rated on a 6-point Likert scale from 1 (strongly disagree) to 6 (strongly agree), with higher scores indicating greater addiction severity. The original instrument reported a Cronbach's alpha of 0.966.

In this study, the SAS-SV items were evaluated as part of the measurement model assessment. Following standard criteria for indicator reliability and construct validity, items with inadequate performance were removed, and six items were retained in the final measurement model. For the retained items, standardized loadings exceeded 0.700, and internal consistency was satisfactory (composite reliability = 0.905; Cronbach's alpha = 0.875), supporting the reliability of the retained SAS-SV indicators in the present sample.

Recent psychometric work in university samples further highlights the importance of evaluating reliability and measurement invariance when applying smartphone- and social-media-addiction scales across subgroups [65].

3.3 Statistical Analyses

IBM SPSS 27.0 (IBM Corp., Armonk, NY, USA) was used to analyze the observed variables, including descriptive statistics to summarize participant characteristics. Shapiro–Wilk tests were conducted to assess univariate normality of the observed variables. Given the departures from normality, bivariate associations were examined primarily using Spearman's rank-order correlations, while Pearson correlations were also computed as a robustness check. In addition, independent-samples t-tests and one-way ANOVAs were conducted to examine group differences (e.g., gender and grade level) in the study variables. Harman's single-factor test was performed to assess common method bias [66].

For the structural model, PLS-SEM analyses were conducted using SmartPLS 4.0 [67]. Given the present research's emphasis on prediction, PLS-SEM was deemed appropriate. Hair et al. [68] recommend that prediction-oriented research adopt a confirmatory composite analysis (CCA) approach, and note that PLS-SEM facilitates the integration of theory testing and predictive goals [69]. Shmueli et al. [69] further proposed an evaluation framework tailored to the predictive nature of PLS-SEM, which has been widely applied in hospitality and tourism research [68].

Following standard PLS-SEM procedures, a two-step approach was employed [70,71]. First, the measurement model was evaluated with respect to indicator reliability, convergent validity, internal consistency, multicollinearity (variance inflation factor, VIF), and discriminant validity, assessed using the

Heterotrait-Monotrait (HTMT) ratio of correlations [72]. Second, the structural model was assessed to test the hypotheses and predictive performance [71].

In addition to the PLS-SEM analyses, we conducted (a) a regularized Gaussian graphical model (GGM) network analysis using EBICglasso to examine conditional dependence relations among constructs, implemented in JASP (version 0.95.4.0) with an EBIC tuning parameter of 0.5 [73]; and (b) a prediction-oriented assessment using PLS-Predict with tenfold cross-validation to evaluate out-of-sample predictive performance at the construct and indicator levels [74].

4 Results

4.1 Preliminary Analyses

Before testing the measurement and structural models, distributional assumptions were examined. Shapiro-Wilk tests indicated that univariate normality was violated for the study variables (W = 0.938–0.985, all p-values < 0.001). Therefore, Spearman's rank-order correlations are reported in Table 2. As shown in Table 2, smartphone addiction was negatively associated with mindfulness (ρ = −0.378, $p < 0.001$) and positively associated with neuroticism (ρ = 0.319, $p < 0.001$). Mindfulness was positively correlated with openness (ρ = 0.155, $p < 0.001$) and conscientiousness (ρ = 0.220, $p < 0.001$), and negatively correlated with neuroticism (ρ = −0.378, $p < 0.001$). The intercorrelations among the Big Five traits were generally in the expected directions. As a robustness check, Pearson correlations showed a highly similar pattern; the only notable difference was that the association between smartphone addiction and conscientiousness was marginal and non-significant under Spearman's rho (ρ = −0.073, $p = 0.059$) but reached significance under Pearson's r (r = −0.082, $p = 0.034$).

Table 2: Means, standard deviations, and correlations among constructs (N = 665).

Constructs	Mean	SD	Correlations among Constructs						
			SA	MI	OP	AG	CO	NE	EX
1. Smartphone addiction (SA)	3.420	1.273	—						
2. Mindfulness (MI)	4.051	0.999	−0.378***	—					
3. Openness (OP)	3.373	1.073	0.019	0.155***	—				
4. Agreeableness (AG)	3.995	0.827	0.006	0.048	0.509***	—			
5. Conscientiousness (CO)	3.961	0.793	−0.073	0.220***	0.468***	0.480***	—		
6. Neuroticism (NE)	3.252	1.062	0.319***	−0.378***	−0.281***	−0.025	−0.134***	—	
7. Extraversion (EX)	3.519	0.959	−0.005	0.036	0.357***	0.303***	0.375***	0.004	—

Note: N = 665. SD, standard deviation. Correlations are Spearman's rank-order correlation coefficients (ρ; two-tailed) and are presented below the diagonal. ***$p < 0.001$.

4.2 Assessment of the Extent of Common Method Variance

To evaluate the presence of common method variance (CMV), Harman's single-factor test was applied to an unrotated exploratory factor analysis. The first factor accounted for 22.41% of the variance, below the 50% threshold, indicating no CMV concern in this study [66].

4.3 Measurement Model

Following Hair et al. [72], an outer loading of 0.70 was adopted as the indicator reliability benchmark, and all retained items met this criterion. Convergent validity was assessed using average variance extracted (AVE), with 0.50 as the reference value [75–77]. Internal consistency reliability was examined via composite reliability (CR), and all constructs exceeded 0.70 [72,75–77]. Based on these criteria, the final scales included three items for openness, agreeableness, conscientiousness, neuroticism, and extraversion, five items for mindfulness, and six items for smartphone addiction. As shown in Table 3, all variance inflation factor (VIF) values were below 5, indicating no multicollinearity concerns [78]. In addition, to facilitate interpretation for readers more familiar with covariance-based SEM, Table 3 also summarizes the classical CFA fit indices (e.g., CFI, GFI, NFI, RMR, and RMSEA) estimated for the current sample as supplementary information.

Table 3: Measurement models of the measures.

Scale/Reference	Item No.	Item Content	FL	VIF	AVE	CR	Cronbach's α	Fit Indices for the Current Sample
The Chinese Big Five Personality Inventory-15 (CBF-PI-15) [63]	OP1	I am imaginative	0.945	2.854	0.786	0.916	0.871	CFI = 0.941 GFI = 0.956 NFI = 0.910 RMR = 0.037 RMSEA = 0.043
	OP2	I am creative	0.926	3.226				
	OP3	I value artistic and aesthetic experiences	0.781	1.852				
	AG1	I am helpful	0.861	1.653	0.753	0.902	0.84	
	AG2	I am of a forgiving nature	0.857	2.393				
	AG3	I am considerate and kind to others	0.885	2.354				
	CO1	I am a reliable worker	0.866	1.985	0.703	0.877	0.793	
	CO2	I stick to my tasks until they are finished	0.795	1.735				
	CO3	I work efficiently	0.854	1.53				
	NE1	I worry about many things	0.792	1.558	0.687	0.868	0.773	
	NE2	I am emotionally unstable	0.833	1.524				
	NE3	I easily feel tense	0.86	1.77				
	EX1	I am full of energy	0.871	2.46	0.712	0.88	0.795	
	EX2	I am enthusiastic	0.931	2.669				
	EX3	I enjoy going out and socializing	0.715	1.335				
Mindful Attention Awareness Scale (MAAS) [36,39]	MI1	It seems I am "running on automatic" without much awareness of what I am doing.	0.769	1.931	0.613	0.888	0.844	CFI = 0.941 GFI = 0.948 NFI = 0.918 RMR = 0.039 RMSEA = 0.043
	MI2	I rush through activities without really paying attention.	0.811	1.839				
	MI3	I get so focused on the goal I want to achieve that I lose touch with what I am doing right now to get there.	0.724	1.638				
	MI4	I perform tasks automatically, without being aware of what I'm doing.	0.828	2.27				
	MI5	I find myself doing things without paying attention.	0.779	1.504				
Smartphone Addiction Scale-Short Version (SAS-SV) [64]	SA1	Won't be able to stand not having a smartphone	0.807	2.341	0.615	0.905	0.875	CFI = 0.948 GFI = 0.951 NFI = 0.930 RMR = 0.037 RMSEA = 0.041
	SA2	Having my smartphone in my mind even when I am not using it	0.782	2.021				
	SA3	I will never give up using my smartphone, even when my daily life is already greatly affected by it.	0.799	2.216				
	SA4	Constantly checking my smartphone so as not to miss conversations between other people on Twitter or Facebook.	0.75	1.76				
	SA5	Using my smartphone longer than I had intended.	0.814	1.963				

Table 3: *Cont.*

Scale/Reference	Item No.	Item Content	FL	VIF	AVE	CR	Cronbach's α	Fit Indices for the Current Sample
	SA6	The people around me tell me that I use my smartphone too much.	0.75	1.657				

Note: FL, factor loadings; VIF, variance inflation factor; AVE, average variance extracted; CR, composite reliability; CFI, comparative fit index; GFI, goodness of fit index; NFI, normed fit index; RMR, root mean square residual; RMSEA, root mean square error of approximation. Classical fit indices (CFAs) are reported at the instrument level as supplementary information for readers familiar with covariance-based SEM; they are not used as evaluation criteria for the PLS-SEM measurement model.

4.4 Discriminant Validity

Discriminant validity was tested using the Heterotrait-Monotrait ratio of correlations (HTMT) method [79], given recent critiques of the Fornell and Larcker [76] criterion. HTMT values above 0.85 [80] or 0.90 [81] may signal insufficient discriminant validity. As reported in Table 4, all HTMT values were below 0.85, supporting satisfactory discriminant validity among the study constructs [80].

Table 4: Discriminant validity: Heterotrait-Monotrait ratio of correlations (HTMT).

Constructs	Mindfulness	Openness	Agreeableness	Conscientiousness	Neuroticism	Extraversion
Mindfulness						
Openness	0.202					
Agreeableness	0.077	0.620				
Conscientiousness	0.286	0.578	0.587			
Neuroticism	0.482	0.369	0.088	0.208		
Extraversion	0.062	0.415	0.319	0.462	0.076	
Smartphone addiction	0.434	0.093	0.079	0.130	0.420	0.053

4.5 Hypothesis Testing

Bootstrapping was used to examine the significance of hypothesized paths in the structural model [82]. This approach evaluates estimates' statistical significance and sampling error [75] and allows inspection of standardized path coefficients (β), significance levels, and R^2 for endogenous constructs. The structural model and standardized path coefficients are presented in Fig. 1, and the corresponding bootstrapping results are summarized in Table 5. The results in Fig. 1 show significant paths for conscientiousness → mindfulness ($\beta = 0.224$, $p < 0.001$), neuroticism → mindfulness ($\beta = -0.372$, $p < 0.001$), mindfulness → smartphone addiction ($\beta = -0.305$, $p < 0.001$), neuroticism → smartphone addiction ($\beta = 0.278$, $p < 0.001$), and openness → smartphone addiction ($\beta = 0.163$, $p = 0.003$). In contrast, agreeableness → smartphone addiction ($\beta = -0.021$, $p = 0.687$), conscientiousness → smartphone addiction ($\beta = -0.018$, $p = 0.693$), extraversion → smartphone addiction ($\beta = -0.048$, $p = 0.379$), openness → mindfulness ($\beta = 0.008$, $p = 0.859$), agreeableness → mindfulness ($\beta = -0.049$, $p = 0.300$), and extraversion → mindfulness ($\beta = -0.040$, $p = 0.421$) were not significant. In particular, the direct path from conscientiousness to smartphone addiction was not supported because its confidence interval included zero (95% CI [−0.100, 0.077]) [83].

Table 5: Results of the bootstrapping procedure.

Path	SE	*t*	*p*	95% CI	Decision
H1a: Openness → Smartphone addiction	0.055	2.945	0.003	0.060, 0.274	Supported
H1b: Agreeableness → Smartphone addiction	0.053	0.403	0.687	−0.134, 0.071	Not Supported
H1c: Conscientiousness → Smartphone addiction	0.046	0.395	0.693	−0.100, 0.077	Not Supported

Table 5: *Cont.*

Path	SE	t	p	95% CI	Decision
H1d: Neuroticism → Smartphone addiction	0.043	6.452	<0.001	0.193, 0.362	Supported
H1e: Extraversion → Smartphone addiction	0.055	0.881	0.379	−0.144, 0.061	Not Supported
H2: Mindfulness → Smartphone addiction	0.039	7.725	<0.001	−0.379, −0.224	Supported
H3a: Openness → Mindfulness	0.048	0.177	0.859	−0.078, 0.108	Not Supported
H3b: Agreeableness → Mindfulness	0.047	1.037	0.300	−0.161, 0.034	Not Supported
H3c: Conscientiousness → Mindfulness	0.046	4.909	<0.001	0.144, 0.320	Supported
H3d: Neuroticism → Mindfulness	0.033	11.226	<0.001	−0.430, −0.300	Supported
H3e: Extraversion → Mindfulness	0.050	0.804	0.421	−0.160, 0.031	Not Supported

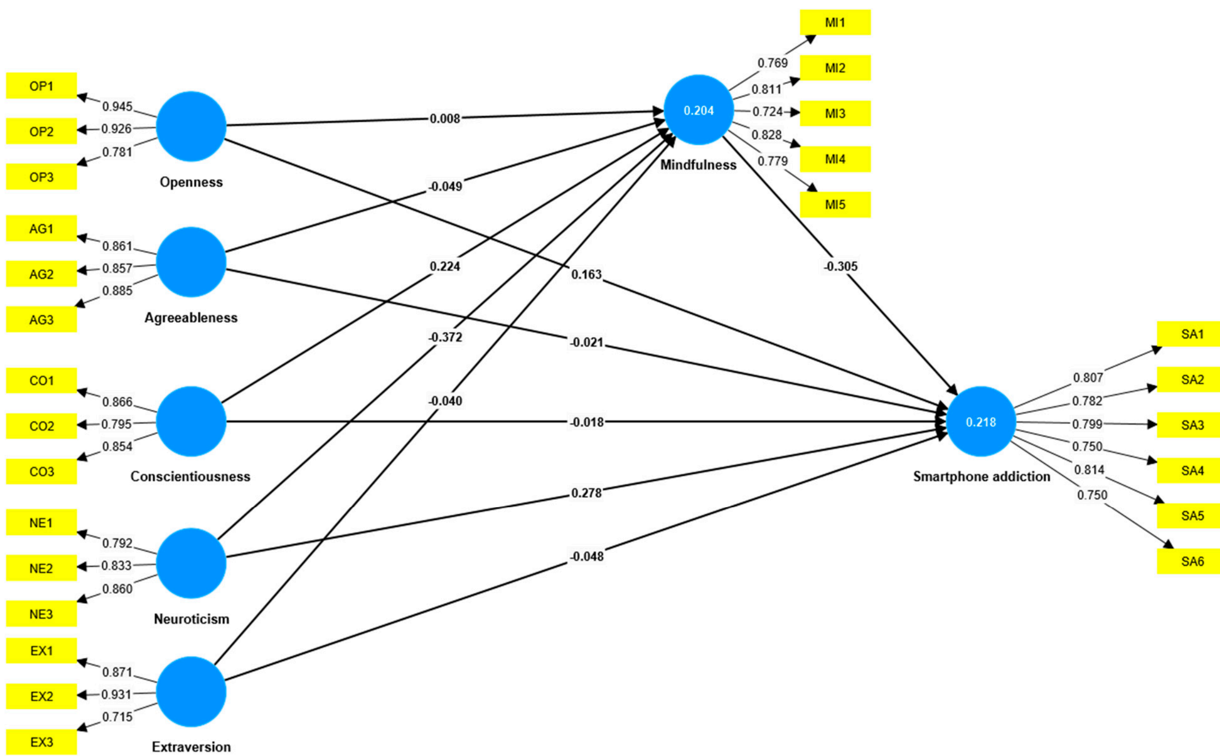

Figure 1: Structural model. Note: SA, smartphone addiction; MI, mindfulness; OP, openness; AG, agreeableness; CO, conscientiousness; NE, neuroticism; EX, extraversion. Values on the structural paths represent standardized path coefficients (β). Values on the measurement model links (between indicators and constructs) represent standardized outer loadings. Values inside the endogenous construct circles represent explained variance (R^2).

Following Hair et al. [72], mediation analysis was performed via bootstrapping to test the indirect effects of mindfulness on the relationship between personality traits and smartphone addiction (see Table 6). Mindfulness significantly mediated the effects of conscientiousness ($\beta = -0.068$, $p < 0.001$) and neuroticism ($\beta = 0.113$, $p < 0.001$) on smartphone addiction. Based on the Variance Accounted For (VAF), the mediation magnitude was substantial for conscientiousness (79.07%) and moderate for neuroticism (28.90%) [72]. Overall, the results highlight mindfulness as a key mechanism linking personality traits to smartphone addiction. Accordingly, H1a, H1d, and H2 were supported, whereas H1b, H1c, and H1e were not supported. Regarding antecedents of mindfulness, H3c and H3d were supported, whereas H3a, H3b, and H3e were not supported. In the mediation analysis, mindfulness significantly mediated the effects of conscientiousness (H4c) and neuroticism (H4d) on smartphone addiction, while H4a, H4b, and H4e were not supported.

Table 6: Mediation effect analysis results.

Hypothesis	β	SE	*t*	*p*	95% CI	Decision
H4a: Openness → Mindfulness → Smartphone addiction	−0.003	0.015	0.176	0.860	−0.029, 0.028	Not supported
H4b: Agreeableness → Mindfulness → Smartphone addiction	0.015	0.015	1.028	0.304	−0.016, 0.043	Not supported
H4c: Conscientiousness → Mindfulness → Smartphone addiction	−0.068	0.016	4.179	<0.001	−0.102, −0.037	Supported
H4d: Neuroticism → Mindfulness → Smartphone addiction	0.113	0.018	6.426	<0.001	0.082, 0.151	Supported
H4e: Extraversion → Mindfulness → Smartphone addiction	0.012	0.015	0.794	0.427	−0.022, 0.040	Not supported

4.6 Explanatory Power of the Model

Model explanatory power was evaluated using the coefficient of determination R^2 obtained from the PLS algorithm in SmartPLS. All R^2 values exceeded the recommended threshold of 0.10 [84]. The R^2 for Mindfulness was 0.204, and for Smartphone addiction, 0.218.

4.7 Partial Correlation Network Analysis

To examine the conditional dependence structure among the study variables and to probe whether conscientiousness has a unique association with smartphone addiction beyond shared variance with mindfulness and the other Big Five traits, we estimated a regularized Gaussian graphical model (GGM) using EBICglasso [73,85]. Edges represent undirected partial correlations between nodes after controlling for all other nodes in the network. The analysis was performed in JASP (0.95.4.0) with weighted and signed edges and an EBIC tuning parameter of 0.5 (N = 665). Table 7 presents the resulting partial correlation weights, and Fig. 2 visualizes the network. The network comprised seven nodes with 14 non-zero edges (14/21; sparsity = 0.333). Mindfulness showed a negative partial correlation with smartphone addiction (weight = −0.262), whereas neuroticism showed a positive partial correlation with smartphone addiction (weight = 0.231) and a negative partial correlation with mindfulness (weight = −0.257). Conscientiousness was positively associated with mindfulness (weight = 0.148). Still, its edge with smartphone addiction was shrunk to zero (weight = 0.000), suggesting that conscientiousness is linked to smartphone addiction primarily through its conditional association with mindfulness rather than via a distinct direct connection.

Table 7: Regularized Gaussian graphical model (EBICglasso) network estimates among constructs: Partial correlation weights (N = 665).

Weight	SA	MI	OP	AG	CO	NE	EX
SA	0.000						
MI	−0.262	0.000					
OP	0.069	0.000	0.000				
AG	0.000	0.000	0.372	0.000			
CO	0.000	0.148	0.228	0.271	0.000		
NE	0.231	−0.257	−0.256	0.075	0.000	0.000	
EX	0.000	0.000	0.177	0.022	0.216	0.060	0.000

Note: Values are regularized partial correlations (edge weights) from an EBICglasso Gaussian graphical model. Edges are undirected and represent conditional associations after controlling for all other nodes. A weight of 0.000 indicates that the edge was set to zero by regularization. The network contained 7 nodes and 14 non-zero edges (14/21; sparsity = 0.333). SA, smartphone addiction; MI, mindfulness; OP, openness; AG, agreeableness; CO, conscientiousness; NE, neuroticism; EX, extraversion.

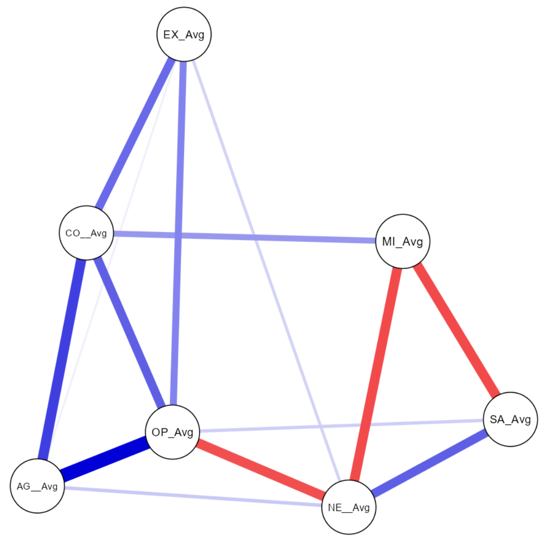

Figure 2: Regularized partial correlation network (EBICglasso Gaussian graphical model). Note: Edges indicate undirected partial correlations controlling for all other nodes; edge thickness reflects absolute weight, and color indicates the sign of the association.

4.8 Predictive Power of the Model

In line with a prediction-oriented assessment procedure for PLS-SEM, PLS-Predict was conducted with tenfold cross-validation to generate predictions at the construct and indicator levels [86]. Predictive relevance was first assessed by verifying that the Q^2 values for latent constructs were greater than zero. Next, predictive power was assessed by comparing the RMSE or MAE differences between the PLS and linear (LM) models. RMSE is used by default, while MAE is preferred when error distributions are highly skewed [86]. If all PLS-LM differences are negative, the model exhibits high predictive power; if most are negative, medium predictive power; if only a few are negative, low predictive power. Regarding predictive relevance, Q^2 values were above zero for both endogenous constructs (mindfulness: Q^2 = 0.066; smartphone addiction: Q^2 = 0.135), indicating adequate predictive relevance. As summarized in Table 8, all Q^2 values exceeded zero, and for most indicators, the PLS model showed a lower RMSE than the LM model, indicating medium predictive power [74,86].

Table 8: PLS-predict results.

Item	Q^2 Predict	PLS		LM		PLS-LM	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
MI1	0.056	1.242	1.002	1.257	1.015	−0.015	−0.013
MI2	0.132	1.181	0.953	1.193	0.953	−0.012	0.000
MI3	0.056	1.241	1.013	1.247	1.017	−0.006	−0.004
MI4	0.110	1.180	0.955	1.199	0.967	−0.019	−0.012
MI5	0.186	1.173	0.963	1.176	0.953	−0.003	0.010
SA1	0.058	1.626	1.390	1.645	1.407	−0.019	−0.017
SA2	0.064	1.522	1.263	1.523	1.268	−0.001	−0.005
SA3	0.031	1.640	1.397	1.652	1.417	−0.012	−0.020
SA4	0.074	1.578	1.325	1.565	1.298	0.013	0.027
SA5	0.116	1.488	1.229	1.481	1.211	0.007	0.018
SA6	0.099	1.517	1.269	1.508	1.255	0.009	0.014

Note: SA, smartphone addiction; MI, mindfulness; PLS, partial least squares; LM, linear models.

4.9 Comparison of Differences in Gender, Grade, and Major on the Measures

Table 9 shows that mindfulness differed significantly by gender and major, whereas smartphone addiction differed significantly by grade. Females scored higher on mindfulness (Mean = 4.136, SD = 0.976) than males (Mean = 3.893, SD = 1.023), $t = 2.977$, $p < 0.01$. By grade, sophomores (Mean = 3.606, SD = 1.212) and seniors (Mean = 3.560, SD = 1.201) reported higher smartphone addiction than juniors (Mean = 3.236, SD = 1.431) and master's students (Mean = 2.826, SD = 1.223). With respect to major, students in the "other majors" category showed higher mindfulness (Mean = 4.382, SD = 0.964) than those in education (Mean = 4.021, SD = 0.988), medical-agricultural-life sciences (Mean = 3.852, SD = 1.174), and science-engineering (Mean = 3.845, SD = 1.126). The latter three groups did not differ significantly from one another.

Table 9: Differences in measures scores among the research sample based on demographic variables.

Demographic Variables	N	Smartphone Addiction Scale (SAS-SV)			Mindful Attention Awareness Scale (MAAS)		
		Mean	**SD**	***F/t***	**Mean**	**SD**	***F/t***
Gender							
Male	235	3.479	1.255	0.886	3.893	1.023	2.977**
Female	430	3.388	1.280		4.136	0.976	
Grade							
1. Freshman	117	3.375	1.130	3.545**	3.909	1.065	2.306
2. Sophomore	143	3.606	1.212	2 > 3, 5	3.909	0.969	
3. Junior	190	3.236	1.431	4 > 3, 5	4.156	0.99	
4. Senior	193	3.56	1.201		4.113	0.978	
5. Master's program	22	2.826	1.223		4.273	0.967	
Major							
A	125	3.419	1.187	0.142	4.166	0.904	2.649*
B	409	3.420	1.301		4.021	0.988	E > B, D, C
C	40	3.467	1.405		3.845	1.126	
D	46	3.496	1.172		3.852	1.174	
E	45	3.307	1.259		4.382	0.964	

Note: $^{*}p < 0.05$; $^{**}p < 0.01$. 1: freshman; 2: sophomore year; 3: junior year; 4: senior year; 5: master's program; A: Major in humanities, social sciences, and business management fields; B: Major in education field; C: Major in natural sciences and engineering; D: Major in medical, biological, and agricultural fields; E: Major in other fields.

5 Discussion

5.1 Relationships between the Big Five Personality Traits and Smartphone Addiction

This study examined links between the Big Five personality traits and smartphone addiction. The results indicated that neuroticism and openness were the primary direct predictors of smartphone addiction, whereas conscientiousness primarily exerted an indirect protective effect through mindfulness.

Neuroticism showed a stable positive association with smartphone addiction, indicating that individuals high in neuroticism tend to use smartphones to regulate negative emotions, which elevates addiction risk [9,32,46]. In addition, neuroticism was negatively related to mindfulness, suggesting that affective lability and rumination undermine self-regulatory capacity and indirectly foster addictive behavior [12,15,22].

By contrast, conscientiousness functioned as a protective trait mainly via a mindfulness pathway. Individuals high in conscientiousness, characterized by self-discipline and regularity, were better able to sustain mindfulness processes and inhibit impulsive smartphone use [19]. Although the direct effect of conscientiousness on smartphone addiction was not significant, conscientiousness was positively associated with mindfulness, and mindfulness mediated the association between conscientiousness and smartphone addiction [20,53].

Openness was positively related to smartphone addiction, implying that preferences for novelty and sensory stimulation may increase usage frequency [42,87], even though some studies report unstable associations [1,32]. As for extraversion and agreeableness, the present study found no significant effects. This pattern aligns with evidence that their associations with smartphone addiction tend to be comparatively small and heterogeneous across studies relative to neuroticism and openness [5,44,45]. Notably, openness showed a negligible zero-order correlation with smartphone addiction ($\rho = 0.019$) but a significant positive direct effect in the structural model ($\beta = 0.163$). This discrepancy is consistent with a suppression effect in multivariable models, in which correlated predictors can mask a variable's unique predictive component until other predictors are controlled [88].

Overall, neuroticism and openness emerged as key direct predictors of smartphone addiction, and the mediating role of mindfulness highlighted conscientiousness as an indirect protective factor, reinforcing the applied value of mindfulness in prevention and intervention strategies for smartphone addiction.

5.2 Relationship between Mindfulness and Smartphone Addiction

Mindfulness showed a significant negative association with smartphone addiction. Individuals with higher trait mindfulness were less likely to develop addictive behaviors, which supports mindfulness as a self-regulatory mechanism [14,21]. The facet of acting with awareness can effectively suppress dependence driven by attentional impulsivity [21].

Woodlief et al. reported that individuals low in mindfulness tend to experience diminished awareness during high-involvement use, which heightens addiction risk [13]. Mindfulness also strengthens executive control and reduces overuse; its protective effect is particularly evident among high-risk groups, such as university students [3]. Individuals with higher mindfulness can more effectively detect the emotions and impulses underlying phone use and respond deliberately [14,50,51].

Mindfulness may strengthen self-control and emotion regulation, thereby supporting psychological well-being and reducing the risk of addictive smartphone use [14,34,50].

In sum, mindfulness is a cultivable psychological disposition with empirical evidence supporting its use in preventing and regulating smartphone addiction. Future research should clarify its internal mechanisms and application strategies. Future work could also assess students' digital health literacy using validated instruments to better tailor campus support and to interpret self-reported or behavioral indicators of use [89–92]. Family-level strategies may complement campus-based programs; for example, mindful parenting approaches and simple affect-labeling practices may help strengthen supportive environments and emotion regulation around digital habits [93–96].

5.3 Relationships between the Big Five Personality Traits and Mindfulness

The present study found significant associations between conscientiousness, neuroticism, and mindfulness, consistent with prior literature. Conscientiousness was positively associated with mindfulness, indicating that individuals with self-discipline and planning skills are more likely to demonstrate present-moment awareness and nonjudgmental attitudes [12,15,19]. The mindfulness facets of self-regulation and acting with awareness directly reflect conscientiousness and its benefits for emotion regulation [12].

In contrast, neuroticism showed a negative association with mindfulness. High-neuroticism individuals, marked by heightened emotional reactivity, rumination, and anxiety, find it difficult to maintain awareness and acceptance within mindfulness processes [15,22,54]. The emotional regulation and clarity emphasized by mindfulness are the psychological resources that individuals high in neuroticism tend to lack [12].

Although openness, agreeableness, and extraversion did not show significant associations with mindfulness here, prior work suggests that links between these traits and mindfulness are often small and can vary across operationalizations (e.g., attention/awareness-focused MAAS versus multi-facet measures) [15,19,52]. For example, openness may be more strongly related to measures of reflective awareness, whereas extraversion may show heterogeneous associations across samples and contexts [15,19]. These results support the status of conscientiousness and neuroticism as core personality predictors of mindfulness tendencies and strengthen the construct validity and applied implications of mindfulness within the context of personality psychology.

5.4 The Mediating Effect of Mindfulness between Big Five Personality Traits and Smartphone Addiction

This study confirmed a significant mediating role of mindfulness in the relationship between conscientiousness and neuroticism, on the one hand, and smartphone addiction, on the other, underscoring mindfulness as a key psychological mechanism in regulating digital behaviors. Individuals high in conscientiousness, who tend to have stronger self-discipline and self-standards, are likelier to cultivate stable mindfulness, thereby reducing impulsive and dependent phone use [12,20,21]. Mindfulness enhances awareness of motives and emotional reactions, promotes self-control, and protects against addictive behaviors [21].

Conversely, individuals high in neuroticism, characterized by anxiety, rumination, and affective instability, tend to lack the awareness and nonjudgmental stance emphasized by mindfulness [19,54]. The present findings indicate that mindfulness can attenuate the adverse link between neuroticism and smartphone addiction, reducing the tendency to use phones as an avoidance tool [9,22]. Through self-regulation and emotional acceptance, mindfulness mitigates the impact of neuroticism on digital addiction [14,97]. Related research also confirms that mindfulness interventions effectively reduce smartphone addiction and associated psychological risks [3,51].

Overall, this study verifies the mediating role of mindfulness in the relationship between personality and behavior and reinforces its practical potential for promoting digital well-being and for behavior regulation [12,13,41,48,49].

5.5 Comparison of Differences in Gender, Grade, and Major on the Measures

To contextualize the main model, mindfulness and smartphone addiction were further examined for differences across demographic subgroups. The study found that females scored significantly higher than males on mindfulness, indicating gender differences in awareness and self-regulation. This aligns with the gender-related perspective discussed by Hanley and Garland [12] and Banfi and Randall [15], and may also reflect cultural expectations regarding emotional expression and introspection [19].

By grade, sophomores and seniors exhibited higher tendencies toward smartphone addiction, possibly because career exploration and academic pressure promote avoidant use behaviors [9,54]. A possible interpretation is that smartphone reliance may fluctuate across academic stages: sophomores may increase their use after adapting to campus routines; juniors may reduce reliance under heavier coursework and capstone demands; seniors may show a rebound under career-planning pressure; and master's students may report lower dependence due to clearer goals and stronger autonomy. This pattern is also consistent with the findings of Marengo et al. [43], who observed associations between neuroticism and smartphone use disorders.

Although differences by major were limited, higher than students in education, natural sciences and engineering, and medical, biological, and agricultural fields, but not significantly different from those in humanities, social sciences, and business management. As noted by Hanley and Garland [12], dispositional factors related to personality structure may be reflected in mindfulness tendencies, and humanities- and arts-related training may be associated with greater reflective attention to experience and self-acceptance [22].

Importantly, these demographic differences can be interpreted through the lens of the study's self-regulation. Specifically, subgroup variation in mindfulness and smartphone addiction is consistent with the proposed mechanism that mindfulness-related regulatory capacity is inversely associated with addictive smartphone behaviors [14,21,50,98]. Because demographic factors were not modeled as moderators in the current structural model, future research may formally test whether the mediation pathways differ across demographic groups (e.g., moderated mediation), thereby clarifying the boundary conditions of the proposed mechanism.

6 Implications

6.1 Theoretical Implications

This study offers several theoretical contributions regarding the mediating role of mindfulness in the relationship between the Big Five personality traits and smartphone addiction. The findings indicate that neuroticism and conscientiousness were associated with mindfulness in directions consistent with the proposed model through negative and positive pathways, respectively, and that these pathways influence smartphone addiction, thereby extending existing frameworks that link personality to digital behavior [12,15].

The mediation model positions mindfulness as a key variable that bridges individual-differences models and self-regulation theory, addressing the limitations of prior research focused on single variables [21,54,56]. In addition, the positive association between openness and smartphone addiction suggests that a strong preference for novelty may heighten the risk of technology-related involvement, extending observations by Mahajan et al. [42] and Woodlief et al. [13]. However, the indirect effect of openness via mindfulness was not supported, indicating that mindful attention and awareness did not statistically explain the association between openness and smartphone addiction in this sample.

By testing both direct and indirect personality effects on mindfulness, the study addresses theoretical questions about inconsistent association strengths noted by Giluk [19] and Stein et al. [22], and strengthens the view of mindfulness as a "metatrait stability" construct [12]. The results also support considering neuroticism as a key target for psychological intervention, echoing recommendations by previous meta-analytic work [12,15,19] and Banfi and Randall [15] to integrate multilevel personality models into future mindfulness interventions.

Furthermore, the structural modeling evidence for mindfulness as a mediator is consistent with conservation of resources theory, which conceptualizes mindfulness as a psychological resource, underscoring its potential for digital health and addiction prevention [3,41,48,49,51]. In sum, the study advances an integrated model linking personality, mindfulness, and addiction, reinforces the theoretical position of mindfulness in technology-related behavior and personality psychology, and offers new perspectives for individualized digital intervention strategies [5,12,22].

6.2 Practical Implications

This study shows that mindfulness significantly mediates the relationships between the Big Five traits, especially neuroticism and conscientiousness, and smartphone addiction, yielding critical practical insights. At the policy level, governments should regard smartphone addiction as a priority issue in youth mental health [4,9]. This emphasis is further warranted given recent evidence of substantial smartphone addiction prevalence in adolescent populations [27].

Ministries of Education could launch a "Mindfulness Literacy Education Promotion Program", incorporate it into higher education and mental health policies, and integrate it with personality screening to deliver mindfulness and digital regulation courses for students who are high in neuroticism and low in conscientiousness [15]. Systems can also integrate "Digital Health Literacy Indicators" to track trends in personality, mindfulness, and addiction risk among students.

In teaching practice, instructors can normalize mindfulness techniques such as mindful breathing, emotion journals, and guided audio to enhance students' present-moment awareness and attentional stability. For students high in neuroticism, approaches that strengthen awareness of distress cues and reduce automatic smartphone checking in response to negative affect may be particularly relevant [54]. For highly conscientious students, task planning and reflective activities can consolidate self-discipline and goal alignment, thereby further supporting mindful self-regulation in daily routines [20]. Instructors should also attend to anxiety and attentional problems among students low in mindfulness and use mindfulness-based techniques to regulate emotion and academic stress [14].

Evidence from randomized controlled research also suggests that mindfulness interventions can strengthen adolescents' psychological resources [34], supporting the feasibility of incorporating brief, structured practices into educational settings. To make these implications more actionable, universities may consider a stepped, low-burden intervention package aligned with students' routine smartphone-use contexts.

For example, institutions could embed brief mindfulness micro-practices (3–5 min) at the start of large-enrollment lectures for 4–6 weeks, focusing on breath awareness and "pause-and-notice" attention resets. In parallel, counseling centers could provide weekly group sessions (30–45 min) led by trained counselors that emphasize breath awareness, emotion labeling, and coping with urges (e.g., noticing cravings to check the phone without immediately acting on them). These activities can be paired with app-based guided exercises and adherence reminders to support daily practice and reduce reliance on one-off workshops.

Importantly, a risk-informed delivery can be implemented in a non-stigmatizing manner: students with higher neuroticism and lower conscientiousness may benefit from more structured support and monitoring, whereas students high in openness may be offered alternative offline novelty and creative engagement options to reduce digital stimulation-seeking [12,15]. To improve intervention effectiveness, schools can provide mindfulness-teaching workshops and personality-oriented course-design training that enhance teachers' sensitivity to stress and addiction risks [15]. Mindfulness can also support differentiated instruction by tailoring strategies to personality profiles, strengthening students' self-discipline and psychological resilience.

In addition, synthesised evidence indicates that mindfulness is associated with lower learning burnout among university students [35], suggesting potential spillover benefits for academic functioning when mindfulness is cultivated consistently. For university students, proactive mindfulness practice is advisable to develop self-awareness for digital restraint and stress detection. Research indicates that mindfulness reduces automatic smartphone use and mitigates avoidant behaviors driven by academic burnout and self-regulatory fatigue [3,13]. Daily mindful breathing and brief awareness exercises for 5–10 min can strengthen present-moment attention and awareness of urges, supporting psychological clarity under pressure [22,36]. Mindfulness apps, behavior logs, and study tools can help students identify use contexts and emotional triggers [21].

For individuals high in openness, offering diverse offline activities and novelty-rich alternatives (e.g., creative projects or exploration-oriented hobbies) may help satisfy their need for stimulation while reducing reliance on smartphones [5]. For individuals high in neuroticism, establishing self-talk and reflective routines can address emotion-regulation difficulties and addiction risk [22]. Given the links between mental distress and problematic smartphone use observed in student populations [31], universities may also integrate routine screening and referral pathways that connect stress-management supports with digital-use counseling.

At the family level, parents' understanding of mindfulness and personality differences can promote their children's self-discipline and digital health. For children high in neuroticism, a noncritical stance can foster emotional safety and regulatory capacity [54]. Families can cultivate a culture of mindfulness through shared practices such as sitting meditation and emotion labeling [97]. Emphasizing routines and positive communication and sustaining support for highly conscientious children will also aid the development of long-term self-management skills [20].

7 Limitations and Scope for Future Research

This study has several limitations. First, convenience sampling was used, and the sample was concentrated in the field of education at a university in Taiwan with an imbalanced gender ratio, which may affect representativeness and external validity [99]. Accordingly, subgroup comparisons (e.g., gender and major) should be interpreted cautiously and replicated in more balanced samples. Future work should adopt stratified random or multi-campus sampling to enhance inferential power [100,101].

Second, data were collected via self-report questionnaires. Although Harman's single-factor test was applied to address common method variance, response bias, and social desirability effects cannot be entirely ruled out [66,102,103]. In addition, mindfulness was assessed using the MAAS-5, which primarily captures mindful attention and awareness rather than the full range of facets; future studies may employ multi-facet measures (e.g., the FFMQ) to examine facet-specific mechanisms [38,39]. Subsequent studies can combine behavioral logs and third-party assessments to strengthen reliability and validity [6,7].

Third, the CBF-PI-15 short form was used. While it shows fundamental validity, each dimension contains only three items, which may not capture fine-grained personality differences [63,104]. Future research may employ the full version or integrate qualitative data to increase explanatory depth.

Fourth, because this study employed a cross-sectional design, the observed associations should not be interpreted causally, and the temporal ordering implied by the mediation model cannot be firmly established. Cross-sectional mediation may be subject to temporal bias and may not accurately represent longitudinal processes [105,106]. Future studies should employ longitudinal designs to validate the directional relationships among personality traits, mindfulness, and smartphone addiction. Fifth, PLS-SEM was used for prediction. Despite an explanatory and predictive performance, covariance-based structural equation modeling (CB-SEM) and multi-group analyses were not conducted for theory testing and comparison, thereby limiting theoretical inference [72]. Future research should combine CB-SEM and multi-group analysis (MGA) to examine model robustness.

Sixth, mindfulness and personality are culturally sensitive. Because this study was situated in a Chinese cultural context, direct generalization to other cultural groups is limited [107]. Cross-cultural comparisons and measurement invariance testing are encouraged to evaluate model generalizability. Overall, future studies should advance the field by employing broader sampling, multi-source data, optimized instruments, diverse designs, and tests of cultural generalizability to deepen theoretical understanding and practical applications.

8 Conclusions

Using an empirical survey of Taiwanese university students, this study confirmed positive associations between neuroticism and smartphone addiction and identified openness as an additional risk-related trait. Mindfulness was a robust protective factor and served as a key self-regulatory mechanism linking personality traits to addictive smartphone behavior.

Importantly, conscientiousness did not show a significant direct association with smartphone addiction; rather, it functioned primarily as an indirect protective factor through mindfulness. These findings strengthen the integration of personality psychology and digital behavior research and underscore the applied potential of mindfulness-based approaches for promoting healthier digital habits and student digital well-being.

In practice, schools are advised to implement mindfulness programs to enhance students' self-awareness and self-regulatory capacity and to prevent smartphone addiction. Educational agencies and policymakers can develop targeted interventions for students with high-risk personality profiles. Because the sample was drawn from students in the education field and the design was cross-sectional, generalization and causal interpretation are limited. Future research can employ multi-group and longitudinal designs and incorporate multi-source data to verify findings.

Acknowledgement: We sincerely thank all anonymous participants for their invaluable contributions. Finally, we are indebted to the National Changhua University of Education, National Chung Hsing University, and National Taiwan Sport University for providing an excellent research environment and administrative support that facilitated this study. AI-assisted tools (e.g., ChatGPT and Grammarly) were used solely for language editing and proofreading. After using these tools, the authors carefully reviewed and revised the text as needed and take full responsibility for the content of this publication.

Funding Statement: This study was partially funded by the National Science and Technology Council of Taiwan (Grant No. NSTC 114-2410-H-018-008), awarded to the first author, Dr. Yao-Chung Cheng. The research team specifically utilized this financial support for data analysis and manuscript preparation.

Author Contributions: Yao-Chung Cheng: Conceptualization; Methodology; Validation; Resources; Funding acquisition; Supervision; Project administration; Writing—review & editing. Der-Fa Chen: Supervision; Project administration; Resources; Writing—review & editing; Correspondence. Kai-Jie Chen: Data curation; Investigation; Software; Formal analysis; Writing—original draft; Writing—review & editing. Kun-Yi Chen: Validation; Formal analysis; Funding acquisition; Writing—review & editing. Wen-Ling Ke: Data curation; Investigation; Writing—original draft. Xie-Chuan Qiu: Writing—original draft. Min-Han Chung: Writing—original draft. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The datasets generated and analyzed during the current study are available from the first author, Yao-Chung Cheng, upon reasonable request.

Ethics Approval: All procedures complied with the Declaration of Helsinki (2013 revision) and applicable institutional and local regulations in the study setting. This study was an anonymous online questionnaire survey of adult university students and involved no clinical intervention or invasive procedures. Participants were informed of the study purpose, confidentiality safeguards, and their right to decline participation or withdraw without penalty, and electronic informed consent was obtained before questionnaire completion. No direct or indirect identifiers were collected. Data were analyzed in aggregate, and access was restricted to the research team. The study was designed as minimal-risk research and was considered to fall within the scope described in the local Human Subjects Research Act and the competent health authority's public notice research categories (MOHW Medical No. 1010265075, 5 July 2012).

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

ANOVA	analysis of variance
AVE	average variance extracted
CBF-PI-15	Chinese Big Five Personality Inventory-15
CFI	comparative fit index
CMV	common method variance
CR (ρc)	composite reliability
FoMO	fear of missing out
G*Power	power analysis software
HTMT	Heterotrait–Monotrait ratio
LM	linear model
MAAS	Mindful Attention Awareness Scale
NFI	normed fit index
PLS	partial least squares
PLS-Predict	PLS predictive procedure
PLS-SEM	partial least squares structural equation modeling
PSU	problematic smartphone use
Q^2	cross-validated redundancy
R^2	coefficient of determination
RMR	root mean square residual
RMSEA	root mean square error of approximation
RMSE	root mean squared error
SmartPLS	PLS-SEM software
SPSS	IBM SPSS Statistics
VIF	variance inflation factor

References

1. Bhayangkara NI, Lerik MDC, Benu JMY. Smartphone addiction reviewed from big five personality in college students. J Health Behav Sci. 2024;6(4):426–37. [CrossRef].
2. Zhang Z, Wu L, Lu C, Guan T. Effectiveness of brief online mindfulness-based intervention on different types of mobile phone addiction: mechanisms of influence of trait mindfulness. Front Psychol. 2025;16:1400327. [CrossRef].
3. Yang H, Huang X, Zhao X, Lu A. Trait mindfulness and cell phone addiction in adolescents: a moderated mediation model. Soc Behav Pers. 2023;51(2):1–9. [CrossRef].
4. Osorio J, Figueroa M, Wong L. Predicting smartphone addiction in teenagers: an integrative model incorporating machine learning and big five personality traits. J Comput Sci. 2024;20(2):181–90. [CrossRef].
5. John N, Sahu M, Sharma MK, Murthy P. Personality traits that predispose or protect in smartphone addiction and their implications for intervention: a narrative review. Cyberpsychol Behav Soc Netw. 2025;28(6):375–86. [CrossRef].
6. Parry DA, Davidson BI, Sewall CJR, Fisher JT, Mieczkowski H, Quintana DS. A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. Nat Hum Behav. 2021;5(11):1535–47. [CrossRef].
7. Andrews S, Ellis DA, Shaw H, Piwek L. Beyond self-report: tools to compare estimated and real-world smartphone use. PLoS One. 2015;10(10):e0139004. [CrossRef].
8. García-Canalejas M, Chamizo-Nieto MT, Rey L. Problematic smartphone use in adolescents: are their emotional abilities and fear of missing out influenced? Behav Psychol. 2025;33:42770. [CrossRef].

9. Yan Y, Chai X, Zheng W, Wang M, Feng X, Heng C, et al. The effect of neuroticism on mobile phone addiction among undergraduate nursing students: a moderated mediation model. BMC Psychiatry. 2024;24(1):810. [CrossRef].
10. Doménech P, Mestre-Escrivá MV, Tur-Porcar AM. Personality traits and emotion regulation in adolescence. Behav Psychol. 2025;33(2):46148. [CrossRef].
11. Errasti-Pérez J, Al-Halabí S, López-Navarro E, Pérez-Álvarez M. Mindfulness: why it may work and why it is sure to succeed. Behav Psychol. 2022;30(1):235–48. [CrossRef].
12. Hanley AW, Garland EL. The mindful personality: a meta-analysis from a cybernetic perspective. Mindfulness. 2017;8(6):1456–70. [CrossRef].
13. Woodlief D, Taylor SG, Fuller M, Malone PS, Zarrett N. Smartphone use and mindfulness: empirical tests of a hypothesized connection. Mindfulness. 2024;15(5):1119–35. [CrossRef].
14. Ru Y, Norlizah HC, Nasuha Burhanuddin NA, Liu H, Dong J. The correlation between mindfulness and problematic smartphone use: a meta-analysis. Addict Behav. 2025;164:108272. [CrossRef].
15. Banfi JT, Randall JG. A meta-analysis of trait mindfulness: relationships with the big five personality traits, intelligence, and anxiety. J Res Pers. 2022;101:104307. [CrossRef].
16. McCrae RR, John OP. An introduction to the five-factor model and its applications. J Pers. 1992;60(2):175–215. [CrossRef].
17. Costa PT, McCrae RR. Normal personality assessment in clinical practice: the NEO personality inventory. Psychol Assess. 1992;4(1):5–13. [CrossRef].
18. Pawlak M, Schmidtler H, Kopala-Sibley DC. Neuroticism and extraversion as predictors of first-lifetime onsets of depression, anxiety, and suicidality in high-risk adolescents. Dev Psychopathol. 2025;37(1):529–40. [CrossRef].
19. Giluk TL. Mindfulness, big five personality, and affect: a meta-analysis. Pers Individ Differ. 2009;47(8):805–11. [CrossRef].
20. Ran Y. The influence of smartphone addiction, personality traits, achievement motivation on problem-solving ability of university students. J Psychol Behav Stud. 2022;2(1):5–16. [CrossRef].
21. Kim M, Seong G, Jeon MJ, Jung YC, Lee D. The mediating effect of attentional impulsivity between mindfulness and problematic smartphone use. BMC Psychiatry. 2024;24(1):294. [CrossRef].
22. Stein JA, Tomfohr-Madsen LM, Bray S, MacMaster FP, Kopala-Sibley DC. Self-acceptance and nonreactive observing predict adolescent psychopathology over and above the big five. Curr Psychol. 2022;41(10):7185–99. [CrossRef].
23. Floros G, Siomos K. Excessive Internet use and personality traits. Curr Behav Neurosci Rep. 2014;1(1):19–26. [CrossRef].
24. Horvath J, Mundinger C, Schmitgen MM, Wolf ND, Sambataro F, Hirjak D, et al. Structural and functional correlates of smartphone addiction. Addict Behav. 2020;105:106334. [CrossRef].
25. Körmendi A, Brutóczki Z, Végh BP, Székely R. Smartphone use can be addictive? A case report. J Behav Addict. 2016;5(3):548–52. [CrossRef].
26. Panova T, Carbonell X. Is smartphone addiction really an addiction? J Behav Addict. 2018;7(2):252–9. [CrossRef].
27. Lee KW, Ching SM, Ali N, Ooi CY, Sidek SKH, Amat A, et al. Prevalence and factors associated with smartphone addiction among adolescents—a nationwide study in Malaysia. Int J Ment Health Promot. 2023;25(2):237–47. [CrossRef].
28. Ye Y, Wang H, Ye L, Gao H. Associations between social media use and sleep quality in China: exploring the mediating role of social media addiction. Int J Ment Health Promot. 2024;26(5):361–76. [CrossRef].
29. Baumeister RF, Heatherton TF, Tice DM. Losing control: how and why people fail at self-regulation. San Diego, CA, USA: Academic Press; 1994.
30. Kardefelt-Winther D. A conceptual and methodological critique of Internet addiction research: towards a model of compensatory Internet use. Comput Hum Behav. 2014;31:351–4. [CrossRef].
31. Gan WY, Chin WL, Huang SW, Tung SEH, Lee LJ, Poon WC, et al. Association between mental distress and weight-related self-stigma via problematic social media and smartphone use among Malaysian University students: an application of the interaction of person-affect-cognition-execution (I-PACE) model. Int J Ment Health Promot. 2025;27(3):319–31. [CrossRef].

32. Roberts JA, Pullig C, Manolis C. I need my smartphone: a hierarchical model of personality and cell-phone addiction. Pers Individ Differ. 2015;79:13–9. [CrossRef].
33. Zhao X, Lai X, Huang S, Li Y, Dai X, Wang H, et al. Long-term protective effects of physical activity and self-control on problematic smartphone use in adolescents: a longitudinal mediation analysis. Ment Health Phys Act. 2024;26:100585. [CrossRef].
34. Zhou A, Yuan Y, Kang M. Mindfulness intervention on adolescents' emotional intelligence and psychological capital during the COVID-19 pandemic: a randomized controlled trial. Int J Ment Health Promot. 2022;24(5):665–77. [CrossRef].
35. Cai Z, Kutty FM, Amran MS. The association between mindfulness and learning burnout among university students: a systematic review and meta-analysis. Int J Ment Health Promot. 2025;27(6):753–69. [CrossRef].
36. Brown KW, Ryan RM. The benefits of being present: mindfulness and its role in psychological well-being. J Pers Soc Psychol. 2003;84(4):822–48. [CrossRef].
37. Kabat-Zinn J. Mindfulness-based interventions in context: past, present, and future. Clin Psychol Sci Pract. 2003;10(2):144–56. [CrossRef].
38. Baer RA, Smith GT, Hopkins J, Krietemeyer J, Toney L. Using self-report assessment methods to explore facets of mindfulness. Assessment. 2006;13(1):27–45. [CrossRef].
39. Reyes-Bossio M, Zapparigli EL, Caycho-Rodríguez T, Carbajal-León C, Castaman LAO, Pino GLH, et al. Cross-cultural validity of the five items mindful attention awareness scale (MAAS-5) in Peru and Mexico during the COVID-19 pandemic. Psicol Reflex Crit. 2022;35(1):12. [CrossRef].
40. Regan T, Harris B, Van Loon M, Nanavaty N, Schueler J, Engler S, et al. Does mindfulness reduce the effects of risk factors for problematic smartphone use? Comparing frequency of use versus self-reported addiction. Addict Behav. 2020;108:106435. [CrossRef].
41. Michaelsen MM, Graser J, Onescheit M, Tuma MP, Werdecker L, Pieper D, et al. Mindfulness-based and mindfulness-informed interventions at the workplace: a systematic review and meta-regression analysis of RCTs. Mindfulness. 2023;14(6):1271–304. [CrossRef].
42. Mahajan R, Gupta R, Bakhshi A. Personality, loneliness, and subjective well-being as predictors mobile phone usage. Int J Appl Soc Sci. 2017;4(11–12):472–82.
43. Marengo D, Sindermann C, Häckel D, Settanni M, Elhai JD, Montag C. The association between the big five personality traits and smartphone use disorder: a meta-analysis. J Behav Addict. 2020;9(3):534–50. [CrossRef].
44. Takao M. Problematic mobile phone use and big-five personality domains. Indian J Community Med. 2014;39(2):111–3. [CrossRef].
45. Kayiş AR, Satici SA, Yilmaz MF, Şimşek D, Ceyhan E, Bakioğlu F. Big five-personality trait and Internet addiction: a meta-analytic review. Comput Hum Behav. 2016;63:35–40. [CrossRef].
46. Pearson C, Hussain Z. Smartphone use, addiction, narcissism, and personality: a mixed methods investigation. Int J Cyber Behav Psychol Learn. 2015;5(1):17–32. [CrossRef].
47. Kim D, Lee Y, Lee J, Nam JK, Chung Y. Development of Korean smartphone addiction proneness scale for youth. PLoS One. 2014;9(5):e97920. [CrossRef].
48. Hobfoll SE. Conservation of resources: a new attempt at conceptualizing stress. Am Psychol. 1989;44(3):513–24. [CrossRef].
49. Hobfoll SE, Halbesleben J, Neveu JP, Westman M. Conservation of resources in the organizational context: the reality of resources and their consequences. Annu Rev Organ Psychol Organ Behav. 2018;5:103–28. [CrossRef].
50. Liu F, Zhang Z, Liu S, Feng Z. Effectiveness of brief mindfulness intervention for college students' problematic smartphone use: the mediating role of self-control. PLoS One. 2022;17(12):e0279621. [CrossRef].
51. Lan Y, Ding JE, Li W, Li J, Zhang Y, Liu M, et al. A pilot study of a group mindfulness-based cognitive-behavioral intervention for smartphone addiction among university students. J Behav Addict. 2018;7(4):1171–6. [CrossRef].
52. Stuart-Edwards A. Mindfulness, subjective, and psychological well-being: a comparative analysis of FFMQ and MAAS measures. Appl Psychol Health Well Being. 2025;17(2):e70019. [CrossRef].
53. Beaulieu DA, Proctor CJ, Gaudet DJ, Canales D, Best LA. What is the mindful personality? Implications for physical and psychological health. Acta Psychol. 2022;224:103514. [CrossRef].
54. Zhao L. Personality traits, mindfulness, and perceived stress in Chinese adults: a sequential explanatory mixed-methods approach. Front Psychol. 2025;15:1498458. [CrossRef].

55. Kayiş AR. Mindfulness, impulsivity and psychological distress: the mediation role of smartphone addiction. Br J Guid Couns. 2022;50(5):791–804. [CrossRef].
56. Dong X, Wen X, Chang Y, Li H. How do short video content characteristics influence short video app addiction? An affective response perspective. Int J Mob Commun. 2024;23(4):425–49. [CrossRef].
57. Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates; 1988.
58. Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. Behav Res Methods. 2009;41(4):1149–60. [CrossRef].
59. Stratton SJ. Population research: convenience sampling strategies. Prehosp Disaster Med. 2021;36(4):373–4. [CrossRef].
60. Comrey AL, Lee HB. A first course in factor analysis. 2nd ed. Hove, UK: Psychology Press; 2013. [CrossRef].
61. Gorsuch RL. Factor analysis. 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates; 1983.
62. Brislin RW. Back-translation for cross-cultural research. J Cross Cult Psychol. 1970;1(3):185–216. [CrossRef].
63. Zhang X, Wang MC, He L, Jie L, Deng J. The development and psychometric evaluation of the Chinese Big Five Personality Inventory-15. PLoS One. 2019;14(8):e0221621. [CrossRef].
64. Kwon M, Kim DJ, Cho H, Yang S. The smartphone addiction scale: development and validation of a short version for adolescents. PLoS One. 2013;8(12):e83558. [CrossRef].
65. Ruckwongpatr K, Paratthakonkun C, Sangtongdee U, Pramukti I, Nurmala I, Angkasith K, et al. Validity, reliability, and measurement invariance of the Thai smartphone application-based addiction scale and Bergen social media addiction scale. Int J Ment Health Promot. 2024;26(4):293–302. [CrossRef].
66. Podsakoff PM, Podsakoff NP, Williams LJ, Huang C, Yang J. Common method bias: it's bad, it's complex, it's widespread, and it's not easy to fix. Annu Rev Organ Psychol Organ Behav. 2024;11:17–61. [CrossRef].
67. Ringle CM, Wende S, Becker JM. SmartPLS 4 [Internet]. Bönningstedt, Germany: SmartPLS; 2024 [cited 2025 Jan 1]. Available from: https://www.smartpls.com.
68. Hair JF, Howard MC, Nitzl C. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. J Bus Res. 2020;109:101–10. [CrossRef].
69. Shmueli G, Ray S, Velasquez Estrada JM, Chatla SB. The elephant in the room: predictive performance of PLS models. J Bus Res. 2016;69(10):4552–64. [CrossRef].
70. Anderson JC, Gerbing DW. Structural equation modeling in practice: a review and recommended two-step approach. Psychol Bull. 1988;103(3):411–23. [CrossRef].
71. Henseler J, Ringle CM, Sinkovics RR. The use of partial least squares path modeling in international marketing. In: Sinkovics RR, Ghauri PN, editors. New challenges to international marketing. Advances in international marketing. Leeds, UK: Emerald Group Publishing Limited; 2009. p. 277–319. [CrossRef].
72. Hair JF, Hult GTM, Ringle CM, Sarstedt M, Danks NP, Ray S. Partial least squares structural equation modeling (PLS-SEM) using R: a workbook. Cham, Switzerland: Springer International Publishing; 2021. [CrossRef].
73. Epskamp S, Borsboom D, Fried EI. Estimating psychological networks and their accuracy: a tutorial paper. Behav Res Methods. 2018;50(1):195–212. [CrossRef].
74. Shmueli G, Sarstedt M, Hair JF, Cheah JH, Ting H, Vaithilingam S, et al. Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. Eur J Mark. 2019;53(11):2322–47. [CrossRef].
75. Chin WW. The partial least squares approach to structural equation modeling. In: Marcoulides GA, editor. Modern methods for business research. Mahwah, NJ, USA: Lawrence Erlbaum Associates; 1998. p. 295–336.
76. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39–50. [CrossRef].
77. Gefen D, Straub D, Boudreau MC. Structural equation modeling and regression: guidelines for research practice. Commun Assoc Inf Syst. 2000;4(7):1–79. [CrossRef].
78. Hair JF, Anderson RE, Tatham RL, Black WC. Multivariate data analysis. 4th ed. Englewood Cliffs, NJ, USA: Prentice Hall; 1995.
79. Henseler J, Ringle CM, Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. J Acad Mark Sci. 2015;43(1):115–35. [CrossRef].

80. Kline RB. Principles and practice of structural equation modeling. 2nd ed. New York, NY, USA: Guilford Press; 2005.
81. Benitez J, Henseler J, Castillo A, Schuberth F. How to perform and report an impactful analysis using partial least squares: guidelines for confirmatory and explanatory IS research. Inf Manag. 2020;57(2):103168. [CrossRef].
82. Wong KKK. Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Mark Bull. 2013;24(1):1–32.
83. Ramayah T, Cheah J, Chuah F, Ting H, Memon MA. Partial least squares structural equation modeling (PLS-SEM) using SmartPLS 3.0: an updated guide and practical guide to statistical analysis. 2nd ed. Kuala Lumpur, Malaysia: Pearson; 2018.
84. Falk RF, Miller NB. A primer for soft modeling. Akron, OH, USA: University of Akron Press; 1992.
85. Friedman J, Hastie T, Tibshirani R. Sparse inverse covariance estimation with the graphical lasso. Biostatistics. 2008;9(3):432–41. [CrossRef].
86. Hair JF. Next-generation prediction metrics for composite-based PLS-SEM. Ind Manag Data Syst. 2020;121(1):5–11. [CrossRef].
87. Sedlmeier P. What mindfulness, and for whom? And why might it work? Mindfulness. 2025;16(3):629–37. [CrossRef].
88. MacKinnon DP, Krull JL, Lockwood CM. Equivalence of the mediation, confounding and suppression effect. Prev Sci. 2000;1(4):173–81. [CrossRef].
89. Van der Vaart R, Drossaert C. Development of the digital health literacy instrument: measuring a broad spectrum of health 1.0 and health 2.0 skills. J Med Internet Res. 2017;19(1):e27. [CrossRef].
90. Kayser L, Karnoe A, Furstrand D, Batterham R, Christensen KB, Elsworth G, et al. A multidimensional tool based on the eHealth literacy framework: development and initial validity testing of the eHealth literacy questionnaire (eHLQ). J Med Internet Res. 2018;20(2):e36. [CrossRef].
91. Norman CD, Skinner HA. eHEALS: the eHealth literacy scale. J Med Internet Res. 2006;8(4):e27. [CrossRef].
92. Thorup CB, Uitto M, Butler-Henderson K, Wamala-Andersson S, Hoffrén-Mikkola M, Schack Thoft D, et al. Choosing the best digital health literacy measure for research: mixed methods study. J Med Internet Res. 2025;27:e59807. [CrossRef].
93. Shorey S, Ng ED. The efficacy of mindful parenting interventions: a systematic review and meta-analysis. Int J Nurs Stud. 2021;121:103996. [CrossRef].
94. Torre JB, Lieberman MD. Putting feelings into words: affect labeling as implicit emotion regulation. Emot Rev. 2018;10(2):116–24. [CrossRef].
95. Niles AN, Craske MG, Lieberman MD, Hur C. Affect labeling enhances exposure effectiveness for public speaking anxiety. Behav Res Ther. 2015;68:27–36. [CrossRef].
96. Vossen HGM, van den Eijnden RJJM, Visser I, Koning IM. Parenting and problematic social media use: a systematic review. Curr Addict Rep. 2024;11(3):511–27. [CrossRef].
97. Xiao B, Zhao H, Hein-Salvi C, Parent N, Shapka JD. Exploring the trajectories of problematic smartphone use in adolescence: insights from a longitudinal study. Br J Dev Psychol. 2025;43(4):1010–26. [CrossRef].
98. Kong L, Zhao M, Huang W, Zhang W, Liu J. The impact of academic anxiety on smartphone addiction among college students: the mediating role of self-regulatory fatigue and the moderating role of mindfulness. BMC Psychol. 2025;13(1):354. [CrossRef].
99. Winton BG, Sabol MA. A multi-group analysis of convenience samples: free, cheap, friendly, and fancy sources. Int J Soc Res Methodol. 2022;25(6):861–76. [CrossRef].
100. Lohr SL. Sampling: design and analysis. 2nd ed. Boca Raton, FL, USA: Chapman and Hall/CRC; 2019.
101. Findley MG, Kikuta K, Denly M. External validity. Annu Rev Polit Sci. 2021;24:365–93. [CrossRef].
102. Conway JM, Lance CE. What reviewers should expect from authors regarding common method bias in organizational research. J Bus Psychol. 2010;25(3):325–34. [CrossRef].
103. Fuller CM, Simmering MJ, Atinc G, Atinc Y, Babin BJ. Common methods variance detection in business research. J Bus Res. 2016;69(8):3192–8. [CrossRef].
104. Rammstedt B, John OP. Measuring personality in one minute or less: a 10-item short version of the Big Five Inventory in English and German. J Res Pers. 2007;41(1):203–12. [CrossRef].

105. Georgeson AR, Alvarez-Bartolo D, MacKinnon DP. A sensitivity analysis for temporal bias in cross-sectional mediation. Psychol Methods. 2025;30(6):1326–44. [CrossRef].
106. Ployhart RE, Vandenberg RJ. Longitudinal research: the theory, design, and analysis of change. J Manag. 2010;36(1):94–120. [CrossRef].
107. Kirmayer LJ. Mindfulness in cultural context. Transcult Psychiatry. 2015;52(4):447–69. [CrossRef].