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Are Teachers Addicted to AI? Analysing Factors Influencing Dependence on Generative AI Through the I-PACE Model

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ABSTRACT

Background: The integration of generative artificial intelligence (AI) into education has revolutionised teaching practices, offering educators advanced tools for lesson planning, content creation, personalised learning and administrative automation. While AI enhances efficiency and instructional effectiveness, concerns have emerged regarding teachers' potential overreliance on these technologies, leading to AI addiction.

Objectives: This study applies the I-PACE model (Interaction of Person-Affect-Cognition-Execution) to explore the psychological and behavioural mechanisms underlying teachers' dependence on generative AI.

Methods: Using survey data from 1750 teachers in Huanghua, China, the study examines factors such as self-efficacy, need for cognition, mood regulation, positive affect, perceived usefulness and cognitive absorption in shaping AI addiction.

Results: Findings indicate that cognitive absorption is the strongest predictor of AI dependence, while perceived usefulness, self-efficacy and positive affect contribute indirectly through reinforcement mechanisms. Notably, mood regulation and need for cognition do not significantly influence AI addiction, suggesting that AI engagement in education is driven more by functional efficiency than emotional dependence.

Conclusions: The results highlight the importance of fostering mindful AI integration in teaching to prevent habitual overreliance. This study provides theoretical contributions by extending the I-PACE model to the context of AI addiction in education and offers practical insights for educators, institutions and policymakers in promoting responsible AI use while maintaining teachers' professional autonomy and cognitive engagement.

1 | Introduction

The integration of generative artificial intelligence (AI) into education has significantly transformed teaching practices, offering educators powerful tools for lesson planning, content creation, personalised learning and assessment automation (BaiDoo-Anu and Owusu Ansah 2023). These AI-driven tools allow teachers to streamline administrative tasks, generate instructional materials and enhance student engagement through adaptive learning technologies (Chan and Tsi 2024). As AI continues to evolve, its role in education is expected to expand, making it an indispensable tool for modern educators (Chiu 2024).

However, alongside these benefits, concerns have emerged regarding the potential over-reliance and addictive tendencies associated with AI use among teachers (Bower et al. 2024). The efficiency, convenience and problem-solving capabilities of generative AI can lead to habitual engagement, where teachers

Practitioner Notes

- What is currently known about the subject matter:
  - Generative AI has transformed education by improving teaching efficiency, lesson planning and content creation.
  - Teachers may become overly reliant on AI, leading to reduced engagement in independent decision-making and problem-solving.
  - Previous studies on digital addiction have focused on gaming and social media, with limited research on AI dependence in professional settings.
- What this paper adds:
  - Demonstrates that cognitive absorption is the strongest predictor of AI addiction among teachers.
  - Finds that perceived usefulness, self-efficacy and positive affect indirectly contribute to AI reliance, while mood regulation and need for cognition do not.
  - Expands the I-PACE model to include AI addiction in education, offering new insights into behavioural and psychological mechanisms.
- Implications of study findings for practitioners:
  - Teachers should be trained to use AI as a supportive tool rather than becoming dependent on it for instructional tasks.
  - Institutions should implement policies that encourage balanced AI integration while preserving teachers' autonomy.
  - Policymakers and AI developers should design AI tools that foster active teacher engagement rather than passive reliance.

increasingly depend on AI for routine decision-making and instructional support (Zhai 2024). This phenomenon may contribute to cognitive offloading, where educators reduce their direct engagement in creative lesson planning and problem-solving, instead relying on AI to generate content and insights (Celik et al. 2022). Over time, this habitual reliance may transition into AI addiction, characterised by difficulty disengaging from AI tools, excessive dependence on AI-generated outputs and diminished autonomy in instructional decision-making (Acosta-Enriquez et al. 2025). While previous research has extensively examined digital addiction in contexts such as social media, gaming and smartphone use, little attention has been given to AI-specific addiction, particularly in professional environments like education (Meng et al. 2022). Unlike passive digital consumption, AI engagement involves interactive, problem-solving and knowledge-generation processes, making its addictive potential unique (Suva and Bhatia 2024; Zhong et al. 2024). Teachers experiencing deep cognitive absorption and emotional reinforcement from AI use may struggle to regulate their engagement, reinforcing habitual dependency patterns. Given the growing adoption of AI-powered tools in education (Du et al. 2025), there is a critical need to examine how dependent teachers have become on generative AI and what factors contribute to this dependence.

To address these concerns, this study applies the I-PACE model (Interaction of Person-Affect-Cognition-Execution) to explore the mechanisms underlying generative AI addiction in educators. The I-PACE framework suggests that technology addiction arises from the interplay of personal traits, cognitive and affective responses and reinforcement mechanisms, which sustain habitual use over time (Brand et al. 2016, 2019, 2025). By analysing key psychological and behavioural factors, such as self-efficacy, need for cognition, mood regulation, positive affect, perceived usefulness and cognitive absorption, this study aims to uncover the pathways leading to AI dependence among teachers.

The findings of this research will provide valuable insights into the mechanisms and drivers of AI dependence in education, offering guidance on how teachers can use AI responsibly without becoming overly reliant on it. Additionally, the study will inform educational institutions and policymakers on strategies to promote balanced AI integration and digital well-being among educators. By investigating AI addiction through the I-PACE model, this research contributes to a deeper understanding of how generative AI impacts teachers' work habits, decision-making and long-term engagement with AI-driven tools.

2 | Literature Review

2.1 | Teacher Behaviour in Generative AI Use

The rapid advancement of generative AI has transformed multiple industries, including education, where AI-powered tools assist in content creation, lesson planning, assessment and personalised learning (Wen et al. 2025). Teachers increasingly integrate AI to enhance instructional efficiency, support student engagement and streamline administrative tasks (Kohnke and Moorhouse 2025). With AI models capable of generating customised teaching materials, answering subject-specific queries and providing real-time feedback, educators benefit from enhanced productivity and improved access to pedagogical resources (Hu et al. 2025). Despite these advantages, prolonged engagement with generative AI may lead to unintended behavioural consequences. Teachers who frequently rely on AI may develop habitual usage patterns, reducing their engagement in independent content creation and decision-making (Bai Doo-Anu and Owusu Ansah 2023). The ease of AI-driven assistance may also contribute to cognitive offloading, where educators delegate tasks to AI rather than actively engaging in problem-solving and instructional design (Kohnke and Moorhouse 2025). Over time, excessive dependence on AI tools may lead to a shift from functional use to habitual reliance, raising concerns about potential AI addiction in educational settings (Bozoglan et al. 2014).

Understanding teacher behaviour in AI use requires examining both the motivational factors that drive AI adoption and the psychological mechanisms that sustain continued engagement. Research suggests that teachers' self-efficacy, cognitive tendencies and emotional responses influence how they integrate AI into their work (Bower et al. 2024; Celik et al. 2022; Hu et al. 2025). However, while prior studies have explored AI adoption and perceived benefits, limited research has investigated the risks of over-reliance and compulsive AI use among educators (Chan and Tsi 2024; Wen et al. 2025). As generative AI continues to evolve, there is an urgent need to analyse the underlying mechanisms that contribute to AI dependency and ensure that AI remains a supportive tool rather than a disruptive force in education.

2.2 | Generative AI Addiction

AI addiction, a form of technology overuse characterised by compulsive engagement and reduced self-regulation, has gained attention as AI systems become more sophisticated and interactive (Huang and Huang 2024). Unlike traditional software applications, generative AI possesses adaptive learning capabilities, personalised interaction features, and real-time problem-solving abilities, making it particularly immersive and engaging (Bower et al. 2024; Brand et al. 2019). As AI tools become more accessible, concerns have emerged regarding excessive AI dependence and its impact on users' cognitive, emotional and behavioural patterns.

Generative AI addiction shares similarities with internet and social media addiction, where users develop strong emotional attachments, deep cognitive absorption and habitual overuse. The defining features of AI addiction include prolonged engagement, difficulty in disengaging, reliance on AI for daily tasks and neglect of real-world problem-solving skills. In an educational context, teachers who become excessively dependent on AI may struggle to complete tasks without AI assistance, experience reduced creativity and exhibit diminished engagement in traditional instructional planning (Comiskey 2024). Several psychological factors contribute to AI addiction, including cognitive immersion, emotional reinforcement and perceived usefulness (Brand et al. 2016, 2019, 2025). The convenience of AI-generated content, combined with instant feedback and adaptive learning capabilities, reinforces continued engagement, creating habit-forming behavioural loops (Renshaw and Carley 2024). Over time, teachers who develop strong cognitive and affective connections with AI may find it challenging to regulate their usage patterns, leading to over-reliance and potential addiction (Dinnie 2024).

Existing studies on digital addiction have primarily focused on gaming, social networking and smartphone use, with limited research on AI-specific addiction behaviours (Galvan and Newman 2025; Li et al. 2025; Piko et al. 2025). As generative AI becomes increasingly integrated into educational systems, understanding the risk factors and behavioural patterns associated with AI dependency is essential for developing strategies to promote responsible AI use (Almulla et al. 2025). This study seeks to address this gap by exploring the psychological mechanisms underlying AI addiction among teachers, providing insights into how educators can harness AI effectively while mitigating the risks of excessive reliance.

2.3 | I-PACE Model

The I-PACE model (Interaction of Person-Affect-Cognition-Execution) provides a comprehensive framework for understanding the development of addictive behaviours in digital environments (Brand et al. 2016, 2019, 2025). It proposes that compulsive technology use emerges from the interplay between personal predispositions, cognitive and affective responses and reinforcement processes over time (Lörsch et al. 2025). Originally designed to explain internet gaming disorder, the model has since been widely applied to various forms of digital addiction, including social media overuse, smartphone addiction and AI-driven interactions (Calaresi et al. 2024; Tie et al. 2025). By focusing on how psychological mechanisms shape technology engagement, the I-PACE model offers a dynamic perspective on behavioural addiction, distinguishing between initial engagement, habitual use and compulsive dependency (Pupi et al. 2024; Zhu and Fong 2025).

In the context of generative AI adoption in education, the I-PACE model serves as an essential theoretical lens for examining teacher dependency on AI tools. Generative AI, with its ability to generate text, automate lesson planning, provide personalised content and enhance instructional efficiency, has become a valuable asset in modern education (Huang and Huang 2024). However, as AI tools become more sophisticated, concerns arise regarding over-reliance and excessive use (Suva and Bhatia 2024). Teachers who frequently turn to AI for assistance may experience a gradual shift from functional use to habitual engagement, eventually forming patterns of dependency and addiction (Comiskey 2024).

The I-PACE framework explains this process by identifying three primary components that contribute to technology addiction (Zhang et al. 2024). Personal characteristics, such as self-efficacy and need for cognition, influence how individuals initially approach technology, shaping their motivation, engagement and confidence in using AI tools (Brand et al. 2019). Affective and cognitive responses, such as mood regulation, positive affect, perceived usefulness and cognitive absorption, further reinforce usage patterns (Brand et al. 2025). For example, teachers who use AI to reduce stress and enhance productivity may experience positive emotional reinforcement, making them more likely to continue and intensify AI engagement (Bower et al. 2024). Over time, these cognitive and emotional responses can create reinforcement loops, where the ease and efficiency of AI-driven interactions decrease self-regulation and increase dependency. This leads to sustained engagement, immersion and, in some cases, compulsive AI use, disrupting normal teaching practices and professional decision-making. Unlike traditional models that focus only on technology adoption or frequency of use (Cheung and Vogel 2013; Dehghani and Mashhadi 2024; Hsu and Lin 2022), the I-PACE model highlights the underlying psychological mechanisms that drive sustained engagement and eventual dependency (Zhang et al. 2024).

Applying the I-PACE framework, this study seeks to uncover the factors contributing to generative AI addiction among teachers. By examining how personal, cognitive and affective factors interact to shape AI dependency, this research aims to provide insights into how educators can integrate AI effectively without developing overreliance. The findings will also inform educational institutions on how to promote balanced and mindful AI adoption, ensuring that AI serves as an enhancing tool rather than a replacement for critical thinking and decision-making.

The literature shows that generative AI enhances teaching efficiency but may also lead to overreliance, reducing teachers'

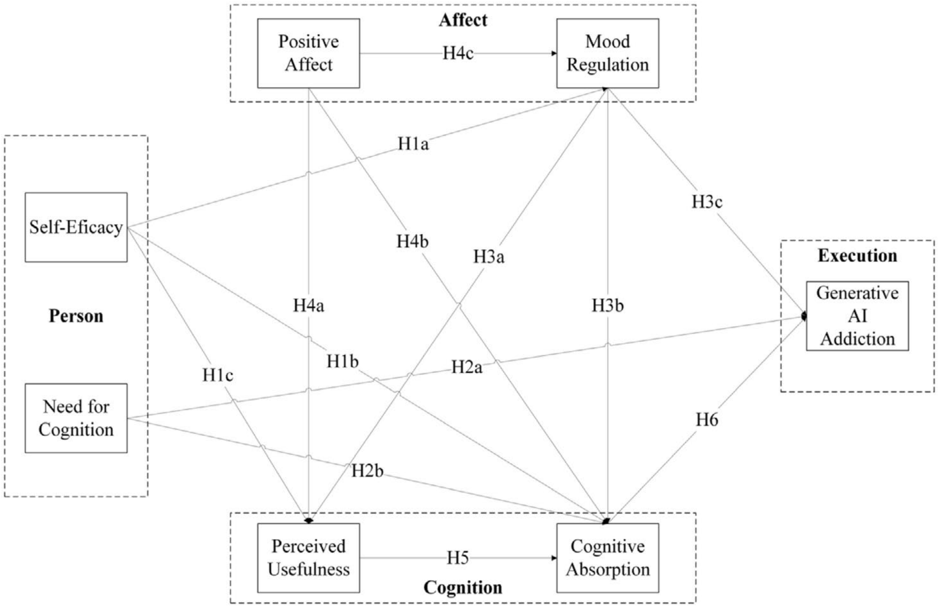

FIGURE 1 | The proposed model.

autonomy and cognitive engagement. While AI addiction has been studied in contexts like gaming and social media, its implications in education remain underexplored. The I-PACE model provides a suitable framework to examine how personal traits, emotional responses and cognitive factors interact to influence AI dependence. This study addresses a gap by applying the I-PACE model to investigate AI addiction among teachers, focusing on both the benefits and risks of deep engagement with AI tools. To achieve this, the study seeks to answer the following research questions:

RQ1. *What factors contribute to teachers' addiction to generative AI?*

RQ2. *To what extent can the I-PACE model explain teachers' addiction to generative AI?*

3 | Methods

3.1 | Hypothesis Development

The I-PACE model (Interaction of Person-Affect-Cognition-Execution) provides a structured approach to understanding how individual characteristics, cognitive and emotional responses and reinforcement mechanisms contribute to addictive behaviours in digital environments. This study applies the I-PACE framework to investigate how personal factors (self-efficacy and need for cognition), affective factors (mood regulation and positive affect) and cognitive factors (perceived usefulness and cognitive absorption) interact to shape generative AI addiction among teachers. The proposed research model is illustrated in Figure 1.

3.1.1 | Self-Efficacy

Self-efficacy refers to an individual's belief in their ability to successfully perform tasks using a particular system (Trusz and Babel 2016; Waddington 2023). In the context of generative AI, teachers with high self-efficacy are likely to be confident in their ability to integrate AI into their professional workflows (Fryer et al. 2020). Previous research has shown that self-efficacy enhances technology adoption, learning outcomes and engagement, as individuals with greater confidence in their skills are more willing to explore and experiment with AI-powered tools (Bewersdorff et al. 2025; Rodríguez-Ruiz et al. 2025).

A strong sense of self-efficacy can lead to greater cognitive immersion, as teachers who feel capable of using AI effectively are more likely to become absorbed in interactions with the technology (Liang et al. 2023). Furthermore, self-efficacy may enhance the perceived usefulness of generative AI, as confident users are more likely to view AI as a valuable tool that complements their expertise (Yao and Wang 2024). Additionally, self-efficacy may contribute to mood regulation, as teachers who trust their ability to use AI effectively may experience lower frustration and greater emotional stability during AI-assisted tasks (Wang et al. 2022). Thus, we propose the following hypotheses:

H1a. *Self-efficacy positively influences mood regulation.*

H1b. *Self-efficacy positively influences cognitive absorption.*

H1c. *Self-efficacy positively influences perceived usefulness.*

3.1.2 | Need for Cognition

Need for cognition is a personality trait that describes an individual's tendency to seek out, engage in, and enjoy effortful cognitive activities (Cacioppo and Petty 1982; Zerna et al. 2024). Within the I-PACE framework, need for cognition is considered a personal predisposition that can shape how users interact with technology through their motivation to explore, process and evaluate complex information (Brand et al. 2016, 2019). Generative AI offers cognitively stimulating opportunities, such as lesson planning, problem-solving and knowledge construction, which may particularly appeal to teachers who enjoy deep thinking and intellectual exploration. These individuals are more likely to invest time and attention in experimenting with AI, critically analysing its outputs, and applying AI-generated insights to enhance their instructional practices.

This sustained and purposeful engagement may contribute to a heightened state of cognitive absorption, where teachers become deeply immersed in AI-assisted tasks (Agarwal and Karahanna 2000). Over time, such intense mental involvement, especially when accompanied by perceived utility and positive reinforcement, may lead to habitual use patterns and eventual overreliance. Teachers who frequently turn to generative AI to satisfy their intellectual curiosity may find it difficult to disengage, particularly if the technology consistently meets their cognitive and professional needs (Tanas et al. 2020; Lin 2009). Based on these theoretical considerations, we propose the following hypotheses:

H2a. *Need for cognition positively influences generative AI addiction.*

H2b. *Need for cognition positively influences cognitive absorption.*

3.1.3 | Mood Regulation

Mood regulation refers to the use of external stimuli to manage emotional states, helping individuals cope with stress, anxiety and cognitive overload (Larsen 2000; Jadhakhan et al. 2022). Teachers often face high workloads, time constraints and complex decision-making tasks, making AI an appealing tool for emotional relief and stress reduction (Qu and Wang 2024). By automating repetitive tasks such as lesson planning, grading and content generation, generative AI can provide a sense of efficiency and control, alleviating teachers' emotional burdens and reinforcing habitual AI engagement (Dehghani and Mashhadi 2024). As teachers increasingly rely on AI for mood regulation, they may develop stronger perceptions of its usefulness, viewing it as an essential tool for reducing workload, enhancing efficiency and improving decision-making. Furthermore, frequent AI use for emotional relief may lead to cognitive absorption, where teachers become deeply immersed in AI interactions and spend extended periods engaging with AI-powered tools. Over time, this dependence on AI for stress relief and efficiency may also contribute to generative AI addiction, as teachers find it difficult to disengage from AI-driven workflows Based on these insights, we propose the following hypotheses:

H3a. *Mood regulation positively influences perceived usefulness.*

H3b. *Mood regulation positively influences cognitive absorption.*

H3c. *Mood regulation positively influences generative AI addiction.*

3.1.4 | Positive Affect

Positive affect reflects pleasurable emotional responses that arise from engaging in an activity, such as joy, excitement, and satisfaction (Dockray and Steptoe 2010; Shiota et al. 2021). When teachers experience positive emotions while using AI, they are more likely to develop a stronger attachment to the tool and engage with it more frequently (Wang et al. 2023). Enjoyable interactions with AI can foster deeper involvement, increasing the likelihood of sustained engagement and immersion in AI-assisted tasks (Huang et al. 2024). Teachers who derive positive emotional experiences from AI use may also perceive it as more useful, reinforcing their belief that AI enhances their productivity, efficiency and instructional effectiveness. Furthermore, positive affect may contribute to cognitive absorption, where teachers become so engaged with AI interactions that they lose track of time and remain deeply focused on AI-generated outputs (Liu and Chang 2024). Additionally, the emotional benefits of AI use may support mood regulation, as teachers use AI not only for professional efficiency but also for emotional comfort in managing work-related stress (Wang et al. 2023). Based on these insights, we propose the following hypotheses:

H4a. *Positive affect positively influences perceived usefulness.*

H4b. *Positive affect positively influences cognitive absorption.*

H4c. *Positive affect positively influences mood regulation.*

3.1.5 | Perceived Usefulness

Perceived usefulness reflects the extent to which individuals believe that a technology enhances their productivity, efficiency and overall work performance (Dhingra and Mudgal 2019; Zou et al. 2024). In an educational setting, teachers are more likely to integrate AI into their workflows if they perceive it as beneficial for lesson planning, research, content creation and classroom management. When AI streamlines tasks and simplifies complex instructional processes, teachers may experience greater engagement and reliance on AI-driven support (Bower et al. 2024). As teachers increasingly recognise the practical benefits of AI, they may also experience higher levels of cognitive absorption, becoming deeply immersed in AI-assisted tasks (Zhang et al. 2023). The more indispensable AI appears in their professional routines, the more likely teachers are to spend extended periods engaging with AI tools, reinforcing a state of deep concentration and interaction. This suggests that perceived usefulness plays a significant role in enhancing cognitive absorption, as teachers who see AI as highly beneficial may find themselves completely engaged and focused on AI-powered tasks (Dehghani and Mashhadi 2024). Based on these insights, we propose the following hypothesis:

H5. *Perceived usefulness positively influences cognitive absorption.*

3.1.6 | Cognitive Absorption

Cognitive absorption refers to deep mental engagement and immersion in an activity, where individuals become so engrossed that they lose track of time and external surroundings (Agarwal and Karahanna 2000; Oz et al. 2023). In the context of generative AI, teachers who experience high cognitive absorption may spend excessive amounts of time interacting with AI tools, fully immersing themselves in AI-driven tasks (Saadé and Bahli 2005). As teachers engage deeply with AI, they may develop habitual usage patterns that lead to increasing reliance on AI-generated outputs for decision-making, content creation and instructional planning. Over time, this deep immersion may evolve into dependency, where teachers feel unable to disengage from AI tools, even when excessive use begins to interfere with their professional autonomy and independent problem-solving skills (Lin 2009). This suggests that cognitive absorption plays a crucial role in reinforcing generative AI addiction, as prolonged and immersive engagement may lead to compulsive AI use. Based on these insights, we propose the following hypothesis:

H6. *Cognitive absorption positively influences generative AI addiction.*

3.2 | Research Instrument

This study employs a structured research instrument to examine the factors influencing teachers' dependence on generative AI, based on the I-PACE model (Interaction of Person-Affect-Cognition-Execution) (Brand et al. 2016, 2019, 2025). The research framework includes seven key constructs, each representing different psychological and behavioural aspects of AI engagement in education. These constructs were identified through a review of existing literature, and their corresponding measurement items were adapted from validated sources to ensure content validity. A five-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), was used to measure all items, providing a robust assessment of variations in participants' perceptions and behaviours. To refine the questionnaire and enhance clarity, a pretest was conducted with 10 educators who frequently use generative AI tools in their teaching practices. These participants reviewed the questionnaire and provided feedback regarding the clarity, relevance and comprehensibility of the items. Based on their input, minor modifications were made to improve the readability of certain statements and ensure that they effectively captured the intended constructs. This pretesting process helped to enhance the reliability of the measurement instrument before its full-scale deployment (Du 2024).

The final research instrument consists of seven constructs, each reflecting a specific dimension of AI engagement in teaching. Self-efficacy (SE) assesses teachers' confidence in their ability to effectively use generative AI for instructional tasks, including troubleshooting and adapting AI-generated insights. Need for cognition (NC) measures teachers' intellectual curiosity and motivation to explore AI-driven innovations for lesson planning and pedagogical improvement. Mood regulation (MR) evaluates how teachers use AI as a tool to manage work-related stress, reduce workload pressure, and maintain emotional well-being. Positive affect (PA) captures the emotional benefits teachers experience, such as excitement, motivation and a sense of accomplishment when integrating AI into their teaching strategies. Furthermore, perceived usefulness (PU) examines teachers' beliefs about the practical benefits of AI, particularly in improving efficiency, productivity and instructional quality. Cognitive absorption (CA) assesses the extent to which teachers become deeply immersed in AI-based tasks, often losing track of time while working with AI-generated content. Lastly, generative AI Addiction (GA) investigates excessive reliance on AI tools, including difficulties in limiting AI use, potential disruptions to teaching autonomy and signs of compulsive engagement. The measurement items for each construct, along with their sources, are presented in Table 1.

3.3 | Data Collection

The survey was conducted in Huanghua, a county-level city located in Hebei Province, China, from 15 January 2025 to 10 February 2025, targeting teachers who actively use or have experience with generative AI in their teaching practices. A structured online questionnaire was distributed primarily through internal WeChat groups managed by a local instructional supervisor, which includes nearly all teachers in Huanghua. Additional distribution channels included institutional email lists and smaller educator networks, ensuring broad and relevant participation. Over the period, 1750 valid responses were collected after a rigorous data-cleaning process. Careless responses (Ward and Meade 2023), as well as those from participants who had never used or were completely unfamiliar with generative AI, were removed to ensure data quality. The final dataset reflects a diverse and representative sample of educators in the city, allowing for a comprehensive examination of the factors influencing teachers' dependence on generative AI.

Ethical approval was obtained from the authors' institutional ethics committee. Informed consent was obtained from all participants prior to data collection. Participants were briefed on the purpose of the study, assured of the confidentiality of their responses and informed of their right to withdraw at any time.

3.4 | Data Analysis

The data analysis involved a structured approach using both descriptive and inferential statistical techniques to examine the relationships between key constructs based on the I-PACE model. Initially, data cleaning and preprocessing were conducted to ensure accuracy and reliability. Descriptive statistics provided insights into demographic distributions and AI usage patterns among teachers. Confirmatory factor analysis (CFA) was used to assess the validity and reliability of the measurement model, ensuring that the constructs were well defined and internally consistent. Structural equation modelling (SEM) was employed to test the hypothesised relationships among variables, examining the direct and indirect effects of psychological and behavioural factors on AI dependence. Model fit indices were evaluated to confirm the robustness of the proposed framework. The analysis aimed to uncover underlying mechanisms driving AI engagement among educators, offering theoretical and practical implications for managing AI reliance in educational settings.

TABLE 1 | Constructs and measurement items.

Construct	Item	Item content	Source
Self-efficacy (SE)	SE1	I feel confident in my ability to use generative AI tools to support my teaching tasks.	Wang and Chuang (2024)
	SE2	I can independently figure out how to use new features of generative AI in my educational activities.	
	SE3	I believe I can troubleshoot issues that arise when using generative AI in my teaching.	
Need for cognition (NC)	NC1	I enjoy exploring how generative AI can improve my lesson plans and teaching strategies.	Lord and Putrevu (2006)
	NC2	I often use generative AI to find innovative ways to explain complex concepts to my students.	
	NC3	I feel intellectually stimulated when I discover new applications of generative AI in education.	
Mood regulation (MR)	MR1	I use generative AI tools to reduce the stress of preparing lesson materials.	Hutchison and Gunthert (2013)
	MR2	When I feel overwhelmed with tasks, I turn to generative AI to ease my workload.	
	MR3	Using generative AI helps me stay calm and focused when I have a lot to do.	
Positive affect (PA)	PA1	I feel excited when I successfully create valuable teaching resources using generative AI.	Joshanloo (2017)
	PA2	Using generative AI tools makes me feel more motivated to experiment with new teaching methods.	
	PA3	I experience a sense of accomplishment when I integrate AI-generated content into my lessons.	
Perceived usefulness (PU)	PU1	Generative AI tools help me prepare high-quality teaching materials more efficiently.	Zou et al. (2023)
	PU2	Using generative AI allows me to focus more on engaging with my students rather than on routine tasks.	
	PU3	Generative AI provides me with valuable ideas and resources that I wouldn't have thought of on my own.	
	PU4	I find generative AI to be a useful tool for improving my productivity as a teacher.	
Cognitive absorption (CA)	CA1	I often lose track of time when I use generative AI tools to prepare my lessons.	Bozoglan et al. (2014)
	CA2	When I use generative AI for teaching tasks, I become so absorbed that I don't notice other things happening around me.	
	CA3	I find myself fully focused and engaged when working with generative AI on educational content.	
Generative AI addiction (GA)	GA1	I often feel that I use generative AI tools more than I should for my teaching tasks.	Hu et al. (2023)
	GA2	I have tried to limit my use of generative AI tools, but I find it difficult to do so.	
	GA3	My reliance on generative AI sometimes interferes with my ability to complete tasks without it.	
	GA4	I feel uneasy or frustrated when I am unable to use generative AI tools.	

4 | Results

4.1 | Descriptive Statistics

Table 2 presents the demographic and behavioural characteristics of the 1750 teachers who participated in the study. The gender distribution indicates that 84.57% of participants identify as female and 15.43% as male, highlighting a predominance of women in the teaching profession within the sample. The age distribution is fairly balanced, with the majority of teachers aged between 25 and 54. Most participants hold either an associate or bachelor's degree, and over half have more than 10 years of teaching experience.

Primary school teachers represent the largest group in terms of teaching level. In relation to AI use, DeepSeek and ERNIE Bot are the most frequently used tools, while other platforms such as ChatGPT, 360 Zhinao and Tencent Hunyuan Assistant also feature prominently. The majority of participants report being somewhat familiar with AI, and usage durations vary, with roughly two-thirds having used AI tools for 3 months or less. AI is predominantly used for lesson preparation, content creation and engaging students, although a notable proportion also use it for professional development and personal interests.

4.2 | Measurement Model

To ensure the reliability and validity of the measurement model, the study conducted a confirmatory factor analysis (CFA), assessing internal consistency, convergent validity and discriminant validity. Table 3 presents the reliability and validity results, including factor loadings, Cronbach's alpha (α), composite reliability (CR) and average variance extracted (AVE). All factor loadings exceed the recommended threshold of 0.70, confirming adequate indicator reliability (Hair et al. 2022). Cronbach's alpha values range from 0.86 to 0.96, and composite reliability (CR) values are all above 0.86, demonstrating strong internal consistency (Fornell and Larcker 1981; Nunnally and Bernstein 1994). Additionally, AVE values range from 0.68 to 0.88, surpassing the minimum threshold of 0.50, thereby supporting convergent validity (Fornell and Larcker 1981).

Discriminant validity was assessed using the Fornell–Larcker criterion, which requires that the square root of the AVE for each construct be greater than its correlations with any other construct (Fornell and Larcker 1981). Table 4 presents the correlation matrix, with the square roots of AVEs shown along the diagonal in bold. The results indicate that each construct shares more variance with its own indicators than with other constructs, confirming discriminant validity.

The model fit indices indicate that the measurement model fits the data well. As shown in Table 5, the comparative fit index (CFI) is 0.96 and the Tucker–Lewis index (TLI) is 0.95, both exceeding the recommended cut-off of 0.95 for good fit. The root mean square error of approximation (RMSEA) is 0.079, which falls within the acceptable range of ≤ 0.08, and the standardised root mean square residual (SRMR) is 0.05, which meets the ≤ 0.08 guideline (Hu and Bentler 1999). Overall, the measurement model demonstrates strong psychometric properties, providing a solid foundation for the subsequent structural model analysis.

4.3 | Structural Model

This study builds a structural model to analyse the relationships between the study constructs. The hypothesis testing results appear in Table 6 and Figure 2. The findings show that self-efficacy (SE) positively influences mood regulation (MR) ($\beta = 0.49$, $p < 0.001$), cognitive absorption (CA) ($\beta = 0.47$, $p < 0.001$) and perceived usefulness (PU) ($\beta = 0.08$, $p < 0.01$), supporting H1a, H1b and H1c. However, Need for cognition (NC) does not significantly predict generative AI addiction (GA) ($\beta = 0.01$, $p = 0.83$) or cognitive absorption (CA) ($\beta = -0.01$, $p = 0.55$), leading to the rejection of H2a and H2b. For mood regulation (MR), it positively influences perceived usefulness (PU) ($\beta = 0.20$, $p < 0.001$), supporting H3a, but does not significantly affect cognitive absorption (CA) ($\beta = 0.09$, $p = 0.09$) or generative AI addiction (GA) ($\beta = -0.03$, $p = 0.65$), rejecting H3b and H3c. Positive affect (PA) positively affects perceived usefulness (PU) ($\beta = 0.74$, $p < 0.001$) and mood regulation (MR) ($\beta = 0.64$, $p < 0.001$), confirming H4a and H4c, but negatively affects cognitive absorption (CA) ($\beta = -0.18$, $p = 0.05$), leading to the rejection of H4b. The results also indicate that perceived usefulness (PU) positively influences cognitive absorption (CA) ($\beta = 0.79$, $p < 0.001$), supporting H5, and that cognitive absorption (CA) positively affects generative AI addiction (GA) ($\beta = 0.75$, $p < 0.001$), confirming H6. These findings suggest that cognitive absorption plays a key role in AI dependence, as teachers who become highly engaged with AI tools are more likely to develop excessive reliance.

Overall, the structural model confirms most of the proposed hypotheses and highlights the psychological and behavioural mechanisms that lead to AI addiction among teachers. The significant relationships between self-efficacy, positive affect, perceived usefulness and cognitive absorption indicate that these factors contribute to teachers' continued AI engagement. However, the findings also suggest that the need for cognition and mood regulation do not directly affect AI addiction, implying that other factors may moderate these relationships. These insights contribute to a deeper understanding of AI dependence in education and provide guidance on how teachers can balance AI use without excessive reliance.

5 | Discussion

5.1 | Factors Contributing to Generative AI Addiction Among Teachers (RQ1)

This section addresses Research Question 1 (RQ1): What factors contribute to teachers' addiction to generative AI? The findings of this study, interpreted alongside existing literature, provide a comprehensive understanding of the psychological and behavioural drivers behind generative AI addiction in educational contexts.

TABLE 2 | Demographic and behavioural characteristics of the study participants.

Measure	Item	Frequency	Percent
Gender	Female	1480	85.57%
	Male	270	15.43%
Age	Below 25	145	8.29%
	25–34	499	28.51%
	35–44	511	29.20%
	45–54	511	29.20%
	Above 55	84	4.80%
Education	Associate degree	853	48.74%
	Bachelor's degree	872	49.83%
	Master's degree	25	1.43%
Teaching years	Less than 1 year	78	4.46%
	1–3 years	234	13.37%
	4–6 years	245	14.00%
	7–10 years	205	11.71%
	More than 10 years	988	56.46%
Teaching level	Kindergarten	162	9.26%
	Primary school	960	54.86%
	Middle school	467	26.69%
	High school	161	9.20%
AI tool used	ChatGPT	214	12.23%
	Claude	53	3.03%
	ERNIE Bot	856	48.91%
	Tencent Hunyuan Assistant	117	6.69%
	Ali Tongyi Qianwen	61	3.49%
	iFlytek Spark Cognition Model	114	6.51%
	Huawei Pangu Model	39	2.23%
	360 Zhinao	230	13.14%
	DeepSeek	1120	64.00%
AI familiarity	Somewhat familiar	1498	85.60%
	Relatively familiar	220	12.57%
	Very familiar	32	1.83%
Duration of use	Less than 1 month	527	30.11%
	1–3 months	549	31.37%
	4–6 months	292	16.69%
	7–12 months	153	8.74%
	More than a year	229	13.09%

(Continues)

TABLE 2 | (Continued)

Measure	Item	Frequency	Percent
Purpose of use	Lesson preparation	1391	79.49%
	Creating teaching content (such as examination papers, exercises)	1080	61.71%
	Marking and evaluation	403	23.03%
	Increasing student engagement	583	33.31%
	Professional development	559	31.94%
	Personal interests or entertainment	612	34.97%
	Others	846	48.34%

The analysis confirms that cognitive absorption is the only direct predictor of generative AI addiction. Teachers who become deeply immersed in AI-supported tasks—such as lesson planning, content generation, or administrative activities—are more likely to develop habitual use patterns, consistent with prior findings on immersion and problematic digital behaviours (Agarwal and Karahanna 2000; Bozoglan et al. 2014). This supports Brand et al.'s (2016, 2019, 2025) I-PACE model, which identifies absorption as a core mechanism in behavioural addiction through reinforcement loops.

Crucially, this cognitive absorption is significantly driven by perceived usefulness. Teachers who believe generative AI enhances their productivity, creativity and instructional quality are more likely to engage intensively with it, increasing the risk of compulsive use (Dehghani and Mashhadi 2024; Zhang et al. 2023). This is aligned with the work of Bower et al. (2024), who found that AI's time-saving and problem-solving features reinforce continued engagement among educators. The perceived pedagogical value of AI tools strengthens the likelihood that functional use evolves into addictive patterns, as teachers may find it increasingly difficult to separate routine instruction from AI assistance.

Self-efficacy, although not a direct predictor of generative AI addiction, significantly influences cognitive absorption, perceived usefulness and mood regulation. This mirrors prior research suggesting that confident users are more willing to explore, experiment and persist in using AI tools (Fryer et al. 2020; Liang et al. 2023; Yao and Wang 2024). While high self-efficacy facilitates meaningful and autonomous AI integration, it may inadvertently raise the likelihood of absorption when teachers become highly effective and efficient in using AI—a finding that builds on Rodríguez-Ruiz et al. (2025) and Bewersdorff et al. (2025).

In contrast, the need for cognition does not significantly impact either cognitive absorption or AI addiction, diverging from earlier studies that associate intellectual curiosity with deeper

TABLE 3 | Reliability and validity results.

Construct	Item	Loading	Cronbach's α	CR	AVE
Self-efficacy (SE)	SE1	0.72	0.86	0.86	0.68
	SE2	0.88			
	SE3	0.85			
Need for cognition (NC)	NC1	0.88	0.92	0.91	0.79
	NC2	0.87			
	NC3	0.87			
Mood regulation (MR)	MR1	0.92	0.95	0.95	0.86
	MR2	0.92			
	MR3	0.94			
Positive affect (PA)	PA1	0.92	0.95	0.95	0.87
	PA2	0.95			
	PA3	0.93			
Perceived usefulness (PU)	PU1	0.95	0.96	0.97	0.88
	PU2	0.90			
	PU3	0.96			
	PU4	0.95			
Cognitive absorption (CA)	CA1	0.93	0.95	0.95	0.88
	CA2	0.94			
	CA3	0.93			
Generative AI addiction (GA)	GA1	0.88	0.93	0.93	0.77
	GA2	0.90			
	GA3	0.88			
	GA4	0.86			

TABLE 4 | Correlation matrix.

	SE	NC	MR	PU	CA	PA	GA
SE	**0.82**						
NC	0.73	**0.88**					
MR	0.43	0.78	**0.93**				
PU	0.31	0.70	0.80	**0.94**			
CA	−0.13	0.06	0.09	0.33	**0.94**		
PA	0.30	0.68	0.78	0.94	0.15	**0.93**	
GA	−0.65	−0.86	−0.84	−0.88	−0.06	−0.92	**0.87**

Note: The square roots of the AVEs are highlighted in bold along the diagonal.

and more sustained engagement in digital environments (Tanas et al. 2020; Cacioppo and Petty 1982). The findings suggest that teachers with a high need for cognition approach AI critically and selectively, avoiding the kind of habitual engagement associated with compulsive use. These results point to a distinction between strategic, reflective use of AI for intellectual exploration and the reinforcement-driven patterns that underlie addiction.

Similarly, mood regulation was not found to directly predict generative AI addiction, despite its significant effects on

TABLE 5 | Model fit indices.

Fix index	CFI	TLI	RMSEA	SRMR
Recommended value	≥0.95	≥0.95	≤0.08	≤0.08
Actual value	0.96	0.95	0.079	0.05

TABLE 6 | Hypotheses test results.

Hypothesis	Path	Path coefficient	*p*	Result
H1a	SE → MR	0.49	***	Supported
H1b	SE → CA	0.47	***	Supported
H1c	SE → PU	0.08	**	Supported
H2a	NC → GA	0.01	0.83	Not supported
H2b	NC → CA	−0.01	0.55	Not supported
H3a	MR → PU	0.20	***	Supported
H3b	MR → CA	0.09	0.09	Not supported
H3c	MR → GA	−0.03	0.65	Not supported
H4a	PA → PU	0.74	***	Supported
H4b	PA → CA	−0.18	0.05	Not supported
H4c	PA → MR	0.64	***	Supported
H5	PU → CA	0.79	***	Supported
H6	CA → GA	0.75	***	Supported

Note: Statistical significance is denoted as ***$p<0.001$, **$p<0.01$ and *$p<0.05$.

perceived usefulness. While previous research has shown that digital technologies can serve as emotional coping tools that reinforce overuse (Hu et al. 2023; Jadhakhan et al. 2022), the current study suggests that teachers use generative AI primarily for task-related stress relief, rather than emotional escapism. This aligns with findings by Qu and Wang (2024) that teachers often turn to AI to manage workload stress but do not necessarily develop maladaptive usage patterns in doing so.

Positive affect also enhances mood regulation and perceived usefulness but does not lead to increased cognitive absorption. This is in contrast with research on social media or gaming (Dockray and Steptoe 2010; Huang et al. 2024), where pleasurable experiences often foster immersion and addiction. In the case of generative AI use in education, emotional enjoyment may enhance engagement and openness to innovation (Liu and Chang 2024), but it does not undermine behavioural regulation. Teachers appear to remain professionally grounded, using AI as a tool rather than as a source of continuous emotional stimulation.

In summary, this study finds that generative AI addiction among teachers is primarily driven by cognitive absorption, with perceived usefulness and self-efficacy acting as key antecedents that indirectly fuel immersive engagement. In contrast, emotional and personality-related factors such as mood regulation, positive affect and need for cognition do not directly trigger addictive behaviour. These findings reinforce the idea that in professional contexts, addiction to AI tools is more likely to emerge from functional overuse and deep task immersion than from emotional dependence. This distinction highlights the importance of promoting mindful and intentional use of generative AI in educational settings, ensuring that pedagogical benefits are balanced with sustained professional autonomy and critical engagement.

5.2 | The I-PACE Model as a Framework for Explaining Generative AI Addiction (RQ2)

This section addresses Research Question 2 (RQ2): To what extent can the I-PACE model explain teachers' addiction to generative AI? The results of this study demonstrate that while the I-PACE model offers a useful conceptual lens for understanding generative AI addiction in education, its explanatory capacity is partial and context-dependent.

The strongest alignment with the I-PACE framework lies in its emphasis on cognitive and reinforcement processes. In particular, the model's prediction that compulsive digital use is maintained by cognitive-emotional engagement is supported by the central role of cognitive absorption in this study. This mirrors previous applications of I-PACE to internet gaming and social media use (Brand et al. 2016, 2019; Pupi et al. 2024), confirming that immersive engagement plays a central role in addictive behaviours, even in task-oriented environments like teaching.

Where the model is less predictive is in its assumptions about personality traits and affective motivators. For instance, the model identifies need for cognition as a key personal predisposition that should influence addiction through sustained mental engagement (Brand et al. 2025; Cacioppo and Petty 1982). However, in this context, that relationship was not observed. This suggests that cognitive curiosity may not translate into addictive use when the technology serves professional, rather than hedonic, purposes. The structure and intentionality of AI use in teaching likely limit the kind of unregulated exploration that drives overuse in leisure contexts (Tanas et al. 2020).

Similarly, mood regulation, an affective mechanism typically linked to compensatory digital behaviour (Hu et al. 2023; Jadhakhan et al. 2022), showed minimal impact on addiction in this study. This contrasts with prior applications of I-PACE to emotionally driven technology use, such as gaming or social media, where emotional relief plays a central reinforcing role (Dockray and Steptoe 2010). In the case of teachers, generative AI appears to serve primarily functional needs, with emotional relief acting more as a secondary benefit than a driver of sustained use. This reflects a context-specific limitation of the model: affective pathways to addiction may be weaker in instrumental and structured environments.

Another noteworthy implication is the limited role of execution-related impairments, which the I-PACE model includes as

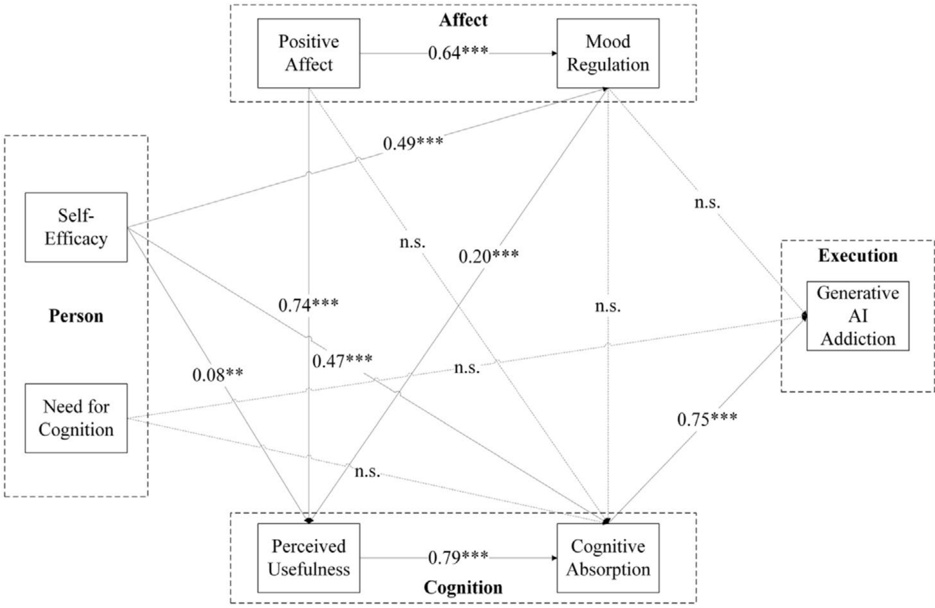

FIGURE 2 | Results of structural model testing. The values represent standardised path coefficients. Significance levels are denoted as $^{**}p<0.01$; $^{***}p<0.001$; n.s.: not significant.

late-stage symptoms of addiction. In this study, participants did report some signs of reliance (e.g., unease when AI is unavailable), but the broader behavioural dysfunctions typical of other digital addictions were less pronounced. This suggests that generative AI addiction in educators may reflect dependence on efficiency and automation, rather than an outright breakdown of self-regulation or control, as seen in entertainment-focused addictions (Renshaw and Carley 2024; Dinnie 2024).

Taken together, these findings suggest that the I-PACE model partially explains generative AI addiction, particularly through its cognitive engagement mechanisms, but its general assumptions regarding emotional and dispositional predictors require adaptation for professional contexts. Unlike passive or escapist technologies, generative AI in education is goal-driven, embedded in work routines and often sanctioned or encouraged by institutions. These features likely suppress some of the affective triggers and personal vulnerabilities emphasised in traditional addiction models.

To enhance its relevance, the I-PACE model could be refined by incorporating contextual moderators such as task structure, institutional norms and tool functionality. As shown in this study, addiction may arise not from emotional compensation, but from habitual reliance on a cognitively absorbing system that is perceived as indispensable for professional performance (Bower et al. 2024; Comiskey 2024). This points to a distinct pathway of work-related AI overuse, where addiction stems from integration, not escapism.

In conclusion, the I-PACE model offers a valuable but incomplete explanation of generative AI addiction among teachers. Its cognitive and behavioural mechanisms are relevant, but its assumptions about emotion- and trait-driven use need rethinking for productivity-based AI contexts. Future theoretical models should incorporate the dual role of AI as both a tool and a cognitive partner, and account for how structurally embedded utility—rather than emotional gratification—can also produce patterns of overuse.

5.3 | Practical Implications

This study's findings offer practical guidance for educators, institutions and policymakers by identifying psychological mechanisms, particularly cognitive absorption, perceived usefulness and positive affect, that contribute to AI addiction. These insights highlight the importance of coordinated responses at multiple levels: equipping educators with reflective strategies, guiding institutional policies to promote balanced integration and informing broader policy frameworks to safeguard professional autonomy. Addressing these areas together is essential for promoting responsible AI use while mitigating the risks of over-reliance.

At the educator level, professional development programmes should aim not only to build technical proficiency, but also to cultivate critical awareness of AI's impact on instructional practices. Since perceived usefulness and cognitive immersion were shown to be key pathways to AI dependence (Zhang et al. 2023; Bozoglan et al. 2014), teachers need support in distinguishing between strategic and habitual use. Training should include reflective practices, such as evaluating when AI enhances teaching effectiveness and when it may undermine creativity or autonomy (Bower et al. 2024). Such practices help teachers retain agency in their pedagogical decisions, even when using advanced AI tools.

At the institutional level, clear guidelines and oversight mechanisms are necessary to ensure that AI serves as a supportive tool rather than a substitute for professional expertise. Given that cognitive absorption intensifies with frequent and seamless AI use, schools and universities should implement frameworks that encourage periodic reflection, teacher validation of AI-generated content and blended instructional approaches (Dehghani and Mashhadi 2024; Chan and Tsi 2024). AI literacy should not be treated as a one-time competency, but as an evolving practice embedded in continuing professional development and school culture.

At the policy level, education authorities must consider how national and regional frameworks can promote sustainable and ethical AI integration. Policymakers should establish standards that limit excessive automation, require human oversight in AI-supported teaching, and incorporate AI-critical literacy into teacher certification and professional standards (Chiu 2024; Comiskey 2024). In collaboration with AI developers, policymakers can also shape the design of tools to include safeguards such as reflection prompts, decision-justification features or usage feedback, which encourage mindful and intentional engagement (Zhong et al. 2024; Hu et al. 2023). Promoting a professional culture where AI is viewed as a complementary tool, rather than a replacement for human judgement, can reinforce teacher autonomy and help maintain cognitive engagement and professional identity (Bower et al. 2024).

By aligning educator training, institutional governance and policy regulation, the education sector can ensure that AI remains a powerful yet measured tool that supports, rather than supplants, the pedagogical expertise of teachers.

5.4 | Limitations

This study presents several limitations that may affect the interpretation of its findings. First, the use of a cross-sectional design restricts the ability to determine causal relationships between psychological factors and generative AI addiction. While the structural equation model highlights associations among variables, it does not confirm the direction of influence.

Second, the study was conducted in Huanghua, China, and the findings may not be generalisable to other regions or educational contexts. Differences in institutional policies, technological infrastructure and cultural attitudes towards AI may shape teachers' behaviours in ways not captured by this research. As such, the results should be interpreted within the context of the local environment in which the data were collected.

Third, all data were collected through self-reported questionnaires, which may introduce response bias. Participants could have misjudged or misrepresented their levels of AI use, emotional responses or behavioural tendencies due to social desirability or lack of self-awareness. Although steps were taken to ensure the clarity and reliability of the instrument, self-reports remain inherently subjective and limited in precision.

5.5 | Future Directions

This study lays the groundwork for several promising avenues of future research into teachers' interactions with generative AI. First, longitudinal research is needed to explore how AI engagement changes over time. While this study provides a snapshot of current behaviours and psychological drivers, it does not capture how patterns of reliance emerge, stabilise or decline. Future studies could track teachers' AI use across academic terms or school years to investigate how sustained exposure influences autonomy, instructional habits or professional identity. Potential research questions include: *How does the frequency and purpose of AI use among teachers change over time?* and *Does long-term engagement with generative AI strengthen or weaken cognitive absorption and perceived usefulness?*

Second, future research would benefit from employing methodological approaches that go beyond self-reported questionnaires. Although survey instruments can capture teachers' perceptions and attitudes, they are vulnerable to bias and cannot reflect actual behaviour with precision. Integrating system log data, screen recordings or observational techniques could offer a more objective understanding of how teachers interact with AI in real-time educational settings. Studies might ask: *What does teachers' actual interaction data reveal about the duration, intensity and context of AI use?* or *How do observed usage behaviours correlate with self-reported cognitive absorption or dependence?*

Third, a multidisciplinary perspective would offer deeper insight into the complexity of generative AI addiction. Psychological constructs such as motivation, emotion regulation and decision-making could be examined alongside technical design factors, user experience principles and ethical considerations. Collaborations between researchers in education, cognitive psychology, human–computer interaction and ethics would allow for more holistic investigations. Relevant research questions include: *How do interface features such as automation, feedback or personalisation contribute to immersive and potentially addictive user experiences?* and *In what ways do pedagogical values and professional identity moderate the impact of AI system design on teacher behaviour?*

Finally, future studies should explore AI engagement in cross-cultural contexts. This study was conducted in a specific regional and institutional setting, and the results may not reflect experiences in other educational systems. Cultural norms, policy frameworks and institutional expectations likely influence how teachers adopt and internalise AI tools. Cross-national comparisons could address questions such as: *How do cultural attitudes towards technology affect teachers' perceived usefulness and emotional responses to AI?* and *Are patterns of AI reliance more pronounced in education systems that emphasise standardisation, accountability or innovation?* By identifying contextual variations, such studies could inform more culturally responsive strategies for AI integration.

6 | Conclusion

This study contributes to the growing body of knowledge on digital behaviour by investigating the psychological and behavioural mechanisms underlying teachers' dependence on generative AI, framed through the I-PACE model. By surveying 1750 educators, the study identifies cognitive absorption as the strongest and only direct predictor of AI addiction, confirming that deep mental immersion—rather than emotional dependence or intellectual curiosity—is the most critical pathway to compulsive AI use. This finding advances existing models of technology addiction by demonstrating that functional and task-related engagement, when reinforced by perceived usefulness, can become habit-forming in professional contexts such as education.

Importantly, the study extends the theoretical application of the I-PACE model beyond entertainment-based technologies to the domain of generative AI in professional settings, a space that has been underexplored (Brand et al. 2025; Suva and Bhatia 2024). It clarifies how constructs like self-efficacy, mood regulation and positive affect shape engagement indirectly, reinforcing usage through cognitive routes rather than through hedonic or affective pathways alone. This nuanced understanding contributes to the refinement of digital addiction theories by showing that work-oriented AI tools, unlike social media or gaming platforms, elicit different psychological dynamics that still carry risks of dependency.

Practically, the study offers timely insights for educators, school administrators and policymakers seeking to integrate AI responsibly in teaching. By identifying the psychological predictors of overreliance, it provides a framework for fostering mindful engagement with AI that supports instructional efficiency without undermining teachers' professional autonomy or creativity. This work not only addresses a critical gap in current literature but also establishes a research foundation for future studies on AI adoption and well-being in educational environments.

Author Contributions

Yiran Du conceived the study, designed the methodology, and led the writing. Mi Tang contributed to data collection and analysis. Kunjie Jia supported experimental design and data processing. Chenghao Wang assisted with interpretation of results and manuscript revisions. Bin Zou provided overall guidance, supervised the project, and reviewed the final manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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