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Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior

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Abstract
Although previous studies have highlighted the problematic artificial intelligence (AI) usage behaviors in educational contexts, such as overreliance on AI, no study has explored the antecedents and potential consequences that contribute to this problem. Therefore, this study investigates the causes and consequences of AI dependency using ChatGPT as an example. Using the Interaction of the Person-Affect-Cognition-Execution (I-PACE) model, this study explores the internal associations between academic self-efficacy, academic stress, performance expectations, and AI dependency. It also identifies the negative consequences of AI dependency. Analysis of data from 300 university students revealed that the relationship between academic self-efficacy and AI dependency was mediated by academic stress and performance expectations. The top five negative effects of AI dependency include increased laziness, the spread of misinformation, a lower level of creativity, and reduced critical and independent thinking. The findings provide explanations and solutions to mitigate the negative effects of AI dependency.

Keywords Artificial intelligence, AI dependency, Academic self-efficacy, Academic stress, Performance expectations, ChatGPT

Introduction

The rapid emergence of Artificial intelligence (AI) as a revolutionary technology is reshaping every aspect of our lives (Lund & Wang, 2023). It has transformed the way we interact with technology and has the potential to drive significant advances in several fields (Lund & Wang, 2023; Zhang et al., 2023a, b). Although people use diverse types of AI, such as AI speakers or virtual assistants, the current study focuses on generative AI, e.g., ChatGPT. This is mainly influenced by the impact of ChatGPT. The release of OpenAI's ChatGPT was a global sensation, with ChatGPT quickly becoming one of the most popular AI technologies (Liebrenz et al., 2023). It set a record among rapidly expanding consumer applications, acquiring a million users within just five days of its release, and achieving a user base of 100 million within two months by November 2022.

Numerous researchers have examined ChatGPT considering its benefits and potential (Dwivedi et al., 2023; Fitria, 2023; Lund & Wang, 2023). However, as Shen et al. (2023) mentioned, ChatGPT is a double-edged sword. Problems related to ethics (Liebrenz et al., 2023), privacy concerns (Paul et al., 2023), and anxiety (Salah et al., 2023) have become public concerns. Moreover, the increasing use of ChatGPT has led to individuals' growing dependence on AI, resulting in instances of misuse and abuse (Kasneci et al., 2023; King & ChatGPT, 2023).

Despite a lack of previous studies, overreliance on AI technology has been predicted to have negative effects on people, such as reduced critical thinking and a decrease in problem-solving abilities. To address these issues, urgent efforts are necessary. To the best of our knowledge, no previous studies have conducted a comprehensive analysis of AI dependency. Considering the necessity and urgency of this problem, the characteristics of vulnerable populations and the psychological factors that impact their actions must be empirically investigated. This study uses ChatGPT to explore university students' AI dependence and misuse behaviors.

In line with previous studies (Jun & Choi, 2015; Mun, 2023), this study posited that academic self-efficacy is a crucial predictor of students' problematic use of AI. The Interaction of the Person-Affect-Cognition-Execution (I-PACE) model was used to provide a theoretical basis for the association between academic self-efficacy and AI dependency. Moreover, other factors, such as academic stress and performance expectations, influence this relationship. Finally, additional analyses were conducted to understand the detrimental impacts of ChatGPT use on university students.

Literature review

IPACE model

The I-PACE model (Brand et al., 2016) serves as a conceptual framework to understand the mechanisms involved in the progression and persistence of addictive behaviors related to specific Internet applications or websites. This model comprises four elements: human, affective, cognitive, and executive. The first element covers individual characteristics, such as personality and psychopathological traits, social cognition, and cognitive vulnerability. The second element consists of the emotional factors that influence an individual's behavior, including emotional responses to different stimuli and coping strategies. The third element includes the cognitive processes and biases that shape individuals. The last element refers to the actual behavior of an individual, such as the degree of technology use, self-control, and decision-making regarding Internet applications. Addictive habits emerge and are maintained through the interactions between these four elements.

As of 2023, this model offers a valuable theoretical foundation for investigating the excessive utilization of technology in diverse settings (Elhai et al., 2018; Hu et al., 2023; Rothen et al., 2018). However, the application of the I-PACE model to investigate the underlying causes and internal processes behind AI dependency remains unexplored. This study is the first to use this model as the primary theoretical basis for investigating AI dependency.

This study focuses on personal factors in the I-PACE model, investigating individual attributes, such as academic self-efficacy and academic stress, which have proven to be strong indicators of problematic behaviors among college students (Li et al., 2020; Mun, 2023;

Parmaksız, 2022). AI is considered a useful tool for students, providing academic and emotional support (Alshater, 2022; Quintans-Júnior et al., 2023). Drawing on this, we predicted that academic self-efficacy and stress are associated with students' performance expectations towards AI despite the lack of prior studies. Moreover, an increase in performance expectations may increase students' reliance on AI. Hence, this study includes performance expectations as an additional crucial element that influences AI dependency in the research framework.

Academic self-efficacy and AI dependency

Self-efficacy, a concept derived from social cognitive theory (Bandura, 1986), refers to a person's confidence in their capacity to perform or master a certain task. However, it varies depending on the task or situation (Pajares, 2002). Academic self-efficacy is a person's belief in their ability to succeed in school (Khan, 2013; Li et al., 2020; Parmaksız, 2022). Individuals with high academic self-efficacy beliefs demonstrate a keen sense of confidence in their ability to effectively plan, organize, and execute academic tasks. They display greater enthusiasm for learning, exert more effort, and demonstrate a higher determination to achieve their objectives compared to those with low academic self-efficacy (Honicke & Broadbent, 2016).

In this study, we define AI dependency as an excessive reliance on AI technologies and applications across various aspects of life, including academic studies, daily routines, and social interactions. This form of dependency is marked not only by the overutilization of AI-assisted tools but also by a significant psychological dependence on these technologies. While the term "dependency" is inherently neutral, our investigation specifically targets the problematic usage behaviors that emerge as a result of this reliance.

According to self-efficacy theory (Jackson et al., 2019), students with low academic confidence are more prone to frustration and may be unable to complete academic activities. In such cases, they may seek external help to compensate for their inability such as ChatGPT, a convenient AI alternative. Using ChatGPT allows students to obtain quick and direct answers by simply asking questions, which may enhance their academic performance in the short term (Alshater, 2022; Rahman & Watanobe, 2023). Consequently, students may rely more on AI for immediate solutions rather than solving problems independently. In the long term, students with low academic self-efficacy are likely to overuse AI.

Within the I-PACE model, the impact of academic self-efficacy on the inappropriate use of technology has been confirmed (Hong et al., 2021; Li et al., 2021). Prior studies have consistently reported that academic self-efficacy is inversely connected with addictive behavior (Beranuy et al., 2009; Odacı, 2013). Consistent with previous studies on AI dependency, we propose the following hypothesis:

H1: Academic self-efficacy is negatively associated with AI dependency.

Mediating role of academic stress

Academic stress is a psychological strain caused by persistent pressure while pursuing an academic goal (Bedewy & Gabriel, 2015; Struthers et al., 2000) and poses a risk of triggering psychological and behavioral issues among students (Reddy et al., 2018). Within the I-PACE model framework, academic stress plays a crucial role as a social cognitive factor contributing to problematic technology use. Earlier studies have highlighted the negative association between academic self-efficacy and academic stress, indicating that a decrease in academic self-efficacy leads to an increase in academic stress (Nielsen et al., 2018; Vantieghem & Van Houtte, 2015).

The stress-coping theory (Lazarus & Folkman, 1984) states that individuals in stressful situations are motivated to find ways to cope with stress and the challenges they encounter. However, ineffective coping mechanisms may increase the probability of adopting maladaptive or addictive behaviors (Compas et al., 2001; Metzger et al., 2017). AI technology provides students with an easy and quick way to access academic information and answers, thus meeting their academic needs in the short term and reducing academic stress (Rani et al., 2023; Zhu et al., 2023). Moreover, studies have shown that AI technologies such as chatbots can alleviate users' psychological problems and thus improve their mental health. For example, Meng and Dai (2021) and Park et al. (2019) suggested that chatting with chatbots helps relieve stress and lightens the mood.

However, such personalized gratification may exacerbate overattachment to AI, leading academically stressed individuals to seek academic and emotional support from it (Rani et al., 2023). Ultimately, individuals become increasingly vulnerable to AI dependency. Based on the associations between academic self-efficacy, academic stress, and AI dependency, we suggest that the relationship between academic self-efficacy and AI dependency is mediated by academic stress. Considering that individuals with low academic self-efficacy tend to experience heightened academic stress, they may increasingly resort to AI as a coping mechanism, resulting in excessive dependence on this technology. Hence, we propose the following hypothesis:

H2: Academic stress mediates the association between academic self-efficacy and AI dependency.

Mediating role of performance expectations

Dwivedi et al. (2019) refers to performance expectations as the degree to which individuals believe that utilizing a specific technology improves their performance. This is an important cognitive aspect that affects the attitudes of (potential) users, which, in turn, affects their willingness to use technology and actual usage. Scholars in various fields have applied performance expectations to various domains to predict user attitudes and acceptance behaviors toward technological products (Chuah et al., 2016; Davis, 1989; Elkaseh et al., 2016).

According to Brand et al. (2016), the I-PACE model proposes that cognitive biases originating from technology-related expectations and illusions can impact the connection between psychological factors and the problematic adoption of technology. Consequently, this study considers the psychological perception of AI as a cognitive bias that potentially moderates the association between AI dependency and its proposed antecedents (academic self-efficacy and academic stress). Therefore, we hypothesized that students with lower academic self-efficacy are likely to have higher expectations and illusions about technology, leading to the overuse of AI as a coping strategy. Consequently, we proposed the following hypothesis:

H3: Performance expectations mediates the association between academic self-efficacy and AI dependency.

Serial mediating roles of academic stress and performance expectations

Academic stress may heighten negative perceptions and emotions (Jun & Choi, 2015), exacerbating individuals' reflections on their academic self-efficacy and AI technologies.

Considering that those who lack academic self-efficacy are more prone to experience academic stress (Nielsen et al., 2018), we argue that they are more likely to perceive AI as a useful tool and subsequently rely more on it (Lin et al., 2021; Pitafi et al., 2020). Thus, we assume that academic stress and performance expectations are serial mediating variables in the association between academic self-efficacy and AI dependency. Hence, we formulated the following hypothesis:

H4: Academic stress and performance expectations serially mediate the effect of academic self-efficacy on AI dependency.

Negative effects of frequent use of AI technology

Previous studies have extensively explored the harm associated with different addictive behaviors (De Wit, 2009; Sriwilai & Charoensukmongkol, 2016; Zeljko, 2022). For example, for university students, problematic behaviors may negatively impact academic performance (Nayak, 2018; Noreen, 2013) and mental health (Babadi-Akashe et al., 2014; Sujarwoto et al., 2023). Accordingly, we suspect that relying on AI has several negative effects on students. Therefore, this study aimed to answer the following research question.

RQ: What are the consequences of AI dependency?

Materials and methods

Participants

To collect data from ChatGPT users, we conducted an online survey in August 2023 in South Korea with the approval of the institutional review board of our university. The survey was conducted using a reputable online survey platform offered by Embrain, a prominent South Korean company specializing in online questionnaires.

University students in Seoul, South Korea, were invited to participate in this study. Participants were selected by asking them if they had any experience using ChatGPT. A total of 300 participants were included in this study. Table 1 presents the demographic characteristics of the participants.

Table 1 Demographic information

		Frequency	Percent
Gender	Male	150	50%
	Female	150	50%
Age	<= 18	39	13%
	19–29	255	85%
	>= 30	6	2%
Education level	Undergraduate	269	90%
	Graduate	31	10%
Usage frequency	Almost daily	30	10%
	Several times a week	134	45%
	Several times a month	136	45%
Usage purpose	Seeking academic assistance (e.g., homework tutoring, concept understanding, research guidance)	251	83%
	Writing support (e.g., translation, proofreading, etc.)	148	49%
	Exploring and learning about new information or topics of interest	121	40%
	Satisfying curiosity or exploring ChatGPT's capabilities	97	32%
	Seeking help with life matters	73	24%
	Passing time or for entertainment	64	21%
	Seeking emotional support or advice	27	9%
	Other (please specify)	2	1%

Measurements

The items used in this study were obtained from previous studies. A professional translator translated the items into Korean to maintain the consistency and equivalence of the items in the Korean questionnaire with their original language. Two bilingual researchers then thoroughly reviewed the translations. All items were rated on a five-point Likert scale.

Academic self-efficacy (Cronbach's α = 0.885)

To assess academic self-confidence among students, the academic self-efficacy questionnaire was used (Nielsen et al., 2018), which comprises seven statements, including "I believe that with sufficient effort throughout the semester, I can excel in the exam." This instrument has been widely used in previous studies (Akanni & Oduaran, 2018; Hitches et al., 2022).

Academic stress (Cronbach's α = 0.702)

Students' academic stress was measured using seven items (You, 2018), including "I am anxious about my grades not being satisfactory" and "I am worried about securing a good job after graduation." The reliability of this instrument has been confirmed in previous studies (Jarvis et al.,2020; Jun & Choi, 2015).

Performance expectations (Cronbach's α = 0.908)

Performance expectations was measured using three items taken from Aronson and Carlsmith (1962), which includes statements such as "I think using ChatGPT will help me solve the problem better." The reliability of this scale has been previously confirmed (Nan et al., 2022; Zhang et al., 2023a).

AI dependency (Cronbach's α = 0.852)

AI dependency was measured using six items developed by Andreassen et al. (2012) and has been validated in previous studies (Hu et al., 2023; Lee-Won et al., 2015). Statements such as "I tried to reduce the use of ChatGPT without success" were included.

Consequences of AI dependency

To understand the negative impacts of ChatGPT overuse among university students, we included an open-ended question at the end of the questionnaire, asking respondents to write freely (in at least two words) about the negative impacts of using ChatGPT.

Data analysis

SPSS version 29 was used for descriptive and correlational analyses. Subsequently, Model 6 in PROCESS developed by Hayes (Hayes, 2012) was used to conduct a mediation effect test. The importance of the mediation effect was examined using 5000 samples and the bias-corrected percentile bootstrap approach.

For the qualitative analysis, two professional translators translated the data from Korean into English. The first and second authors then examined the data by combining identical data (e.g., critical thinking, Critical thinking, and critical think). In case of ambiguities, all the authors negotiated until they reached a consensus. Finally, the data were visually analyzed using word clouds.

Table 2 Descriptive statistics and correlation coefficients

	ASF	AID	AS	PE
ASF	1			
AID	-0.116*	1		
AS	-0.217**	0.242**	1	
PE	-0.081	0.575**	0.164**	1
Mean	3.796	2.806	3.568	3.782
SD	0.862	0.788	0.587	0.732

Note ASF, academic self-efficacy; AID, AI dependency; AS, academic stress; PE, performance expectations; SD, standard deviation; * $p<0.05$, ** $p<0.001$.

Table 3 Chain mediation model of academic stress and AI dependency

Dependent variable	Independent variable	b	SE	t	95% CI	
					LLCI	ULCI
AS	ASF	-0.217	0.039	-3.834***	-0.224	-0.072
PE	ASF	-0.048	0.050	-0.820	-0.139	0.057
	AS	0.154	0.073	2.627**	0.048	0.335
AID	ASF	-0.040	0.044	-0.841	-0.123	0.049
	AS	0.143	0.065	2.954**	0.064	0.320
	PE	0.548	0.051	11.568***	0.490	0.691

Note ASF, academic self-efficacy; AID, AI dependency; AS, academic stress; PE, performance expectations; b, standardized regression coefficient; CI, confidence interval; LLCI, lower limit confidence interval; ULCI, upper limit confidence interval; * $p<0.05$, ** $p<0.001$, *** $p=0.000$.

Table 4 Mediating effects of academic self-efficacy and AI dependency

	EFFECT	SE	T	LLCI	ULCI
Total effect of ASF on AID	-0.106	0.053	-2.014*	-0.209	-0.002
Direct effect of ASF on AID	-0.037	0.044	-0.841	-0.123	0.049
Indirect effects of ASF on AID					
Total indirect effect of ASF on AID	-0.069	0.035		-0.142	-0.005
Indirect effect 1: ASF → AS → AID	-0.028	0.015		-0.062	-0.006
Indirect effect 2: ASF → PE → AID	-0.024	0.032		-0.088	0.034
Indirect effect 3: ASF → AS → PE → AID	-0.017	0.009		-0.037	-0.002

Note ASF, academic self-efficacy; AID, AI dependency; AS, academic stress; PE, performance expectations; * $p<0.05$, ** $p<0.001$, *** $p<0.000$.

Results

Analysis of descriptive and correlative data

As shown in Table 2, significant correlations were observed among academic self-efficacy (Mean=3.796, SD=0.862), AI dependency (Mean=2.806, SD=0.788), academic stress (Mean=3.568, SD=0.587), and performance expectations (Mean=3.782, SD=0.732). Academic self-efficacy was negatively correlated with AI dependency (r = -0.116, $p<0.05$) and academic stress (r = -0.217, $p<0.05$). However, academic self-efficacy did not correlate with performance expectations (r = -0.081, $p>0.05$). Academic stress (r=0.242, $p<0.05$) and performance expectations (r=0.575, $p<0.05$) were positively correlated with AI dependency. Academic stress was positively correlated with performance expectations (r=0.164, $p<0.05$).

Mediation analysis

Tables 3 and 4; Fig. 1 show the findings of the mediation study.

No statistically significant relationship was found between academic self-efficacy and AI dependency (β = −0.040, SE=0.044, 95% CI [−0.123, 0.049]), thus not supporting H1.

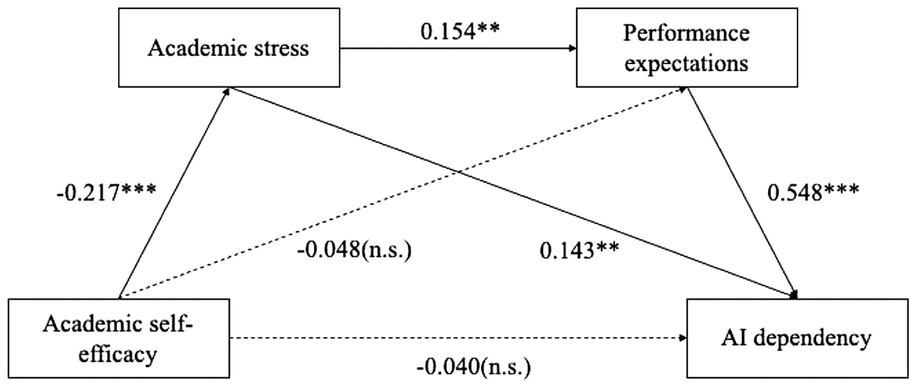

Fig. 1 Model Note: * $p<0.05$, ** $p<0.001$, *** $p<0.000$, n.s., non-significant

Table 5 Top 10 consequences of AI dependency

Consequence	Frequency
Increased laziness	113
Restricted creativity	112
Increased incorrect information	67
Restricted critical thinking	56
Restricted independent thinking	47
Restricted information-seeking ability	17
Increased plagiarism rate	13
Increased copyright infringement	12
Restricted problem-solving ability	14
Restricted information-judgment ability	6

The results of the mediation analysis indicated a significant negative relationship between academic self-efficacy and academic stress (β = -0.217, SE=0.039, 95% CI [-0.224, -0.072]). Moreover, academic stress was associated with AI dependency (β=0.143, SE=0.065, 95% CI [0.064, 0.320]). It was found that academic stress acted as an intermediary variable between academic self-efficacy and AI dependency, thus supporting H2 (β = -0.028, SE=0.015, 95% CI [-0.062, -0.006]).

Furthermore, although academic self-efficacy did not significantly impact the performance expectations of AI (β = -0.048, SE=0.050, 95% CI [-0.139, 0.057]), performance expectations had a significant impact on AI dependency (β=0.548, SE=0.051, 95% CI [0.490, 0.691]). Notably, performance expectations did not act as an intermediary variable between academic self-efficacy and AI dependency (β = -0.024, SE=0.032, 95% CI [-0.088, 0.034]), thus not supporting H3.

Moreover, academic stress exhibited a positive association with performance expectations (β=0.154, SE=0.073, 95% CI [0.048, 0.335]). A significant consecutive indirect influence of academic self-efficacy on AI dependency, mediated through academic stress and performance expectations, was found (β = -0.017, SE=0.009, 95% CI [-0.037, -0.002]), thus supporting H4.

Word Cloud analysis

AI dependency has several negative effects on students. Table 5 lists the top 10 consequences of AI dependency. Among them, students widely mentioned increased laziness (N=113), plagiarism (N=13), incorrect information (N=67), decreased creativity (N=112), reduced critical (N=56) and independent thinking (N=47), lower levels of information-seeking (N=17), problem-solving (N=14), and information-judgment abilities (N=6), and possibility of copyright issues (N=12).

Figure 2 shows the negative impacts mentioned by the students more than three times.

Discussion

This study explored the association between academic self-efficacy and AI dependency, with academic stress and performance expectations as mediators using the I-PACE model. This study also investigated the potential consequences of AI dependency.

Further analysis

Contrary to our predictions, there was no strong association between academic self-efficacy and AI dependency. This is inconsistent with previous studies (Li et al., 2020; Odaci, 2011; Parmaksız, 2022), indicating that low academic efficacy does not necessarily lead to problematic behavior among students. However, this study identified an indirect connection between academic self-efficacy and AI dependency mediated by academic stress. Therefore, although academic self-efficacy does not directly affect students' problematic AI usage behavior, students with low academic self-efficacy still rely on AI when they are under academic pressure. Zhu et al. (2011) stated that people have a general tendency to believe that Internet technology serves as a valuable tool for research and education. According to the stress-coping theory (Lazarus & Folkman, 1984), when students suffer from academic stress, they tend to seek academic support to alleviate it. Our findings validate this; among the students, 84% reported that they use ChatGPT for academic help, such as homework tutoring, conceptual understanding, and research guidance. Interestingly, although previous studies have reported that people may seek emotional help from conversational agents when experiencing stress (Meng & Dai, 2021), only 9% of the students in our study used ChatGPT to seek psychological support. Therefore, in line with existing studies (Bergdahl & Bergdahl, 2002;

Fig. 2 Consequences of AI dependency

Wilks, 2008), this study confirms that successfully seeking academic help may considerably alleviate students' stress.

Furthermore, this investigation revealed that low academic self-efficacy did not affect users' AI performance expectations. However, a significant relationship between performance expectations and AI dependency was found. Consistent with the results of Dwivedi et al. (2019) and Nan et al. (2022), performance expectations is an important predictor of user adoption behavior. Although it has rarely been used as a potential predictor in previous studies on addictive behaviors (Han et al., 2017), it was a significant variable in the present study. This may be due to the uniqueness of the functionality of ChatGPT and the actual student usage behavior; most students used ChatGPT for academic assistance (84%) and writing support (49%).

Additionally, this study showed that academic self-efficacy was indirectly related to AI dependency through mediation of academic stress and performance expectations. This finding suggests that students with low academic self-efficacy exhibit higher levels of academic stress, resulting in increased expectations from AI technology and thus leading to higher levels of AI dependency. This aligns with the cognitive-behavioral framework (Davis, 2001), which states that low academic self-efficacy is an external event that leads to academic stress among students. Therefore, students believed that AI provided an alternative way to solve problems, leading to AI dependency.

Finally, as emphasized by Ray (2023), although AI technology provides students with easy and quick access to information, AI misuse cannot be ignored. The participants in this study reported diverse issues, among which a decrease in personal ability (e.g., creativity, critical thinking, and independent thinking) and an increase in laziness and plagiarism rates deserve further attention. Therefore, in line with Mhlanga (2023), guiding students toward the correct and appropriate use of AI is crucial.

Theoretical and practical contributions

The findings of the current study have significant theoretical and practical implications. To the best of our knowledge, this is one of the first studies exploring the internal antecedents and potential consequences of AI dependency. Moreover, this study examined academic stress and performance expectations as potential consecutive mediators of the relationship between academic self-efficacy and AI dependency. This study also contributes to existing literature. Explorations of this topic have enriched research on problematic behaviors and AI-related topics. Furthermore, this study expanded the utilization of the I-PACE model to examine problematic behavior. This demonstrates the relevance and explanatory capacity of the theoretical framework within the scope of our study. In addition to adding to the literature on the application of variables, such as academic self-efficacy and academic stress, this study extended the application of performance expectations in the I-PACE model.

From a practical perspective, the results suggest that more time and energy should be invested to reduce students' academic stress and mitigate AI-dependent behaviors. Additionally, guiding students toward reasonable use of AI technology and improving their AI literacy (Ng et al., 2021) are necessary to ensure that the potential of AI technology can be fully utilized and that its negative impacts can be mitigated. Finally, addressing misinformation and enhancing the reliability of AI technology are crucial tasks that requires continuous improvement.

Limitations and future studies

Although this study made substantial contributions, its limitations must be acknowledged and addressed in future studies. First, data collection was cross-sectional; therefore, causal relationships between the variables could not be confirmed. Future studies should conduct a more in-depth study using methods such as longitudinal observations. Additionally, this study was conducted among college students in South Korea; therefore, the findings may not be generalizable to other populations. Future studies could enrich the literature on the antecedents and consequences of AI dependency using a sample of college students from other countries.

Moreover, the analyses of consequences were based on students' self-reports, making the findings highly subjective. Future studies should conduct an in-depth analysis of the consequences of AI dependency from the perspective of empirical research. Finally, in this study, we explored college students' reliance on AI from a broad perspective, without considering and separating the two specific viewpoints: the acceptable use of AI as a tool for assistance within the constraints set by academic courses and the unacceptable use of AI for contract cheating—a cheap and reliable means to circumvent academic integrity (Manoharan et al., 2023). Therefore, we recommend that future studies reevaluate college students' dependence on AI by taking these distinct aspects into account, offering deeper insights into both the legitimate and illicit use of AI in academic environments. In addition, as suggested by Nora and Zhang (2010), the relationship between self-efficacy and cheating behavior could serve as a potential set of research variables for future studies exploring AI dependency.

Conclusions

To investigate the internal antecedents and potential consequences of AI dependency, this study examined the relationships among academic self-efficacy, academic stress, performance expectations, and AI dependency using the I-PACE model. Using a sample of 300 college students in Seoul, South Korea, the results showed that academic self-efficacy was not significantly associated with AI dependency. However, this association was mediated by academic stress and performance expectations. The consequences of AI dependency varied; the top five negative effects were increased laziness, the spread of misinformation, decreased creativity, and reduced critical and independent thinking. This study theoretically expanded on previous studies by providing potential intervention recommendations to reduce students' AI dependency.

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None.

Author contributions
Zhang Shunan: conceptualization, methodology and writing- original draft preparation; Zhao Xiangying: conceptualization and investigation; Zhou Tong: methodology and software; Jang Hyun Kim: conceptualization, supervision, funding acquisition and writing- reviewing and editing.

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

Declarations

Competing interests
The authors declare that they have no competing interests.

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References
Akanni, A. A., & Oduaran, C. A. (2018). Perceived social support and life satisfaction among freshmen: Mediating roles of academic self-efficacy and academic adjustment. *Journal of Psychology in Africa*, *28*(2), 89–93. https://doi.org/10.1080/14330237.2018.1454582.

Alshater, M. (2022). M. Exploring the role of artificial intelligence in enhancing academic performance: A case study of ChatGPT. *Available at SSRN*. https://doi.org/10.2139/ssrn.4312358.

Andreassen, C. S., Torsheim, T., Brunborg, G. S., & Pallesen, S. (2012). Development of a Facebook addiction scale. *Psychological Reports*, *110*(2), 501–517. https://doi.org/10.2466/02.09.18.PR0.110.2.501-517.

Aronson, E., & Carlsmith, J. M. (1962). Performance expectancy as a determinant of actual performance. *The Journal of Abnormal and Social Psychology*, *65*(3), 178. https://doi.org/10.1037/h0042291.

Babadi-Akashe, Z., Zamani, B. E., Abedini, Y., Akbari, H., & Hedayati, N. (2014). The relationship between mental health and addiction to mobile phones among university students of Shahrekord, Iran. *Addiction & Health*, *6*(3–4), 93. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4354213/.

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs NJ*, *1986*, 23–28. https://goo.su/iEzU.

Bedewy, D., & Gabriel, A. (2015). Examining perceptions of academic stress and its sources among university students: The perception of academic stress scale. *Health Psychology Open*, *2*(2), 2055102915596714. https://doi.org/10.1177/2055102915596714.

Beranuy, M., Oberst, U., Carbonell, X., & Chamarro, A. (2009). Problematic internet and mobile phone use and clinical symptoms in college students: The role of emotional intelligence. *Computers in Human Behavior*, *25*(5), 1182–1187. https://doi.org/10.1016/j.chb.2009.03.001.

Bergdahl, J., & Bergdahl, M. (2002). Perceived stress in adults: Prevalence and association of depression, anxiety and medication in a Swedish population. *Stress and Health: Journal of the International Society for the Investigation of Stress*, *18*(5), 235–241. https://doi.org/10.1002/smi.946.

Brand, M., Young, K. S., Laier, C., Wölfling, K., & Potenza, M. N. (2016). Integrating psychological and neurobiological considerations regarding the development and maintenance of specific internet-use disorders: An Interaction of person-affect-cognition-execution (I-PACE) model. *Neuroscience & Biobehavioral Reviews*, *71*, 252–266. https://doi.org/10.1016/j.neubiorev.2016.08.033.

Chuah, S. H. W., Rauschnabel, P. A., Krey, N., Nguyen, B., Ramayah, T., & Lade, S. (2016). Wearable technologies: The role of usefulness and visibility in smartwatch adoption. *Computers in Human Behavior*, *65*, 276–284. https://doi.org/10.1016/j.chb.2016.07.047.

Compas, B. E., Connor-Smith, J. K., Saltzman, H., Thomsen, A. H., & Wadsworth, M. E. (2001). Coping with stress during childhood and adolescence: Problems, progress, and potential in theory and research. *Psychological Bulletin*, *127*(1), 87. https://doi.org/10.1037/0033-2909.127.1.87.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *Mis Quarterly*, 319–340. https://doi.org/10.2307/249008.

Davis, R. A. (2001). A cognitive-behavioral model of pathological internet use. *Computers in Human Behavior*, *17*(2), 187–195. https://doi.org/10.1016/S0747-5632(00)00041-8.

De Wit, H. (2009). Impulsivity as a determinant and consequence of drug use: A review of underlying processes. *Addiction Biology*, *14*(1), 22–31. https://doi.org/10.1111/j.1369-1600.2008.00129.x.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*, 719–734. https://doi.org/10.1007/s10796-017-9774-y.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., & Ahuja, M. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642.

Elhai, J. D., Tiamiyu, M., & Weeks, J. (2018). Depression and social anxiety in relation to problematic smartphone use: The prominent role of rumination. *Internet Research*, *28*(2), 315–332. https://doi.org/10.1108/IntR-01-2017-0019.

Elkaseh, A. M., Wong, K. W., & Fung, C. C. (2016). Perceived ease of use and perceived usefulness of social media for e-learning in Libyan higher education: A structural equation modeling analysis. *International Journal of Information and Education Technology*, *6*(3), 192. https://doi.org/10.7763/IJIET.2016.V6.683.

Fitria, T. N. (2023). Artificial intelligence (AI) technology in OpenAI ChatGPT application: A review of ChatGPT in writing English essay. *ELT Forum: Journal of English Language Teaching*, *12*(1), 44–58. https://doi.org/10.15294/elt.v12i1.64069.

Han, S., Kim, K. J., & Kim, J. H. (2017). Understanding nomophobia: Structural equation modeling and semantic network analysis of smartphone separation anxiety. *Cyberpsychology Behavior and Social Networking*, *20*(7), 419–427. https://doi.org/10.1089/cyber.2017.0113.

Hayes, A. F. (2012). PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling. In: University of Kansas, KS. http://www.afhayes.com/public/process2012.pdf.

Hitches, E., Woodcock, S., & Ehrich, J. (2022). Building self-efficacy without letting stress knock it down: Stress and academic self-efficacy of university students. *International Journal of Educational Research Open*, *3*, 100124. https://doi.org/10.1016/j.ijedro.2022.100124.

Hong, W., Liu, R. D., Ding, Y., Jiang, S., Yang, X., & Sheng, X. (2021). Academic procrastination precedes problematic mobile phone use in Chinese adolescents: A longitudinal mediation model of distraction cognitions. *Addictive Behaviors*, *121*, 106993. https://doi.org/10.1016/j.addbeh.2021.106993.

Honicke, T., & Broadbent, J. (2016). The influence of academic self-efficacy on academic performance: A systematic review. *Educational Research Review*, *17*, 63–84. https://doi.org/10.1016/j.edurev.2015.11.002.

Hu, B., Mao, Y., & Kim, K. J. (2023). How social anxiety leads to problematic use of conversational AI: The roles of loneliness, rumination, and mind perception. *Computers in Human Behavior*, *145*, 107760. https://doi.org/10.1016/j.chb.2023.107760.

Jackson, A., Mentzer, N., & Kramer-Bottiglio, R. (2019). Pilot analysis of the impacts of soft robotics design on high-school student engineering perceptions. *International Journal of Technology and Design Education*, *29*(5), 1083–1104. https://doi.org/10.1007/s10798-018-9478-8.

Jarvis, J. A., Corbett, A. W., Thorpe, J. D., & Dufur, M. J. (2020). Too much of a good thing: Social capital and academic stress in South Korea. *Social Sciences*, *9*(11), 187. https://doi.org/10.3390/socsci9110187.

Jun, S., & Choi, E. (2015). Academic stress and internet addiction from general strain theory framework. *Computers in Human Behavior*, *49*, 282–287. https://doi.org/10.1016/j.chb.2015.03.001.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., & Hüllermeier, E. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274.

Khan, M. (2013). Academic self-efficacy, coping, and academic performance in college. *International Journal of Undergraduate Research and Creative Activities*, *5*(1), 4. https://doi.org/10.7710/2168-0620.1006.

King, M. R., & ChatGPT. (2023). A conversation on artificial intelligence, chatbots, and plagiarism in higher education. *Cellular and Molecular Bioengineering*, *16*(1), 1–2. https://doi.org/10.1007/s12195-022-00754-8.

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. Springer publishing company. https://goo.su/8sRkSa.

Lee-Won, R. J., Herzog, L., & Park, S. G. (2015). Hooked on Facebook: The role of social anxiety and need for social assurance in problematic use of Facebook. *Cyberpsychology Behavior and Social Networking*, *18*(10), 567–574. https://doi.org/10.1089/cyber.2015.0002.

Li, L., Gao, H., & Xu, Y. (2020). The mediating and buffering effect of academic self-efficacy on the relationship between smartphone addiction and academic procrastination. *Computers & Education*, *159*, 104001. https://doi.org/10.1016/j.compedu.2020.104001.

Li, Y., Li, G. X., Yu, M. L., Liu, C. L., Qu, Y. T., & Wu, H. (2021). Association between anxiety symptoms and problematic smartphone use among Chinese university students: The mediating/moderating role of self-efficacy. *Frontiers in Psychiatry*, *12*, 581367. https://doi.org/10.3389/fpsyt.2021.581367.

Liebrenz, M., Schleifer, R., Buadze, A., Bhugra, D., & Smith, A. (2023). Generating scholarly content with ChatGPT: Ethical challenges for medical publishing. *The Lancet Digital Health*, *5*(3), e105–e106. https://doi.org/10.1016/S2589-7500(23)00019-5.

Lin, C. W., Lin, Y. S., Liao, C. C., & Chen, C. C. (2021). Utilizing technology acceptance model for influences of smartphone addiction on behavioural intention. *Mathematical Problems in Engineering*, *2021*, 1–7. https://doi.org/10.1155/2021/5592187.

Lund, B. D., & Wang, T. (2023). Chatting about ChatGPT: How may AI and GPT impact academia and libraries? *Library Hi Tech News*, *40*(3), 26–29. https://doi.org/10.1108/LHTN-01-2023-0009.

Manoharan, S., Speidel, U., Ward, A. E., & Ye, X. (2023, June). Contract Cheating–Dead or Reborn? In *2023 32nd Annual Conference of the European Association for Education in Electrical and Information Engineering (EAEEIE)* (pp. 1–5). IEEE. https://doi.org/10.23919/EAEEIE55804.2023.10182073.

Meng, J., & Dai, Y. (2021). Emotional support from AI chatbots: Should a supportive partner self-disclose or not? *Journal of Computer-Mediated Communication*, *26*(4), 207–222. https://doi.org/10.1093/jcmc/zmab005.

Metzger, I. W., Blevins, C., Calhoun, C. D., Ritchwood, T. D., Gilmore, A. K., Stewart, R., & Bountress, K. E. (2017). An examination of the impact of maladaptive coping on the association between stressor type and alcohol use in college. *Journal of American College Health*, *65*(8), 534–541. https://doi.org/10.1080/07448481.2017.1351445.

Mhlanga, D. (2023). Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning. *Education, the Responsible and Ethical Use of ChatGPT Towards Lifelong Learning (February 11, 2023)*. https://doi.org/10.2139/ssrn.4354422.

Mun, I. B. (2023). Academic stress and first-/third-person shooter game addiction in a large adolescent sample: A serial mediation model with depression and impulsivity. *Computers in Human Behavior*, *145*, 107767. https://doi.org/10.1016/j.chb.2023.107767.

Nan, D., Lee, H., Kim, Y., & Kim, J. H. (2022). My video game console is so cool! A coolness theory-based model for intention to use video game consoles. *Technological Forecasting and Social Change*, *176*, 121451. https://doi.org/10.1016/j.techfore.2021.121451.

Nayak, J. K. (2018). Relationship among smartphone usage, addiction, academic performance and the moderating role of gender: A study of higher education students in India. *Computers & Education*, *123*, 164–173. https://doi.org/10.1016/j.compedu.2018.05.007.

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, 100041. https://doi.org/10.1016/j.caeai.2021.100041. 2.

Nielsen, T., Dammeyer, J., Vang, M. L., & Makransky, G. (2018). Gender fairness in self-efficacy? A rasch-based validity study of the General Academic self-efficacy scale (GASE). *Scandinavian Journal of Educational Research*, *62*(5), 664–681. https://doi.org/10.1080/00313831.2017.1306796.

Nora, W. L. Y., & Zhang, K. C. (2010). Motives of cheating among secondary students: The role of self-efficacy and peer influence. *Asia Pacific Education Review*, *11*, 573–584. https://doi.org/10.1007/s12564-010-9104-2.

Noreen, A. (2013). Relationship between internet addiction and academic performance among university undergraduates. *Educational Research and Reviews*, *8*(19), 1793–1796. https://doi.org/10.5897/ERR2013.1539.

Odaci, H. (2011). Academic self-efficacy and academic procrastination as predictors of problematic internet use in university students. *Computers & Education*, *57*(1), 1109–1113. https://doi.org/10.1016/j.compedu.2011.01.005.

Odacı, H. (2013). Risk-taking behavior and academic self-efficacy as variables accounting for problematic internet use in adolescent university students. *Children and Youth Services Review*, *35*(1), 183–187. https://doi.org/10.1016/j.childyouth.2012.09.011.

Pajares, F. (2002). Gender and perceived self-efficacy in self-regulated learning. *Theory into Practice*, *41*(2), 116–125. https://doi.org/10.1207/s15430421tip4102_8.

Park, S., Choi, J., Lee, S., Oh, C., Kim, C., La, S., Lee, J., & Suh, B. (2019). Designing a chatbot for a brief motivational interview on stress management: Qualitative case study. *Journal of Medical Internet Research*, *21*(4), e12231. https://doi.org/10.2196/12231.

Parmaksız, İ. (2022). The mediating role of personality traits on the relationship between academic self-efficacy and digital addiction. *Education and Information Technologies*, *27*(6), 8883–8902. https://doi.org/10.1007/s10639-022-10996-8.

Paul, J., Ueno, A., & Dennis, C. (2023). ChatGPT and consumers: Benefits, pitfalls and future research agenda. *International Journal of Consumer Studies*, *47*(4), 1213–1225. https://doi.org/10.1111/ijcs.12928.

Pitafi, A. H., Kanwal, S., & Khan, A. N. (2020). Effects of perceived ease of use on SNSs-addiction through psychological dependence, habit: The moderating role of perceived usefulness. *International Journal of Business Information Systems*, *33*(3), 383–407. https://doi.org/10.1504/IJBIS.2020.105831.

Quintans-Júnior, L. J., Gurgel, R. Q., Araújo, A. A. D. S., Correia, D., & Martins-Filho, P. R. (2023). ChatGPT: The new panacea of the academic world. *Revista Da Sociedade Brasileira De Medicina Tropical*, *56*, e0060–2023. https://doi.org/10.1590/0037-8682-0060-2023.

Rahman, M. M., & Watanobe, Y. (2023). ChatGPT for education and research: Opportunities, threats, and strategies. *Applied Sciences*, *13*(9), 5783. https://doi.org/10.3390/app13095783.

Rani, P. S., Rani, K. R., Daram, S. B., & Angadi, R. V. (2023). Is it feasible to reduce academic stress in Net-Zero Energy buildings? Reaction from ChatGPT. *Annals of Biomedical Engineering*, 1–3. https://doi.org/10.1007/s10439-023-03286-y.

Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems*. https://doi.org/10.1016/j.iotcps.2023.04.003.

Reddy, K. J., Menon, K. R., & Thattil, A. (2018). Academic stress and its sources among university students. *Biomedical and Pharmacology Journal*, *11*(1), 531–537. https://doi.org/10.13005/bpj/1404.

Rothen, S., Briefer, J. F., Deleuze, J., Karila, L., Andreassen, C. S., Achab, S., Thorens, G., Khazaal, Y., Zullino, D., & Billieux, J. (2018). Disentangling the role of users' preferences and impulsivity traits in problematic Facebook use. *PloS One*, *13*(9), e0201971. https://doi.org/10.1371/journal.pone.0201971.

Salah, M., Alhalbusi, H., Abdelfattah, F., & Ismail, M. M. (2023). Chatting with ChatGPT: Investigating the impact on Psychological Well-being and self-esteem with a focus on harmful stereotypes and job Anxiety as Moderator. https://doi.org/10.21203/rs.3.rs-2610655/v2.

Shen, Y., Heacock, L., Elias, J., Hentel, K. D., Reig, B., Shih, G., & Moy, L. (2023). ChatGPT and other large language models are double-edged swords. *Radiology*, *307*(2), e230163. https://doi.org/10.1148/radiol.230163.

Sriwilai, K., & Charoensukmongkol, P. (2016). Face it, don't Facebook it: Impacts of social media addiction on mindfulness, coping strategies and the consequence on emotional exhaustion. *Stress and Health*, *32*(4), 427–434. https://doi.org/10.1002/smi.2637.

Struthers, C. W., Perry, R. P., & Menec, V. H. (2000). An examination of the relationship among academic stress, coping, motivation, and performance in college. *Research in Higher Education*, *41*, 581–592. https://doi.org/10.1023/A:1007094931292.

Sujarwoto, Saputri, R. A. M., & Yumarni, T. (2023). Social media addiction and mental health among university students during the COVID-19 pandemic in Indonesia. *International Journal of Mental Health and Addiction*, *21*(1), 96–110. https://doi.org/10.1007/s11469-021-00582-3.

Vantieghem, W., & Van Houtte, M. (2015). Are girls more resilient to gender-conformity pressure? The association between gender-conformity pressure and academic self-efficacy. *Sex Roles*, *73*, 1–15. https://doi.org/10.1007/s11199-015-0509-6.

Wilks, S. E. (2008). Resilience amid academic stress: The moderating impact of social support among social work students. *Advances in Social Work*, *9*(2), 106–125. https://doi.org/10.18060/51.

You, J. W. (2018). Testing the three-way interaction effect of academic stress, academic self-efficacy, and task value on persistence in learning among Korean college students. *Higher Education*, *76*(5), 921–935. https://doi.org/10.1007/s10734-018-0255-0.

Zeljko, B. (2022). Internet addiction disorder (IAD) as a consequence of the expansion of Information technologies. *International Journal of Cognitive Research in Science Engineering and Education*, *10*(3), 155–165. https://doi.org/10.23947/2334-8496-2022-10-3-155-165.

Zhang, S., Che, S., Nan, D., & Kim, J. H. (2023a). How does online social interaction promote students' continuous learning intentions? *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1098110.

Zhang, S., Shan, C., Lee, J. S. Y., Che, S., & Kim, J. H. (2023b). Effect of chatbot-assisted language learning: A meta-analysis. *Education and Information Technologies*, 1–21. https://doi.org/10.1007/s10639-023-11805-6.

Zhu, Y. Q., Chen, L. Y., Chen, H. G., & Chern, C. C. (2011). How does internet information seeking help academic performance? The moderating and mediating roles of academic self-efficacy. *Computers & Education*, *57*(4), 2476–2484. https://doi.org/10.1016/j.compedu.2011.07.006.

Zhu, Z., Qin, S., Yang, L., Dodd, A., & Conti, M. (2023). Emotion regulation tool design principles for arts and design university students. *Procedia CIRP*, *119*, 115–120. https://doi.org/10.1016/j.procir.2023.03.085.

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