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Metacognition mediates the relationship between anxiety and smartphone addiction in university students

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This study aims to explore the influencing factors of smartphone addiction among university students and further examine the mediating role of metacognition in the relationship between anxiety elements and smartphone addiction. Researchers conducted a structured questionnaire survey on 736 university students from three universities(Hunan University of Science and Technology, Anhui University of Finance & Economics, and Hunan Normal University), measuring their self-reported responses on six constructs: academic anxiety, social anxiety, future anxiety, positive metacognition, negative metacognition, and smartphone addiction. The study interpreted the non-compensatory and non-linear relationships between predictors and smartphone addiction by applying the Structural Equation Modeling - Artificial Neural Network (SEM-ANN) method. The findings revealed that academic anxiety had no significant impact on smartphone addiction, nor did social and future anxiety on positive metacognition and social anxiety on negative metacognition. Furthermore, positive metacognition did not play a mediating role between anxiety and smartphone addiction, nor did negative metacognition between social anxiety and smartphone addiction. The remaining hypotheses were validated. Additionally, according to the normalized importance derived from the multilayer perceptron, the study identified the most critical predictive factor as negative metacognition (100%), followed by future anxiety (49.19%), social anxiety (29.52%), positive metacognition (16.51%), and academic anxiety (10.73%). Lastly, the study presents theoretical and practical implications regarding smartphone addiction among university students.

Keywords Academic anxiety, Social anxiety, Future anxiety, Metacognition, Smartphone addiction

The widespread adoption of smartphones has dramatically reshaped daily life, particularly among university students, who are one of the most active and vulnerable user groups[1]. While smartphones provide convenience, their excessive use has led to growing concerns about smartphone addiction (SA)—a behavioral addiction characterized by tolerance, loss of control, and continued use despite negative consequences[2]. Recent surveys reveal that 38.6% of Chinese university students suffer from SA[3], linking it closely to psychological problems such as depression, anxiety, and stress[4,5]. This high prevalence among university students may be explained by several factors. As digital natives, college students are deeply integrated into mobile technology ecosystems. During the university years, increased academic pressure, social adjustment challenges, and greater autonomy combine to heighten their reliance on smartphones[6]. Moreover, compared to other age groups, university students often have more flexible schedules and fewer external constraints, which further increase their vulnerability to excessive smartphone use[7].

In response to these challenges, scholars have identified several psychological drivers of SA, with anxiety being one of the most critical[2,8]. However, anxiety is a multidimensional construct, and academic anxiety (AA), social anxiety (SOA), and future anxiety (FA) may exert distinct influences on smartphone usage behaviors[4,5,9]. Despite the growing literature, the nuanced pathways through which these different forms of anxiety contribute to SA remain underexplored. Moreover, much of the current research tends to rely on linear modeling techniques, limiting the ability to capture complex, non-linear relationships between psychological factors and technology-related behaviors.

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To address these gaps, this study not only investigates the impact of different anxiety elements on SA but also introduces a methodological innovation by integrating Structural Equation Modeling (SEM) with Artificial Neural Networks (ANN). While SEM effectively identifies linear and compensatory relationships, it often falls short in capturing non-linear, non-compensatory interactions. In contrast, ANN can model complex, non-linear structures and provides high predictive accuracy. By combining SEM and ANN, this study offers a more comprehensive and precise understanding of the mechanisms driving SA among university students, representing a significant advancement in behavioral research methodology.

To anchor the investigation, this study focuses on two critical psychological constructs beyond anxiety: positive metacognition (PM) and negative metacognition (NM). Metacognition - individuals' beliefs about and regulation of their cognitive processes - plays a fundamental role in behavior. PM promotes adaptive cognitive strategies, while NM is associated with repetitive negative thinking and emotional dysregulation[10]. In technology usage contexts, PM and NM may mediate the relationships between anxiety and SA, influencing how individuals cope with stress and regulate their smartphone behaviors[11–14].

Given these theoretical and methodological considerations, this study sets out to achieve two main objectives: (1) To explore how AA, SOA, and FA influence SA among university students, with PM and NM as potential mediators; (2) To apply a hybrid SEM-ANN approach to both validate hypothesized relationships and predict the key drivers of SA.

Based on these objectives, the research addresses the following questions:

(1) What factors influence SA among university students?
(2) How do PM and NM mediate the relationships between different anxiety elements and SA?
(3) Which factors are most critical in predicting SA according to normalized importance metrics?

Based on survey data from 736 Chinese university students, this study employs a hybrid approach that integrates SEM and ANN to systematically investigate the impact mechanisms of three types of anxiety—AA, SOA, and FA—on SA. Particular emphasis is placed on the mediating roles of PM and NM. The contributions of this study are threefold. First, it provides a more nuanced analysis by differentiating among distinct forms of anxiety (AA, SOA, FA), rather than conceptualizing anxiety as a unitary construct. Second, it elucidates the mediating mechanisms of PM and NM, thereby advancing metacognitive models of behavioral addiction. Third, it introduces an innovative methodological framework that combines SEM with ANN, enabling the exploration of complex, non-linear relationships underlying SA—an advancement beyond the limitations of traditional linear models.

Literature review

Current research on smartphone addiction among university students

SA has emerged as a growing concern among university students in recent years. It is generally characterized by compulsive usage, withdrawal symptoms, and disruptions to daily functioning[15]. Existing studies have explored the underlying mechanisms of SA from multiple perspectives, including personality traits[16], emotional regulation[17], and self-control[18], offering valuable theoretical insights into its development. However, most of these studies have treated anxiety as a unidimensional construct, overlooking the possibility that different types of anxiety may influence addictive behavior through distinct pathways. While this approach offers simplicity, it constrains a more nuanced understanding of the internal structure of anxiety within the addiction mechanism. Therefore, there is a pressing need to distinguish among types of anxiety and investigate their differentiated pathways in contributing to SA.

Differentiated types of anxiety and their mechanisms of influence

Academic anxiety

AA refers to students' feelings of tension and worry in response to academic tasks or examination pressure, and it is a commonly experienced emotional state among university students[19]. Prior research has shown that AA can trigger internet addiction and academic procrastination through avoidance motivation[20]. In the smartphone use, students may turn to their phones for short-term relief when overwhelmed by academic stress, potentially leading to dependency[21]. Although the positive association between AA and SA has been established, this relationship's specific pathways and underlying mechanisms remain underexplored.

Social anxiety

SOA refers to an intense fear of negative evaluation in social situations, often resulting in avoidance behaviors[22]. In digital media use, SOA has been closely linked to social media addiction[23], as individuals may immerse themselves in virtual social platforms to escape the discomfort of real-life interactions[24]. Among university students, SOA has significantly predicted irrational smartphone use. However, whether it holds stronger explanatory power compared to other types of anxiety remains an open question.

Future anxiety

FA is a persistent concern about uncertainty and potential negative outcomes in the future, a condition particularly prevalent among university students facing pressures related to graduation and career decisions[25]. Research has indicated that FA is closely associated with problem avoidance, anxiety-driven immersion, and media use aimed at immediate gratification[26]. Despite its relevance, FA has often been overlooked in SA research, and its relative influence compared to other types of anxiety remains unclear. This study incorporates FA alongside AA and SOA within a unified model to examine differences in their effects and underlying mechanisms.

The mediating role of metacognition between anxiety and addiction

Metacognitive theory emphasizes the critical role of individuals' beliefs about and control over their cognitive processes in regulating emotions and behaviors[27]. PM refers to the belief that repetitive thinking aids in self-regulation. In contrast, NM involves concerns about the uncontrollability and dangerousness of one's thoughts (Spada et al., 2008). NM has been consistently linked to various forms of behavioral addiction[28]. In contrast, the protective role of PM has shown inconsistent effects across different studies[29]. Despite growing interest, existing research has yet to thoroughly examine how PM and NM differentially mediate the relationships between distinct types of anxiety and SA. To address this gap, the present study incorporates both kinds of metacognition as mediating variables within the anxiety–SA pathway model, aiming to identify their regulatory mechanisms and functional heterogeneity.

Hypothesis

AA and SA

The characteristic of AA is a sustained focus and fear related to learning, academic tasks, and academic performance[30]. AA is often associated with students' academic expectations, fear of academic failure, and uncertainty about their future career prospects[31]. Over time, numerous researchers have begun to explore the relationship between AA and excessive dependency on smartphones. When facing academic pressures, students may view smartphones as a means to escape reality and seek psychological comfort[13,32,33]. For example, Carbonell, Chamarro[34] emphasized that students plagued by AA tend to immerse themselves more frequently in their phones, especially in social and entertainment applications, exacerbating their dependency on smartphones. Similarly, research by Mei, Hu[35] indicated that highly anxious students, due to relatively weaker self-control, are more prone to developing a dependency on smartphones. In this study, it is posited that the higher the level of AA among university students, the more likely it is to lead to SA. Therefore, the following hypothesis is proposed:

H1 AA among university students significantly positively impacts SA.

SOA and SA

SOA primarily describes an individual's persistent unease and worry when interacting with others in public settings[36]. This concern often involves fear of others' evaluations, overly critical self-assessment of one's behavior in public, and worries about being excluded or rejected[37,38]. Multiple studies have indicated that individuals with SOA are more likely to use smartphones, particularly social media applications. As SOA is often accompanied by self-doubt about one's social skills, research by Kadavala, Tiwari[39] suggested that the reliance of socially anxious individuals on social media may interact with their real-world social predicaments, creating a vicious cycle that makes them more susceptible to SA. Li, Xu[40] also mentioned that because of the tendency of socially anxious individuals to avoid real-life social situations, they might be more likely to develop a stronger dependency on social networks in the virtual world. In this study, SOA influences smartphone usage behavior on multiple levels, particularly the excessive use of social applications, thereby increasing the risk of SA. Consequently, the following hypothesis is proposed for this study:

H2 SOA among university students significantly positively impacts SA.

FA and SA

FA primarily concerns an individual's worry about uncertainties and potential risks associated with the future[41]. Multiple studies have revealed a close connection between concerns about the future and people's smartphone usage behaviors[42–44]. For instance, Cheng, Liu[43] found that individuals with FA tend to frequently use social media and news apps on smartphones, seeking to alleviate their uncertainty about the future by obtaining more information. Notably, Przepiorka, Blachnio[44] pointed out in their research that people who are deeply anxious about the future might be more inclined to use various smartphone apps for comfort, attempting to mitigate their worries and fears about the future in this way. In this study, it is posited that the higher the level of FA among university students, the more likely it is to lead to SA. Therefore, the following hypothesis is proposed:

H3 FA among university students significantly positively impacts SA.

Mediating role of PM

PM involves an individual actively evaluating, adjusting, and optimizing their learning strategies and behaviors when faced with learning challenges, promoting more effective learning[45,46]. This typically includes a positive assessment of one's cognitive resources, proactive strategy selection, and ongoing reflection and adjustment of the learning process[47–49]. Recent studies have revealed a complex relationship between AA and PM[50,51]. Silaj, Schwartz[50] found that university students with higher levels of AA tend to exhibit lower positive metacognitive strategies in learning tasks. Moreover, Wolters, Won[51] showed that as AA increases, students' positive metacognitive abilities decrease, indicating a significant negative impact of AA on PM. In this study, university students' academic challenges and pressures may exacerbate their AA, further affecting their PM.

In recent years, many studies have extensively focused on the relationship between PM and SA[11,29,52–54]. For example, Chen, Ma[52] revealed that in the initial stages of addictive behavior development, PM in university students helps them recognize the dangers of SA, thereby reducing their smartphone usage. In this study, given the clear dependence on smartphones among university students in the digital age, the impact of PM on SA is more significant. Therefore, the following hypotheses are proposed for this study:

H4 AA among university students significantly negatively impacts PM.

H5 PM among university students significantly negatively impacts SA.

H6 PM mediates the relationship between AA and SA among university students.

The mediating role of PM in the relationship between SOA and SA has been validated in previous studies[10,38,52,55,56]. Nordahl and Wells[56] noted that university students with SOA might use positive metacognitive strategies more frequently to control their emotions and behaviors. Gilan[55] found that students troubled by SOA tend to use smartphones more, partly because smartphones provide a way to avoid direct face-to-face interactions, allowing for indirect social interactions and information acquisition on their devices. Shi, Chen[10] further suggested that anxiety helps activate PM in smartphone use, thereby avoiding SA. In this study, SOA may influence smartphone usage behavior through PM, leading to SA. Therefore, the following hypotheses are proposed:

H7 SOA among university students significantly negatively impacts PM.

H8 PM mediates the relationship between SOA and SA among university students.

The relationship between FA and PM has been extensively studied[57–61]. Teng, Wang[61] suggest that individuals with FA are more likely to adopt positive metacognitive strategies to adjust their thinking and behavior. Luo, Zhao[60] explain that this might be due to their enhanced monitoring of emotions and the need to manage concerns about the future, leading them to reflect more deeply on their expectations and worries. Additionally, Anyan, Morote[57] indicate that to understand a broader range of future possibilities, they might more frequently resort to smartphones for information searching and acquisition, potentially exacerbating their dependence on these devices. In this study, FA is hypothesized to adjust individuals' smartphone usage habits through positive metacognitive strategies on different levels, especially frequent use, thereby increasing dependency on smartphones. Based on these theories and findings, the following hypotheses are proposed:

H9 FA among university students significantly negatively impacts PM.

H10 PM mediates the relationship between FA and SA among university students.

Mediating role of NM

NM represents the harmfulness and uncontrollability of repetitive thinking, as well as its adverse impact on social functioning (e.g., "Repetitive thinking makes my problems uncontrollable"), which may increase anxiety[46]. There is a significant correlation between AA and NM[28,59,62,63]. For instance, the study by Yousefi, Barzegar[63] indicates that students with higher levels of AA are more inclined to use NM.

NM is key in predicting smartphone usage problems[10,64]. Research by Liu, Fang[65] suggests that NM in university students is a sufficient condition and a significant cause of SA. Yang, Wang[30] further highlight that stronger NM leads to perceived uncontrollability over smartphone use among university students, especially its interference in daily life and social activities. In this study, negative metacognitive strategies are related to smartphone usage, particularly in the excessive use of social applications, thereby increasing the risk of SA. Based on these insights, the following hypotheses are proposed:

H11 AA among university students significantly positively impacts NM.

H12 NM among university students significantly positively impacts SA.

H13 NM mediates the relationship between AA and SA among university students.

Numerous studies have identified a predictive relationship between SOA and NM[66–70]. For instance, the study by Thew, Ehlers[70] found a positive correlation between SOA and NM. Similarly, research by Santoft, Salomonsson[69] indicates a close relationship between the level of SOA and the level of NM. These studies demonstrate the connection between SOA and NM. In this research, negative metacognitive strategies are closely linked to the manifestation of SOA, particularly in the context of excessive use of social applications, exacerbating the risk of SA. Therefore, the following hypotheses are proposed:

H14 SOA among university students significantly positively impacts NM.

H15 NM mediates the relationship between SOA and SA among university students.

The existing literature indicates a positive relationship between FA and NM[57,71–73]. Anyan, Morote[74] emphasize that anxiety about the future can exacerbate students' NM, meaning that the more anxious students are, the more negatively they may evaluate their ways of thinking. Nguyen, Lal[71] note that individuals anxious about the future may overuse their smartphones to seek relief. In this study, students influenced by negative metacognitive strategies are more inclined to use smartphones for information acquisition, undoubtedly increasing the risk of dependency and addiction. Therefore, the following hypotheses are proposed:

H16 FA among university students has a significant positive impact on NM.

H17 NM mediates the relationship between FA and SA among university students.

Based on the above research hypotheses, this study proposes the following hypothetical model (Fig. 1).

Methodology

Samples and data collection

This study collected data and tested the hypothesized model using the online survey platform Wenjuanxing (http://www.sojump.com). Data collection was conducted from June 10 to October 12, 2024. Prior to participation, all respondents were informed of the study's purpose and relevant details to ensure voluntary involvement based on informed consent. Each participant signed a written informed consent form before completing the questionnaire, acknowledging their understanding of the research procedures, the voluntary nature of their participation, and the confidentiality of their responses.

Regarding sample selection, this study adopted a snowball sampling method, randomly recruiting participants from undergraduate students at three universities: Hunan University of Science and Technology, Anhui University of Finance and Economics, and Hunan Normal University. Initially, the researchers distributed the questionnaire link via the three universities' learning management systems and social media platforms, inviting students who were willing to participate to complete the survey. Subsequently, students who had completed the questionnaire were encouraged to share the link with their peers and invite them to participate, thereby enhancing the diversity and representativeness of the sample. All participants voluntarily clicked the link and completed the questionnaire. This sampling strategy facilitated the collection of a heterogeneous sample, encompassing students with varied demographic characteristics, including gender and academic year.

Ethical considerations were thoroughly addressed throughout the participant recruitment process. The study protocol was reviewed and approved by the Ethics Committee of Anhui University of Finance and Economics (Approval No.: AUFE-2024-05-0021), and it adhered to the principles outlined in the Declaration of Helsinki and other relevant ethical guidelines.

The inclusion criteria for participants were as follows: (1) undergraduate students enrolled at one of the selected universities; (2) individuals aged 18 years or older; and (3) participants who voluntarily agreed to take part in the study and provided written informed consent. The exclusion criteria included: (1) individuals under the age of 18; (2) participants who did not provide informed consent; and (3) incomplete or invalid responses, which were excluded from the final analysis. In total, 736 valid questionnaires were successfully collected. The basic demographic characteristics of the participants were as follows: (1) Gender: 353 males (48.0%) and 383 females (52.0%); (2) Age: the majority of participants were between 18 and 20 years old (61.4%); (3) Grade: 268 freshmen (36.4%), 204 sophomores (27.7%), and 221 juniors (30.0%).

To assess the representativeness of the sample, a chi-square test was conducted. The results indicated no significant difference between the gender distribution of the sample and the overall population ($p = 0.517$), suggesting that the sample was representative. The diversity and size of the sample provided a solid foundation for the external validity of the study findings, ensuring that the conclusions drawn are broadly applicable to the undergraduate student population within the studied context.

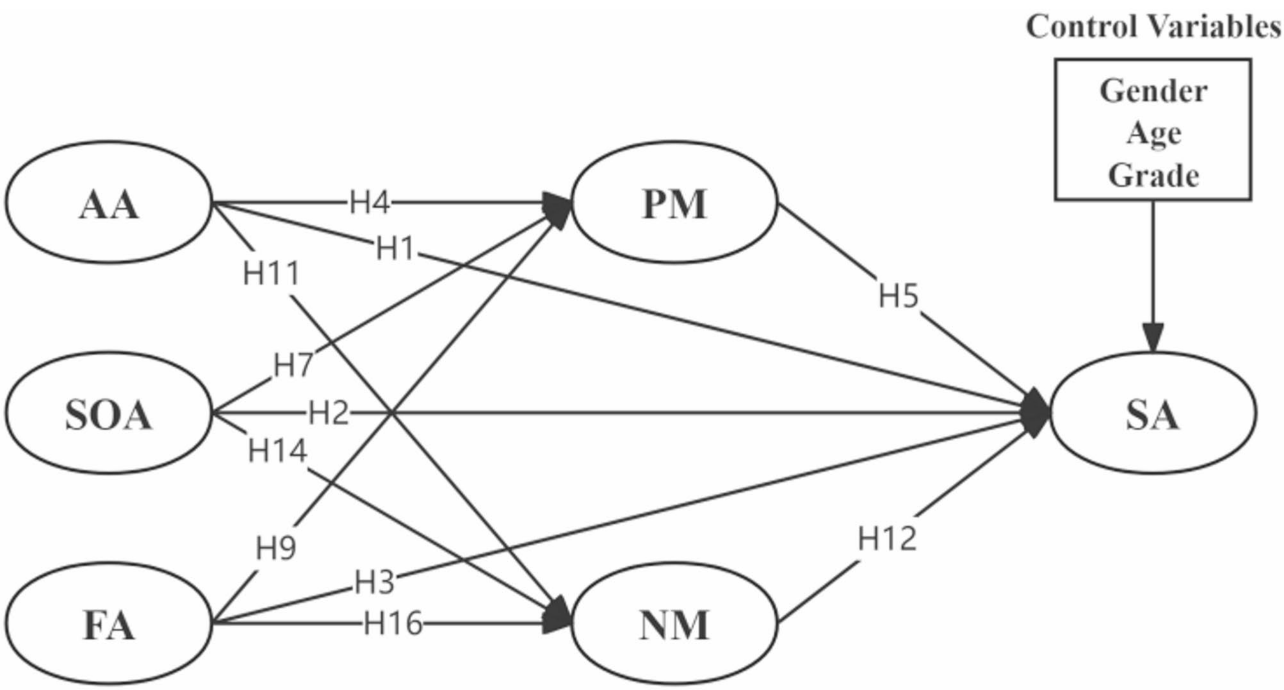

Fig. 1. Hypothetical model.

Measurement

The survey consists of two parts: The first part collects demographic information of the participants. The second part involves the constructs relevant to this study. The constructs in this study are assessed using established scales, which have been appropriately modified to fit the context and objectives of the research. Apart from demographic factors, each construct is measured using a Likert five-point scale, ranging from (1) "Strongly Disagree" to (5) "Strongly Agree." Appendix A provides a detailed list of the scales used in this study.

The AA Scale was adapted from Cassady, Pierson[75] and is primarily used to measure the level of anxiety experienced by students in academic settings. The scale uses a 5-point Likert response format (1 = strongly disagree, 5 = strongly agree) and consists of 9 items (e.g., "I feel so much pressure to complete assignments that I often procrastinate."). It is a unidimensional scale with no reverse-scored items. The total score ranges from 9 to 45, with higher scores indicating greater levels of anxiety experienced in academic contexts. The scale demonstrated excellent internal consistency in this study, with a Cronbach's alpha of 0.937. This scale is well-suited for the university student population targeted in this study and effectively captures their emotional responses to academic tasks, exam pressure, and performance evaluations. It is particularly useful in high-demand, competitive university environments, offering strong explanatory power and applicability for understanding students' psychological states and behavioral patterns.

The SOA Scale was adapted from Zhan, Wei[76] and is primarily used to measure students' feelings of anxiety in social situations. The scale adopts a 5-point Likert format (1 = strongly disagree, 5 = strongly agree) and consists of 4 items (e.g., "I feel nervous if someone corrects me on social media."). It is a unidimensional scale with no reverse-scored items. The total score ranges from 4 to 20, with higher scores indicating greater levels of anxiety experienced during social interactions. The scale demonstrated high internal consistency in the current study sample, with a Cronbach's alpha of 0.889. This scale is well-suited for the social contexts relevant to university students, particularly in the widespread social media use era. It effectively captures students' emotional responses to online feedback, interactions, and interpersonal relationships, offering strong contextual relevance and research value for analyzing contemporary university students' social pressures and psychological states.

The FA Scale was adapted from Chen, Li[42] and is primarily used to assess students' anxiety related to uncertainty and potential risks concerning the future. The scale uses a 5-point Likert format (1 = strongly disagree, 5 = strongly agree) and consists of 5 items (e.g., "I feel afraid when I think about possible crises or difficulties in the future."). It is a unidimensional scale with no reverse-scored items. The total score ranges from 5 to 25, with higher scores indicating greater uncertainty and anxiety about the future. The scale demonstrated strong internal consistency in the current study sample, with a Cronbach's alpha of 0.919. This scale is well-suited for the university student population targeted in this study, especially in the context of increasing employment pressure, social change, and uncertainty about personal development. It effectively captures students' psychological responses to future life, career, and societal environments, providing valuable insights into the sources of their anxiety and its potential impact on behavior.

The PM Scale was adapted from Shi, Chen[10] and is primarily used to assess individuals' positive monitoring and regulation of their own thought processes in various situations. The scale uses a 5-point Likert format (1 = strongly disagree, 5 = strongly agree) and consists of 8 items (e.g., "Using a smartphone helps me relieve stress."). It is a unidimensional scale with no reverse-scored items. The total score ranges from 8 to 40, with higher scores indicating stronger positive metacognitive regulation abilities. The scale demonstrated high internal consistency in the current study sample, with a Cronbach's alpha of 0.938. This scale is particularly suitable for analyzing university students' psychological self-regulation behaviors in digital environments, as examined in this study. It effectively captures how students use positive thinking strategies to cope with stress and regulate emotions, making it especially relevant for exploring the interaction between smartphone use and emotional well-being.

The NM Scale was also adapted from Shi, Chen[10] and is primarily used to assess individuals' maladaptive regulatory patterns during cognitive monitoring, such as excessive rumination, worry, and feelings of losing control. The scale adopts a 5-point Likert format (1 = strongly disagree, 5 = strongly agree) and consists of 9 items (e.g., "I cannot control my smartphone use."). It is a unidimensional scale with no reverse-scored items. The total score ranges from 9 to 45, with higher scores indicating a stronger tendency toward negative metacognitive patterns. The scale demonstrated excellent internal consistency in the current study sample, with a Cronbach's alpha of 0.944. This scale is highly suitable for examining the psychological distress and self-regulation difficulties experienced by university students in the context of mobile device use. It provides valuable insights into the cognitive mechanisms underlying issues such as anxiety and addiction, thereby offering theoretical support for targeted psychological interventions.

The SA Scale was adapted from Chen, Li[42] and is primarily used to measure students' level of dependence on smartphone use. The scale adopts a 5-point Likert format (1 = strongly disagree, 5 = strongly agree) and consists of 9 items (e.g., "I feel lost without my phone."). It is a unidimensional scale with no reverse-scored items. The total score ranges from 9 to 45, with higher scores indicating a greater degree of smartphone addiction. The scale demonstrated good internal consistency in the current study sample, with a Cronbach's alpha of 0.927. This scale is well-suited for the university student population targeted in this study, especially in the context of frequent mobile device usage. It accurately assesses students' dependence on smartphones and the potential behavioral and psychological impacts. The scale holds significant research value for understanding the mechanisms underlying addictive behaviors.

In addition to the primary research variables, this study also introduced several control variables to eliminate potential confounding effects of respondent characteristics on the outcome variable. The control variables included gender, age, and grade (see Fig. 1).

Data analysis

This study adopted the following data analysis procedures to enhance the rigor and transparency of the analytical process. First, SPSS 26.0 was used to calculate descriptive statistics for all variables, including means and standard deviations. Subsequently, SmartPLS 4.0 was employed to conduct Partial Least Squares-Structural Equation Modeling (PLS-SEM) to evaluate the measurement model's reliability and validity and test the hypothesized structural relationships. Specifically, factor loadings, Cronbach's α, composite reliability (CR), and average variance extracted (AVE) were calculated to assess internal consistency reliability and convergent validity. Discriminant validity was examined using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT).

In evaluating the structural model, this study employed bootstrapping (with 5,000 resamples) to obtain path coefficients, t-values, and p-values for assessing the significance of relationships among variables. Additionally, each endogenous variable's coefficient of determination (R^2) was reported to evaluate the model's explanatory power. Multicollinearity was assessed using the Variance Inflation Factor (VIF), and all VIF values were below 3.3, indicating no multicollinearity concerns. Mediation effects were tested using the bootstrapping method recommended by Nitzl, Roldan[77], and the Variance Accounted For (VAF) was calculated to determine the type of mediation effect—whether complete, partial, or not.

A Multilayer Perceptron (MLP) Artificial Neural Network (ANN) model was constructed at the prediction analysis stage using IBM SPSS 26.0. The input layer consisted of variables found to be significant in the SEM phase. The model was trained and tested using 10-fold cross-validation to prevent overfitting. Root Mean Square Error (RMSE) values for the training and testing sets were reported to evaluate model fit. Finally, sensitivity analysis was conducted to compute the normalized importance of each input variable, allowing the identification of the most critical predictors of SA among university students.

Results

Measurement model

The assessment of the measurement model requires testing the reliability and validity of the questionnaire and data. For reliability assessment, it can be measured by examining the factor loadings of each variable. According to Byrne[78], factor loadings exceeding 0.70 indicate high reliability. As shown in Table 1, the factor loadings for each item exceeded 0.70, suggesting they have high reliability.

Internal consistency can be evaluated using composite reliability and Cronbach's alpha coefficients. In this study, Cronbach's alpha coefficients ranged from 0.889 to 0.947, which meets the acceptable standard (a threshold of 0.7 is considered acceptable)[79]. Moreover, according to Hair Jr, Hair Jr[80], composite reliability values between 0.60 and 0.70 are considered acceptable, and values between 0.70 and 0.90 are generally considered satisfactory. In this study, the composite reliability values for all items ranged from 0.913 to 0.951, conforming to the aforementioned standards.

Convergent validity can be measured through the AVE. In this study, the AVE values ranged between 0.668 and 0.729, surpassing the threshold of 0.5. According to Henseler, Ringle[81], this is within an acceptable range, indicating that the results have passed the convergent validity test.

Discriminant validity refers to the extent to which a construct is distinct from other constructs within a model[82]. The Fornell-Larcker criterion is a method used for testing discriminant validity[83]. According to this criterion, the condition for establishing discriminant validity is that the square root of the AVE for each construct should be greater than the correlation coefficients between that construct and all other constructs in the model[81]. Table 2 shows that the square root of the AVE for each construct is greater than its highest correlation coefficient with any other construct. Therefore, the results meet the requirements for discriminant validity.

The HTMT, introduced by Henseler et al. (2015), is the second criterion for assessing discriminant validity. According to Gefen, Rigdon[84], the HTMT value between any two constructs should not exceed 0.90. Table 3 shows that when using the HTMT criterion to evaluate the discriminant validity of the measurement model, all values are below the critical threshold of 0.90. Therefore, the results meet the requirements for discriminant validity.

Structural model

For the structural model analysis in this study, several indicators can be used, including tests for multicollinearity, significance testing of path coefficient estimates, and the coefficient of determination (R^2). These indicators can help evaluate the model's reliability and explanatory power.

Multicollinearity test

Following the recommendation of Hair, Hult[85], a multicollinearity test can be conducted to determine multicollinearity issues in the model. According to the rule of thumb, all variables' VIF values should be below 3.3[85]. Table 4 shows that the VIF values for all variables range from 1.151 to 2.956, indicating no multicollinearity problems.

Significance test

In the structural model, significance testing aims to determine the impact of exogenous variables on endogenous variables. Table 5; Fig. 2 show that NM ($\beta = 0.536$; $t = 17.287$; $p = 0.000$), FA ($\beta = 0.254$; $t = 6.857$; $p = 0.000$), SOA ($\beta = 0.142$; $t = 3.877$; $p = 0.000$), and PM ($\beta = 0.056$; $t = 2.329$; $p = 0.023$) have a direct and significant positive impact on SA. Therefore, hypotheses H2, H3, H5, and H12 are supported. However, AA ($\beta = 0.051$; $t = 1.389$; $p = 0.166$) does not have a direct and significant positive impact on SA. Hence, hypothesis H1 is not supported. AA ($\beta = -0.172$; $t = 2.548$; $p = 0.011$) significantly positively impacts PM, supporting hypothesis H4. SOA ($\beta = 0.091$; $t = 1.388$; $p = 0.172$) and FA ($\beta = 0.071$; $t = 1.107$; $p = 0.198$) do not have a significant positive relationship with PM.

Constructs	Loadings	Cronbach's alpha	CR	AVE
PM	0.813	0.938	0.945	0.682
	0.841			
	0.856			
	0.812			
	0.833			
	0.821			
	0.811			
	0.820			
NM	0.810	0.944	0.951	0.681
	0.789			
	0.860			
	0.828			
	0.816			
	0.871			
	0.821			
	0.803			
	0.827			
SA	0.803	0.927	0.943	0.672
	0.825			
	0.798			
	0.796			
	0.852			
	0.843			
	0.821			
	0.819			
FA	0.831	0.919	0.931	0.729
	0.842			
	0.921			
	0.841			
	0.832			
SOA	0.852	0.889	0.913	0.725
	0.869			
	0.831			
	0.852			
AA	0.788	0.937	0.948	0.668
	0.812			
	0.823			
	0.826			
	0.851			
	0.820			
	0.802			
	0.81			
	0.822			

Table 1. Reliability and validity.

Thus, hypotheses H7 and H9 are not supported. FA ($\beta = 0.489$; $t = 9.451$; $p = 0.000$) and AA ($\beta = 0.242$; $t = 4.732$; $p = 0.000$) significantly positively impact NM, validating hypotheses H16 and H11. However, SOA ($\beta = -0.012$; $t = 0.196$; $p = 0.749$) has no significant relationship with NM. Hence, hypothesis H14 is not validated.

In addition, this study examined the effects of the control variables on the outcome variable. The results showed that none of the control variables had a statistically significant effect ($p < 0.05$). Specifically, the findings were as follows: age ($\beta = -0.003$, $t = 0.025$), gender ($\beta = -0.013$, $t = 0.447$), and grade ($\beta = -0.121$, $t = 1.572$).

Coefficient of determination (R^2)

The R^2 measures the extent to which the independent variables explain the dependent variable. According to Chin[86], R^2 values can be interpreted as strong (0.67), moderate (0.33), and weak (0.19). Table 6 shows that the R^2 for SA is 0.788, which falls into the strong category. This indicates that the model can explain 78.8% of the variance in the endogenous latent variable of SA.

	AA	SA	FA	PM	SOA	NM
AA	**0.817**					
SA	0.649	**0.818**				
FA	0.698	0.752	**0.854**			
PM	0.286	0.351	0.258	**0.826**		
SOA	0.740	0.661	0.742	0.271	**0.851**	
NM	0.581	0.722	0.655	0.332	0.528	**0.826**

Table 2. Fornell-Larcker criteria. The value of the diagonal is the square root of AVE.

	AA	SA	FA	PM	SOA	NM
AA						
SA	0.711					
FA	0.762	0.832				
PM	0.310	0.382	0.269			
SOA	0.831	0.753	0.852	0.297		
NM	0.621	0.889	0.708	0.371	0.562	

Table 3. Heterotrait-Monotraitcriteria.

	AA	SA	FA	PM	SOA	NM
AA		2.598		2.508		2.508
SA						
FA		2.956		2.489		2.489
PM		1.151				
SOA		2.801		2.782		2.781
NM		1.916				

Table 4. Multicollinearity Test.

hypothesis	Relationships	Path coefficient	T	*P*	Results
H1	AA→SA	0.051	1.389	0.166	Not supported
H2	SOA→SA	0.142	3.877	0.000	Supported
H3	FA→SA	0.254	6.857	0.000	Supported
H4	AA→PM	-0.172	2.548	0.011	Supported
H5	PM→SA	0.056	2.329	0.023	Supported
H7	SOA→PM	0.091	1.388	0.172	Not supported
H9	FA→PM	0.071	1.107	0.198	Not supported
H11	AA→NM	0.242	4.732	0.000	Supported
H12	NM→SA	0.536	17.287	0.000	Supported
H14	SOA→NM	-0.012	0.196	0.749	Not supported
H16	FA→NM	0.489	9.451	0.000	Supported

Table 5. Significance test.

Common method bias

CMB refers to a non-causal association among sample data in research, which may arise due to the use of the same method, timing, survey instruments, or subjective judgments of the researcher. This bias can interfere with the accuracy of research findings, making the observed associations potentially spurious[87]. CMB is assessed through two methods.

Firstly, the Harman single-factor test suggests that no single factor explains most variance[88]. The results show that the largest single factor accounts for 26.017% of the variance, well below the critical threshold of 50%[88]. Secondly, the marker variable technique is used, which involves adding a theoretically unrelated marker variable to the research model to test for common method bias[89]. The maximum shared variance estimate with

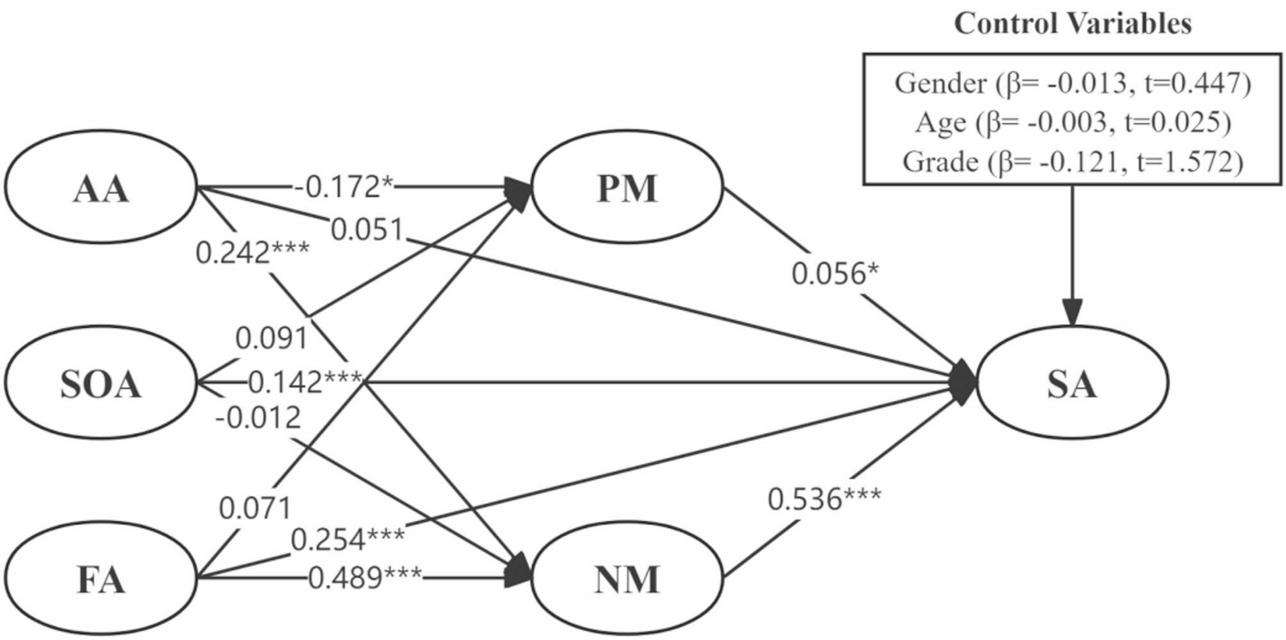

Fig. 2. Path Coefficient. *:$p < 0.05$;***:$p < 0.001$.

Constructs	R^2
SA	0.788
PM	0.096
NM	0.524

Table 6. Explanatory power.

Relationships	Indirect effect	T	*P*	Direct effect	T	*P*	Mediating type	VAF(%)
Mediation effect of PM								
AA→PM→SA	0.088	1.632	0.121	0.051	1.389	0.166	NM	NA
SOA→PM→SA	0.049	1.119	0.272	0.142	3.877	0.000	NM	NA
FA→PM→SA	0.003	0.918	0.349	0.254	6.857	0.000	NM	NA
Mediation effect of NM								
AA→NM→SA	0.132	4.507	0.000	0.051	1.389	0.166	FM	NA
SOA→NM→SA	-0.004	0.191	0.847	0.142	3.877	0.000	NM	NA
FA→NM→SA	0.259	8.871	0.000	0.254	6.857	0.000	CPM	56.27%

Table 7. Mediation effect analysis. FM - Full Mediation; CPM – Complementary Partial Mediation; NA – Not Applicable; NM – No Mediation.

other factors is 0.0157 (1.57%), considered very low[90]. Therefore, based on the results of these two tests, it can be inferred that no significant common method bias is present.

Mediation effect analysis

Mediation analysis was used to assess the mediating effects of metacognition on the relationship between anxiety elements and SA. A bootstrapping method based on PLS-SEM was employed for mediation analysis[77]. The significance of direct and indirect effects and the product of these effects' signs was examined to understand the type and magnitude of mediation effects. Table 7 summarizes the results of the mediation analysis. The results revealed that NM mediates the relationship between AA, FA, and SA. However, there was no mediation effect found in the relationship between SOA and SA.

Additionally, PM did not act as a mediator in the relationship between anxiety elements and SA. Subsequently, the direct effects were analyzed to assess the nature and magnitude of mediation for AA and FA constructs. The direct effect of AA was not significant, suggesting a complete mediation, while the direct effect of FA was

Training			Testing			Total samples
N	SSE	RMSE	*N*	SSE	RMSE	
584	61.690	0.3471	152	24.096	0.3181	736
587	62.231	0.3418	149	26.091	0.3378	736
590	57.852	0.3375	146	29.889	0.3451	736
583	60.159	0.3382	153	31.508	0.3682	736
579	60.641	0.3401	157	28.789	0.3488	736
581	62.649	0.3396	155	22.949	0.3251	736
588	55.948	0.3238	148	27.471	0.3469	736
591	65.021	0.3489	145	25.319	0.3338	736
582	63.487	0.3430	154	27.408	0.3542	736
589	61.379	0.3371	147	25.521	0.3423	736
Mean	61.1057	0.3397	Mean	26.9041	0.3420	
Sd		0.0068	Sd		0.0144	

Table 8. Root mean square of error values.

Artificial neural network (ANN)	AA	FA	PM	SOA	NM
ANN 1	8.54%	45.18%	11.59%	24.31%	95.45%
ANN 2	11.26%	50.67%	17.13%	25.63%	96.18%
ANN 3	8.14%	41.48%	6.04%	30.87%	93.22%
ANN 4	15.35%	41.39%	21.39%	35.65%	94.51%
ANN 5	5.46%	50.34%	19.08%	25.77%	92.11%
ANN 6	10.19%	47.79%	24.78%	28.92%	95.47%
ANN 7	8.83%	48.54%	22.23%	23.04%	93.87%
ANN 8	6.18%	45.59%	10.36%	29.72%	96.02%
ANN 9	13.24%	44.36%	11.78%	39.86%	95.34%
ANN 10	14.66%	51.67%	12.36%	16.55%	97.27%
Mean importance	10.19%	46.70%	15.67%	28.03%	94.94%
Normalized importance (%)	10.73%	49.19%	16.51%	29.52%	100.00%

Table 9. Sensitivity analysis.

significant, indicating partial mediation. The VAF value for FA and the signs of direct and indirect effects (VAF = 56.27%) suggest that the mediating effect of NM is complementary partial mediation for FA[77].

Artificial neural network analysis
In the next phase, similar to the approach of Liébana-Cabanillas, Marinković[91], significant factors from the PLS-SEM path analysis were used as input neurons for the ANN model. The rationale for applying ANN includes non-normal data distribution and non-linear relationships between exogenous and endogenous variables. Additionally, ANN demonstrates robustness to noise, outliers, and smaller sample sizes. It is also adaptable to non-compensatory models, where a decrease in one factor does not necessitate an increase in another. The ANN analysis was implemented using the neural network module of IBM SPSS. ANN algorithms can capture linear and non-linear relationships and do not require a normal distribution[92]. The algorithm learns through training and uses a feedforward-backpropagation (FFBP) algorithm for predictive analysis[93]. Multilayer perceptrons and sigmoid activation functions were utilized for input and hidden layers[94]. Through multiple rounds of learning, errors can be minimized to improve prediction accuracy further[95]. Like Leong, Jaafar[96], 80% of the sample was used for training and the remainder for testing. To avoid the possibility of overfitting, a ten-fold cross-validation procedure was conducted, and the Root Mean Square Error (RMSE) was obtained[97]. Table 8 shows that the average RMSE values for the training and testing processes were 0.3397 and 0.3420, respectively, confirming a very good fit of the model.

A sensitivity analysis was conducted to measure the predictive strength of each input neuron (Table 9). This involved calculating the normalized importance of these neurons by dividing their relative importance by the maximum importance, presented in percentage terms[98]. The results indicate that NM is the most important predictor, with a normalized importance of 100%. This is followed by FA, with a normalized importance of 49.19%, and then SOA (29.52%), PM (16.51%), and AA (10.73%).

Discussion
This study aimed to examine the factors influencing SA among university students and to further analyze the mediating roles of PM and NM in the relationship between anxiety and addictive behavior. The study confirmed

most of the proposed hypotheses by employing a hybrid approach that combines SEM and ANN. It was able to explain 78.8% of the variance in addictive behavior. The following section presents a systematic discussion of the findings concerning the three research questions, grounded in the dominant theoretical frameworks.

First, what factors influence smartphone addiction (SA) among university students?

The findings revealed that SOA and FA significantly and positively predicted SA, whereas AA did not exert a significant effect. The predictive role of SOA aligns with the Compensatory Internet Use Theory[99], which posits that individuals tend to use smartphones to avoid real-world social discomfort. This result also echoes the findings of Kadavala, Tiwari[39], highlighting the strong association between social avoidance and virtual dependence. Similarly, the significant effect of FA supports the perspective proposed by Przepiorka, Blachnio[44], suggesting that concerns about future uncertainty drive students to rely on smartphones for short-term psychological relief.

In contrast, AA did not significantly predict SA, which diverges from the findings of Carbonell, Chamarro[34]. This discrepancy may indicate a shift in how university students regulate academic pressure. Instead of resorting to smartphone use as a form of avoidance, students may increasingly turn to offline coping strategies such as social interaction, physical activity, or engagement in the arts. Alternatively, they may use smartphones primarily as educational tools rather than as a source of distraction. This finding suggests the need for future research to differentiate between types of smartphone use (e.g., active vs. passive, academic vs. entertainment-related) when examining the relationship between AA and SA.

Second, do PM and NM mediate the relationships between different types of anxiety and SA?

The results indicate that NM significantly mediates the pathways from AA and FA to SA, showing a full mediation effect in the AA-SA relationship and a partial mediation effect in the FA-SA relationship. These findings are consistent with Wells[100] metacognitive theory, which emphasizes the pivotal role of negative thinking beliefs in bridging anxiety and behavioral addiction. For instance, NM reinforces students' maladaptive beliefs about smartphone use—such as "I can't control my smartphone use"—thereby intensifying addictive behaviors. This supports prior findings by Liu, Fang[65] and Sun, Zhu[62], underscoring NM's critical function in explaining irrational technology use. In contrast, PM did not exhibit a significant mediating effect between anxiety and SA. This result partially contradicts the findings of Unal-Aydin, Obuca[29]. Two possible explanations can be proposed. First, when anxiety is intense, the regulatory capacity of PM may be suppressed, leading students to seek immediate emotional relief rather than engage in reflective or strategic thinking. Second, while PM may help manage cognitive load, its influence may be more pronounced in contexts related to academic motivation and performance rather than in daily behavioral addiction processes. These findings suggest that interventions targeting SA through PM may require the involvement of additional regulatory factors, such as executive functioning, self-control, or digital literacy, to be effective.

Third, which variables are most critical in predicting SA among university students?

According to the normalized importance analysis based on the ANN, NM emerged as the strongest predictor (normalized importance = 100%), followed by FA(49.19%), SOA(29.52%), PM (16.51%), and AA (10.73%). These results further underscore the central role of NM in non-linear predictive models and highlight the varying degrees of influence among different types of anxiety. The ranking suggests that compared to task-oriented anxiety, such as AA, relationship-based anxiety and future-oriented anxiety are more likely to prompt students to engage in escapist behaviors, leading to increased smartphone dependence. Moreover, although PM did not demonstrate a significant mediating effect in the SEM path model, it still exhibited moderate predictive power in the ANN analysis. This finding implies the presence of potential non-linear influence mechanisms, suggesting that PM may interact with other factors or operate under specific conditions in shaping addictive behavior.

Theoretical implications

First, this study offers a nuanced examination of the anxiety-related factors underlying SA among university students by distinguishing among three dimensions: AA, SOA, and FA. It systematically analyzes the differential effects of these subdimensions on addictive behavior, thereby enriching the theoretical framework of SA research within the university student population. At the theoretical level, this study advances our understanding of how distinct components of anxiety contribute to the development of SA. It highlights the unique roles that specific types of anxiety play in the addiction pathway, moving beyond generalized assumptions and providing a more fine-grained perspective on the psychological mechanisms that drive technology-related behavioral addictions.

Second, this study explores the mediating roles of PM and NM in the development of SA, thereby extending the application of metacognitive theory within the domain of behavioral addiction research. In particular, the significant mediating effect of NM provides a theoretical foundation and direction for future interventions targeting SA. It suggests that metacognitive intervention strategies may be a promising pathway for regulating problematic digital behaviors.

Finally, from a methodological perspective, this study departs from the predominantly linear modeling approaches used in prior research by innovatively adopting a two-stage SEM-PLS-ANN modeling strategy. By integrating a linear compensatory model (PLS) with a non-linear, non-compensatory model (ANN), this approach provides a more realistic depiction of the complex interactions among variables. Traditional linear models assume substitutability among predictors-an assumption that may not hold in the context of SA. For instance, a decrease in AA cannot necessarily compensate for an increase in SOA. Through its non-compensatory mechanism, the ANN model identifies the most influential predictors, thereby enhancing both the explanatory power and predictive accuracy of the model. This methodological innovation offers new insights for quantitative research in behavioral addiction, demonstrating the value of hybrid modeling in capturing non-linear dynamics and uncovering key predictive patterns.

Practical implications

This study examined how different forms of anxiety (AA, SOA, and FA) and metacognition (PM and NM) influence SA among university students and revealed several key findings: (1) NM emerged as the most critical predictor of SA; (2) FA and SOA exert direct positive effects on SA; (3) AA indirectly affects SA through the mediating role of NM; (4) Although PM has a suppressive effect on addiction, it does not serve as a significant mediator between anxiety and SA. These findings contribute to the theoretical development of behavioral addiction, university student mental health, and the psychology of technology use but also offer meaningful, practical implications for various stakeholders—including policymakers, educational institutions, and technology developers.

Implications for policymakers

Given that the study finds that FA and SOA significantly increase the risk of AA among university students, policymakers should consider how to reduce students' anxiety levels through systematic interventions to prevent the spread of behavioral addiction. Specifically, the government can establish dedicated mental health support programs in universities, offering regular psychological counseling and emotional regulation training for groups with high levels of employment-related and social anxiety; Promote digital health literacy education policies by incorporating responsible smartphone use and emotional management into national-level compulsory education modules for university students; Set up special funds for youth mental health to support universities in establishing prevention and intervention centers for SA, providing systematic support services. Through these measures, student anxiety levels can be effectively reduced, and the expansion of SA among university students can be curbed.

Implications for educational institutions

This study highlights that the development of NM is a key psychological mechanism underlying SA among university students, which presents new challenges for mental health education in higher education institutions. Educational institutions should systematically integrate metacognitive training modules into mental health curricula, teaching students concrete strategies for identifying and managing negative automatic thoughts; Offer elective courses on digital self-discipline and emotional regulation to guide students in developing healthy smartphone usage habits and positive emotional coping strategies; Collaborate with campus counseling centers to develop workshops on anxiety management and metacognitive intervention, with particular attention to students at high risk for FA and SOA; Incorporate smartphone use management features into "smart campus" platforms—such as app usage time monitoring and usage reminders—to help students better balance their online and offline activities. Through such educational interventions, institutions can promote the development of positive cognitive and emotional regulation patterns at the source, thereby reducing students' risk of addiction.

Implications for enterprises and technology developers

Given the central role of NM in SA among university students, smartphone application developers and technology companies should focus on enhancing users' positive cognitive experiences and self-regulation abilities. Specific recommendations include optimizing health reminder features within apps, such as adding usage duration alerts and mandatory break functions, to help users build self-control awareness; Developing emotion recognition and intervention systems that detect signs of excessive use and proactively deliver mindfulness exercises or emotional regulation resources; Launching emotion-focused wellness applications for university students, integrating features such as career planning and social skills training to help alleviate FA and SOA; Strengthening transparent algorithm design by clearly disclosing content recommendation mechanisms to users, thereby reducing addiction-like behavior driven by algorithmic content loops. By using technology to support mental health and well-being, these measures can effectively reduce the risk of addiction and enhance users' digital health literacy.

Limitations and future work

Despite considering various factors such as AA, FA, SOA, NM, and PM in SA, this study has some limitations. First, it mainly relies on questionnaire surveys for data collection, which may limit the in-depth understanding of participants' smartphone usage habits and addictive behaviors. Surveys depend on self-reporting and are prone to respondents' subjectivity. Future research could consider more objective data collection methods, such as tracking smartphone app usage or physiological indicators, combined with in-depth interviews and case studies to obtain richer and more authentic data. Secondly, this study's choice of explanatory variables is somewhat limited, focusing on anxiety and metacognition factors. However, the causes of SA may be multifaceted, and other variables such as self-esteem, personality traits, social support, and family environment could also significantly influence SA. Future research should consider more potential influencing factors, using a more comprehensive model to explore and predict SA. Including these variables can provide a more comprehensive theoretical framework and offer a basis for developing more targeted intervention strategies. Lastly, this study is mainly based on cross-sectional research and does not reveal the long-term changes in SA over time. Future research should conduct longitudinal studies to better understand the evolution of these behaviors over time and their long-term impacts.

Conclusion

This study explored the factors influencing SA among university students. Further, it examined the mediating roles of PM and NM in the relationship between anxiety elements and SA. It was found that different types of anxiety have distinct mechanisms of influence on SA among university students. Through empirical research on 736 university students' self-reported data for 16 hypotheses, the study results showed that AA has no significant impact on SA, SOA, and FA have no significant impact on PM, and SOA has no significant impact on NM. Additionally, PM does not mediate between anxiety and SA, nor does NM between SOA and SA. Apart from these, the other hypotheses were validated. This research contributes to understanding the relationships and potential mechanisms between various anxieties, metacognition, and SA among university students. At the same time, it provides scientific support for educators to develop reasonable usage guidelines and for developers to design applications that assist in managing anxiety.

Data availability
The data that support the findings of this study are available on request from the corresponding author.

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Conceptualization: Ziya Hua; Methodology: Xiuna Han; Formal analysis and investigation: Yan Ji; Writing - original draft preparation: Yan Ji; Writing - review and editing: Ziya Hua; Supervision: Xiuna Han. All the authors have read and agreed to the published version of the manuscript.

Declarations

Competing interests

The authors declare no competing interests.

Ethical approval

The researchers confirms that all research was performed in accordance with relevant guidelines/regulations applicable when human participants are involved (e.g., Declaration of Helsinki or similar). This study was approved by the Ethics Committee of Anhui University of Finance & Economics, with the approval number: AUFE-2024-05-0021.

Informed consent

Informed consent was obtained from all participants involved in the study.

Additional information

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