Understanding AI anxiety and GAI adoption among university students in Thailand

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ABSTRACT

Advancements in generative artificial intelligence (GAI) have heightened expectations for its role in educational transformation. This study investigates how AI-related anxiety, perceived usefulness, self-efficacy, and institutional support influence Thai university students' intention to adopt GAI. Although prior research has explored AI in education, predictors of students' behavioral intention toward GAI remain insufficiently examined, particularly in the Thai context. A quantitative approach was employed, and data were collected through an online survey from sample of 450 university students in Bangkok, Thailand. Structural equation model (SEM) was used for analysis. Results show that sociotechnical blindness and job-replacement concerns significantly and positively affect students' intention to use GAI. Social factors and facilitating conditions increase perceived usefulness and self-efficacy but do not directly influence intention. Perceived usefulness negatively predicts intention, while self-efficacy shows no significant direct effect. Mediation analyses reveal partial effects through perceived usefulness and self-efficacy. AI-related anxiety has a stronger influence on Thai university students' adoption of GAI than social or environmental factors, highlighting the need for targeted support to reduce concerns. These findings call for coordinated action among higher education authorities, university policymakers, and students to establish clear, coherent guidelines for AI use in academia. A forward-looking policy framework is urgently required to ensure responsible and effective integration of AI in Thai higher education.

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1. INTRODUCTION

Thailand's higher education sector is currently undergoing rapid transformation, presenting unique challenges related to technological adoption and fostering a growth mindset. This research is situated within this context. Despite the rise in artificial intelligence (AI) usage, its adoption in the Thai education sector remains in its infancy. Technological infrastructure and pedagogical approaches vary across institutions in Thailand. AI is profoundly reshaping job markets. A report by the McKinsey Global Institute predicts that up to 30% of current work undertakings could be automated by the year 2030, potentially leading to the displacement of 400 to 800 million workers [1]. In light of this growing demand for AI skills, it is imperative for higher education institutions to proactively prepare their graduates by fostering a passion for learning about AI [1].

The COVID-19 pandemic instigated an unprecedented surge in the digitalization of teaching and learning, which has prompted school leadership, teachers, and students to switch rapidly to online virtual learning modes [2]. Generative artificial intelligence (GAI) is the latest global force poised to revolutionize learning and teaching [2]. The rapid advancement of AI has led to the creation of groundbreaking GAI technologies that directly impact education at all levels, such as ChatGPT [3]. These GAI technologies, and those that will follow, are already reshaping the educational landscape. GAI innovations are not merely technological advancements; they represent a paradigm shift for more all-encompassing and adaptive responses towards educational practices, especially in the Thai context. In this editorial, the authors explore the rise of GAI and its implications for university students and school leaders in creating a supportive environment for the use of GAI. We also delve into the challenges of AI in human daily lives, such as the fear of job replacement and sociotechnical blindness, and the opportunities associated with AI. Finally, we consider the impact of this technological disruption on university students' learning and their perception of the leadership guidance of the use of GAI for academic purposes and reflect on how it may alter or influence the role of university leaders in policy directives.

This study aims to conduct a detailed investigation focusing on four primary objectives, viz, first, to examine the perceived level of students' anxiety towards AI. Secondly, to investigate the efficacy of students learning how to use GAI based on the third objective, the perceived usefulness of AI. Lastly, we explored the perception of the university's supportive environment through visible policies on students' intention to use GAI. Despite the extensive research on AI in education, different theories and variables have been used in predicting university students' behavioral intention toward GAI. However, its policy impacts in educational applications remain relatively underexplored, creating a research gap. This critical research gap is important to be explored because understanding the factors that influence students' intention to use GAI technology is essential for effective policy from the university leadership to integrate GAI technology into educational settings. The authors explicitly explored and evaluate the Thai policy effectiveness and readiness in dealing with the AI anxiety among university students. We also explored the risks of not educating and preparing younger generation for AI technology in Thai context. We intended to provide a holistic understanding of the role of an effective supportive environment, which might help to alleviate the anxiety of AI in enhancing teaching and learning in the higher education sector of Thailand. The following questions were addressed in this study:
- What is the perceived level of university students' anxiety towards AI?
- What is the self-efficacy of students learning how to use AI, based on their perceived usefulness of AI?
- How does the perceived university's supportive environment through visible policies impact students' intention to use AI?

2. THE COMPREHENSIVE THEORETICAL BASIS

This section clearly defines the concepts and theories adopted in this study. Thailand's higher education scholars often focus on the extent to which new technology, particularly GAI, is used in educational settings, particularly by university students and teachers, due to its potential to revolutionize teaching and learning methodologies [4]. For instance, the widespread adoption and deployment of GAI are closely linked to the reception and propensity of university students to utilize it. Scholars have employed various variables and concepts, such as the theory of planned behavior and the theory of rational action, to investigate university students' intentions to utilize GAI. In this study, we adopted and integrated variables derived from the literature, including sociotechnical blindness, job replacement, social factors, facilitating conditions, perceived usefulness, and self-efficacy in learning AI, to examine university students' intention to use GAI. This section explores all the variables adopted in this study.

AI, from its inception in 1956, has marked a groundbreaking moment in the history of technological development and is epitomized by Newell and Simon [5] the development of the "thinking machine program," which aimed to understand and emulate human reasoning to solve complex problems. This technological breakthrough paved the way for the development and application of AI in education today. Currently, AI is rapidly transforming the educational landscape across contexts. AI in education is a field that explores how AI technologies can enhance leadership decision-making processes to support teaching and learning. In the education sector, AI has been useful, particularly in English language learning [6], through adaptive learning tools, intelligent tutoring systems, and complex advisory platforms. According to Chiu *et al.* [7] recommendations for transforming higher education, GAI in the education sector aims to personalize educational experiences for students to enhance their learning efficacy.

Intention, as defined by Sheeran [8], refers to a "course of action or plan that an actor considers necessary and intends to undertake to accomplish a specific behavior." Similarly, Ajah [9] defined adoption intention as a decision to adopt and use a particular innovation. Ajzen *et al.* [10] broadly defined intention as a "motivational factor and a person's willingness to engage in certain behaviors. In this study, the intention of university students to use GAI refers to their intended decision to adopt and use GAI for learning activities and purposes.

AI anxiety includes sociotechnical blindness and job replacement. Researchers have begun to focus on the psychological and behavioral effects of AI anxiety on students. Sociotechnical blindness "combines some of the subjective and psychological dimensions of agency with the structured hardness of technological systems, policy styles, organizational behaviors, and political cultures" [11]. Sociotechnical blindness is "the study of how individuals approach new technologies and how their perceptions, understanding, and expectations originate and unravel, offering insights on the multidimensional relation between technology and society" [11]. According to Wang *et al.* [12], job replacement AI anxiety is defined as the fear or unease an individual feels due to anticipated negative outcomes and risks related to GAI use. AI anxiety is defined as the fear or unease an individual experiences due to anticipated negative outcomes and risks associated with AI technology [12], [13]. Specifically, there is a fear that AI exacerbates social inequality, compromises privacy rights, and even poses existential threats to humanity [13].

Supportive environmental factors include social factors and facilitating conditions. Social influence refers to the degree to which managers, peers, and academic institutions or organizations encourage or expect their members to use technology [14], while facilitating conditions refer to the belief that adequate environmental support from the institution or organization, and technical support, are available for students to learn and to use GAI technology [14]. Additionally, facilitating conditions are defined as the extent to which an individual perceives that an organizational and technical infrastructure exists to support the use of the system [15].

Perceived usefulness is defined as a crucial factor that influences people's acceptance or rejection of new technology. Individuals tend to adopt or reject new technology based on their belief that it will enhance their study activities. This concept applies to the perceived usefulness of GAI. Perceived usefulness refers to an individual's belief about how much a system will enhance his/her learning performance [15]. Self-efficacy, which is the last variable in this study, is a fundamental concept in learning, and it refers to a student's belief in their ability to accomplish specific tasks [16]. It encompasses their confidence in their academic abilities, their capacity to organize and carry out actions to attain desired levels of performance, and their assessments of their ability to excel in assignments, courses, or academic activities [16]. As shown in Figure 1, the proposed conceptual framework of the research adopted variables from recent studies to test the relationship between the variables. The sources of the variables were fully discussed in the methodology section of this study. This framework displayed the hypotheses of the study.

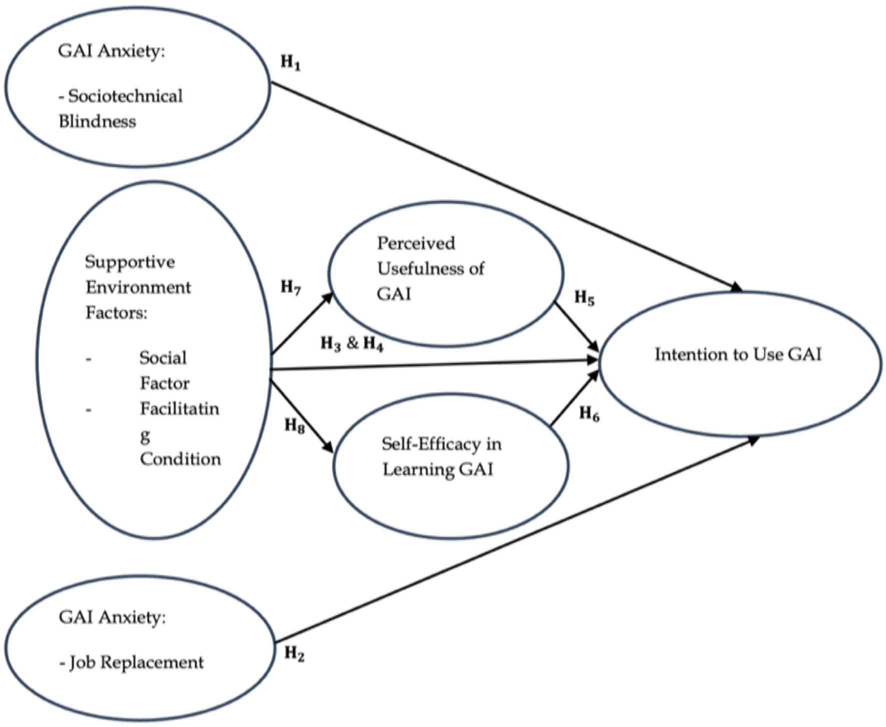

Figure 1. Conceptual framework

3. METHOD

3.1. Population and samples, research instrument, and collection of data

In this research, we adopted a quantitative research method. Initially, a pilot test was conducted using a sample of 50 respondents as recommended [17] to test the level of understanding and timing to complete the questionnaire. After the pilot test and feedback, we adjusted for clarity before the research instruments were finalized. The questionnaire was distributed via Google Form to undergraduate university students in Bangkok, Thailand, from early July to the end of September 2025. A total of 450 questionnaires were collected. There was no missing data because an incomplete response could not be submitted unless all the parts of the questionnaire were filled out. We adopted Mahalanobis method [18] for the data cleaning. The outliers from the datasets that contained missing data were removed, and only 400 survey responses were used for the data analysis after the data cleaning process. Wolf *et al.* [19] suggested a range of sample size requirements from 30 to 460 cases when using the structural equation model (SEM) of analysis. Recent studies on students' AI learning and adoption intention have used a sample of 301 to 460. For instance, Wang *et al.* [12] studied using a sample size of 327. Also, Chen *et al.* [13] studied with a sample size of 387. Additionally, Shaengchart *et al.* [20] used 400 sample size to investigate. Therefore, we adopted a sample size requirement of 400 valid cases, which is sufficient for our SEM analysis.

A self-administered questionnaire was used as the instrument for data collection in this study. The questionnaire consisted of two parts. The first part collected demographic data, while the second part included 32 items to measure the constructs. All scale items were adopted from previous research published in top-tier journals, which have been tested and validated. Item-anxiety of job replacement (AJR1), was removed due to low factor loading. To validate the measurement instrument of this study, a review was conducted by two experts in the field of educational technology to assess the content validity of the scale. Here are the variables, the number of items, and the reference sources for the scale items used in this research: first, the intention to use AI has 4 items, and perceived usefulness of AI also has 4 items, adopted from Chai *et al.* [21]. Second, AI anxiety factors include: sociotechnical blindness with 6 items, and job replacement with 4 items, adopted from An *et al.* [15]. Third, supportive environmental factors encompass social factors and facilitating conditions, each with 4 items, adopted from Venkatesh *et al.* [22]. Lastly, self-efficacy has 6 items, adopted from Chen *et al.* [13]. The survey employed a 5-point Likert scale, ranging from 1 to 5 (1 representing strongly disagree and 5 representing strongly agree).

3.2. Data analysis: measurement validity and reliability

Before conducting the final SEM path analysis, all four stages of data analysis: i) exploratory factor analysis (EFA); ii) confirmatory factor analysis (CFA); iii) validity and reliability analysis; and iv) SEM —were successfully performed using AMOS SPSS version 23. First, we tested for sample adequacy with the Kaiser–Meyer–Olkin (KMO) test, which showed an overall value of approximately .9, exceeding the acceptable threshold of .6 [23], as seen in Table 1. Next, we evaluated the construct validity—discriminant and convergent validity- to confirm the measurement instruments. Discriminant and convergent validity were established through EFA and CFA factor loadings (>.5) using principal component analysis in SPSS and maximum likelihood output in AMOS.

Additionally, validity was supported by average variance extracted (AVE) and composite reliability (CR). One item, AJR1–Job replacement, was removed due to a low factor loading. For acceptable levels of validity and reliability, Hair *et al.* [24] recommended thresholds of CFA and AVE>.5, and CR>.7, both were satisfied in this study, as presented in Table 2 and Figure 2. Several fit indices were also used to assess the model's goodness of fit in Tables 3 and 4, including Chi-square minimum/degree of freedom (CMIN/DF)<5, root mean square error of approximation (RMSEA)<.10, goodness of fit index (GFI)>9, comparative fit index (CFI)>.90, Tucker–Lewis index (TLI)>.90, among others, following criteria from Meyers *et al.* [25]. Data analysis was performed using AMOS 23.0 graphical software. All fit criteria were met, indicating no issues with validity or reliability in the construct of this study.

Table 1. KMO and Bartlett's test

KMO measure of sampling adequacy		.841
Bartlett's test of sphericity	Approx. Chi-square	12229.587
	df	496
	Sig.	.000

Source: KMO and Bartlett's test, SPSS-23 output

Table 2. Rotated component matrix, CFA: extracted from (SPSS-23) pattern matrix

Variables	Factors 1	2	3	4	5	6	7
ASE4	.919						
ASE5	.917						
ASE6	.887						
ASE3	.877						
ASE2	.821						
ASE1	.719						
AJR3		.885					
AJR4		.883					
AJR5		.877					
AJR2		.868					
AJR6		.865					
SESF3			.918				
SESF2			.907				
SESF1			.904				
SESF4			.898				
SEFC2				.919			
SEFC4				.915			
SEFC1				.905			
SEFC3				.894			
ABI2					.839		
ABI1					.829		
ABI3					.811		
ABI4					.780		
ASB3						.862	
ASB2						.854	
ASB1						.803	
ASB4						.800	
PU3							.844
PU1							.770
PU4							.749
PU2							.695

Note. Extraction method: principal component analysis.
Rotation method: varimax with Kaiser normalization.
a. Rotation converged in 6 iterations.

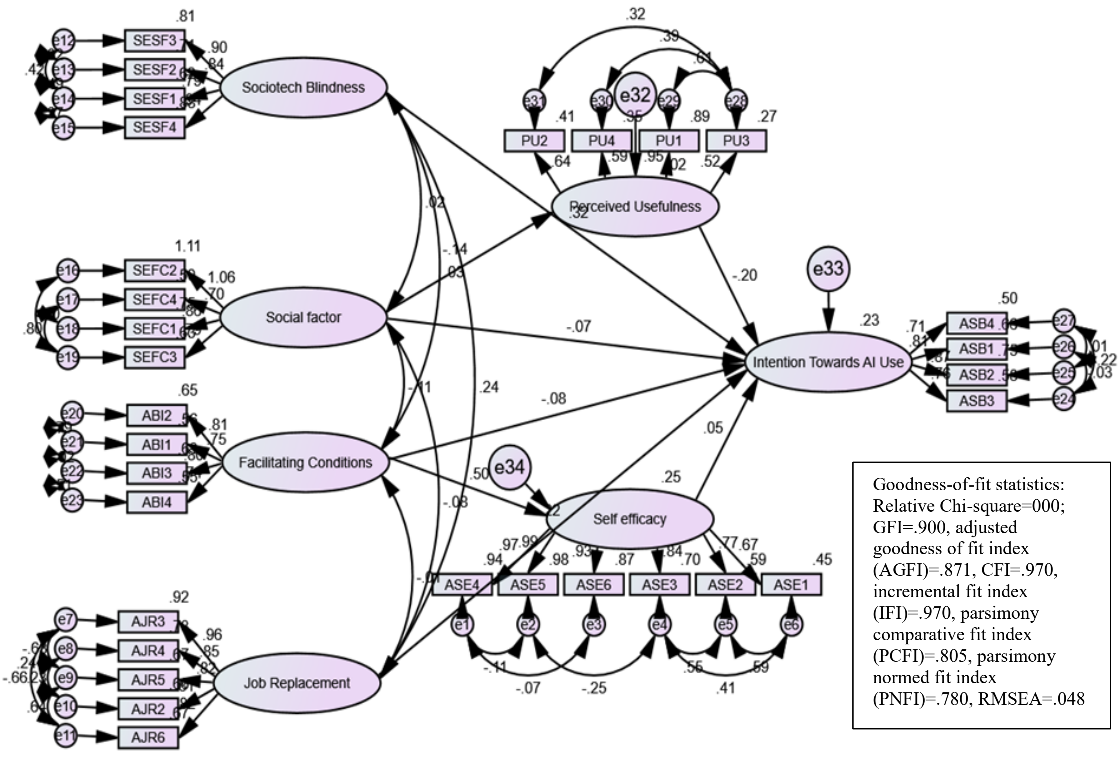

Figure 2. Path analytical model of the study

Table 3. Model validity measures

Variables	CR	AVE	MSV	MaxR(H)	Self-efficacy	Job replacement	Socio-technical blindness	Social factor	Facilitating conditions	Intention towards AI use	Perceived usefulness
Self-efficacy	.948	.754	.311	.989	.869						
Job replacement	.932	.733	.088	.959	.060	.856					
Sociotechnical blindness	.918	.737	.114	.947	.043	.221***	.859				
Social factor	.921	.749	.024	1.679	-.051	-.082†	.019	.865			
Facilitating-conditions	.856	.599	.274	.870	.489***	-.028	.057	-.121*	.774		
Intention towards AI use	.866	.619	.114	.879	-.064	.296***	.338***	-.042	-.118†	.787	
Perceived usefulness	.806	.519	.311	.906	.558***	.045	.184**	-.155**	.523***	-.126*	.721

Validity concerns: no validity concerns here. Extracted from master validity tool, AMOS plugin.
Significance of correlations: †p<.100; *p<.050; **p<.010; ***p<.001. Source: thresholds from Hu and Bentler [26].
"Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives SEM" [26].

Table 4. Statistical results for evaluating the overall model goodness of fit

	Absolute			Relative			Parsimonious	
Indices	Criteria value	Results	Indices	Criteria value	Results	Indices	Criteria value	Results
Chi-square	p>.05	.000	CFI	>.90	.970	PCFI	>.50	.805
CMIN/DF	<5.0	1.903	TLI	>.90	.964	PNFI	>.50	.780
GFI	>.90	.900	IFI	>.90	.970			
AGFI	>.80	.871						
RMSEA	<.10	.048						

Goodness of fit criteria adapted from Meyers *et al.* [25]

4. RESULTS

4.1. Demographic profile of the respondents

A total of 400 data points collected from undergraduate students in Bangkok, Thailand, were eligible for analysis in this study. From the results, most of the respondents were male. Though the difference between the genders was inconsequential. The male respondents were 54.26%, whereas the females were 45.75% female, respectively. Moreover, most of the respondents were sophomores, accounting for 51% of the respondents, followed by the juniors 28.75%, freshmen 18%, and a small fraction of the seniors 2.25%. In addition, the respondents were mostly in the business administration major, accounting for 72.25%, followed by engineering majors 25.75%, and science and tech majors 2%. Figure 2 presents the output of path analysis for the model of the study. The output was extracted from SEM (AMOS-23) and subsequent section explained the causal effect of the variables in detailed.

4.2. Summary of result

As shown in Table 5, the result of the data analysis showed that sociotechnical blindness, the fear of job replacement by AI, and their perceived usefulness influenced students' intention to use GAI. However, self-efficacy in learning AI, the social factor, and the facilitating conditions were found to be statistically insignificant; thus, they were not critical factors influencing students' intention to use GAI. Unexpectedly, the social factor influences the perceived usefulness of GAI, while the facilitating conditions similarly influenced self-efficacy in learning GAI. Although social factors and facilitating conditions were insignificant in predicting students' intention to use GAI directly, they showed a positive relationship with perceived usefulness and self-efficacy in learning AI. The implication will be discussed.

Table 5. Summary of results from the hypothesis testing extracted (AMOS-23)

Hypothesized relationship			Standardized estimates (β)	Significance	Findings
H_1: Sociotechnical blindness	→	Intention to use GAI	.261	***	Supported
H_2: Job replacement	→	Intention to use GAI	.159	***	Supported
H_3: Social Factor	→	Intention to use GAI	.080	.123	Not supported
H_4: Facilitating conditions	→	Intention to use GAI	.034	.247	Not supported
H_5: Perceived usefulness of AI	→	Intention to use GAI	-.653	.003	Supported
H_6: Self-efficacy in learning AI	→	Intention to use GAI	-.087	.361	Not supported
H_7: Social Factor	→	Perceived usefulness of AI	-.048	.041	Supported
H_8: Facilitating conditions	→	Self-efficacy in learning AI	.579	***	Supported

Note: significance of regression weight: †p<.100, *p<.050, **p<.010, ***p<.001 two-tailed

5. DISCUSSION

Anxiety associated with using GAI, which included sociotechnical blindness and job replacement, was the main factor influencing students' intention in this present study and in the Thai context. First, H_1: sociotechnical blindness and intention to use GAI were statistically significant (β=.261, p<.001). Secondly, H_2: job replacement and intention to use GAI were statistically significant and crucial factors in fostering students' intentions to learn AI (β=.159, p<.001). These were consistent with previous research [12], [13], [27], [28]. This result implies that anxiety associated with using GAI, such as sociotechnical blindness and job replacement are very crucial determinant factor in the minds of the younger generation. The practical implication is that the students expressed a genuine concern about their future jobs and the skills needed to fill the positions. Also, the findings indicate that students are concerned about privacy issues, such as the leakage of personal information, arising from AI technology, which can lead to psychological pressure and anxiety. Hence the need for stakeholders' intervention.

Subsequently, H_3 and H_4: supportive environments, which include social factors and the facilitating conditions, were statistically insignificant in this study. The social factor, H_3 (β=.080, p>.10) and the facilitating conditions, H_4 (β=.034, p>.10), respectively. These findings concurred with Ursavaş *et al.* [29]. Also, Wang *et al.* [12] discovered that social norms were unsatisfactorily predictive of students' intentions to use AI in China. These findings suggested that social influence is not significantly associated with the intention to use GAI in the Thai university context. However, several studies [15], [30], [31] found that subjective factors had an influence on students' intentions to use GAI tools. To that regards, another findings [30], [31] suggested that social factors (subject norms) positively influence users' behavioral intentions to use ChatGPT. Moreover, the facilitating conditions' effect on students' intention to use GAI was insignificant in this study. This result supported the findings of Choe and Woo [14] which revealed that facilitating conditions were not significantly linked to the intention to use GAI. However, Wang *et al.* [1] found that facilitating conditions have a positive relationship with intention. Additionally, Kelly *et al.* [32] revealed that supportive environmental factors, both social and facilitating conditions, were crucial in fostering students' intentions to use GAI. The theoretical implication is that the AI in education phenomenon is inconclusive. The theories and variable cannot be generalized, for instance in the context of Thai university students, our study results challenge the traditional assumptions about social pressures influencing technology adoption intention. Contrary to popular belief, supportive environments are not the most significant factors in students' intention to use GAI. Instead, the anxiety students felt, both on the societal level and regarding the potential replacement of human labor and its impact on their future job prospects, played a much more significant role. While social pressure or university policies, whether positive or supportive, were not as pressing concerns for students, the anxiety they experienced was a major factor in their decision-making process. This enriches the ongoing literature to add new knowledge from different perspectives.

Successively, the impact of perceived usefulness of GAI on students' intention to adopt the AI technology is statistically significant and negative, H_5 (β=-.653, p<.001). This result aligned with several recent studies [1], [33], [34]. However, Almogren *et al.* [30] results found relationship between trust in ChatGPT and perceived usefulness, were not significant factors for students intentions. Furthermore, other researchers have found a weak and insignificant relationship between perceived usefulness and the intention to use GAI [31]. Additionally, Makkonen *et al.* [35] analysis revealed an insignificant effect between perceived usefulness and the intention to continue using GAI at work. Despite the contradictory results, overwhelming research supports the viewpoint presented in our findings. From practical implication viewpoint, these findings implies that Thai university students are considering adopting GAI or any new technology because they believe it will enhance their study activities and help them prepare for future jobs, rather than being influenced by social pressure or the university environment. This shows the real intentions of students and will help university policy makers in shaping the right policy framework to enhance the adoption. Furthermore, according to the results, H_6: self-efficacy in learning GAI on students' intention to adopt the AI technology is statistically significant and negative (β=-.087, p<.1). These findings support the results of [12], [21], [36]. This indicates that Thai students' interest in learning GAI to gain more knowledge of the new technology is negatively related to their interest in adopting it. This might be due to AI anxiety, as the more knowledge they gain about AI and the more threatened they feel about their future job prospects, the less likely they are to develop a positive intention to use GAI. This has both theoretical and practical implication; theoretically, it added a new knowledge about the AI concepts from literature. The newer technology springs up the more the students need to catch up with the trends thereby putting enormous pressure on them. This requires more research for inadept understanding. On the practical implication, it reveals the need to address AI anxiety in the university curriculum.

The result of H_7 and H_8 had a statistical significance. H_7: social factor had a significant negative influence on the perceived usefulness of AI (β=-.048, p<.050), and H_8: facilitating conditions' influence on self-efficacy in learning AI were statistically significant (β=.579, p<.001). Despite the contradictory results of our findings on supportive environmental factors, i.e., social factors and facilitating conditions on students intention to use GAI; supportive social factor on perceived usefulness of AI, and the facilitating conditions on self-efficacy results were consistent with previous research [12], [13], [22], [27], [28]. Also, this study provides evidence that supportive environments, such as friends in the university, motivate students to recognize the benefits of using GAI to complete school assignments more quickly and efficiently. The findings implies practically that supportive university facilities and clear policies on the ethical use of GAI in school assignments and projects serve as motivating factors for students to learn and educate themselves about AI technology. Additionally, these results underscores the theoretical implication of the importance of creating an enabling and supportive learning environment that provides students with adequate resources, training, and technical assistance to foster their intentions to learn and use GAI [32]. Moreover, our study reveals that students with a high level of social support from the university environment are more likely to perceive the usefulness of GAI. Furthermore, conducive, supportive, and readily available learning conditions contribute to an increase in students' self-efficacy in learning AI.

This study identified two instances of mediating effects. First, it examined whether perceived usefulness and a social factor mediated the path from perceived usefulness to behavioral intention to use GAI. Table 6 shows that the total and direct effects were not statistically significant, but the indirect effect was. Second, it examined whether self-efficacy and facilitating conditions mediated the path from self-efficacy to behavioral intention to use GAI. Table 6 reveals that the total and direct effects were not statistically significant, but the indirect effect was. These results suggested the presence of an indirect mediation effect on both paths, indicating a partial mediating effect. These results aligned with Wang *et al.* [12]. It suggested that while supportive environments, such as social factors and facilitating conditions, did not directly influence students' intention to use GAI, social influence from classmates, friends, and university policies supporting facilities played a crucial role in shaping students' perceptions of learning to use GAI. These policies emphasized the importance and usefulness of GAI in completing school tasks effectively and efficiently.

Table 6. Mediation analysis results

Path					Effect type	Point estimate	Mediation type
Social factor	→	Perceived usefulness of AI	→	Intention to use GAI	Total effect	-.136	Partial (indirect mediation)
					Indirect effect	.000	
					Direct effect	-.136	
Facilitating conditions	→	Self-efficacy	→	Intention to use GAI	Total effect	.500	Partial (indirect mediation)
					Indirect effect	.000	
					Direct effect	.579	

Note: significance of regression weight: † p<.100, * p<.050, ** p<.010, *** p<.001 two-tailed.

5.1. Limitations and recommendations for further studies

This study has several limitations. First, the sample was limited to undergraduate students in Bangkok, which restricts the generalizability of the findings. Future research should include participants from other provinces, regions, and ASEAN countries to capture broader cultural and educational differences. Second, the study employed a quantitative design based on a specific conceptual model, which may have excluded other relevant factors influencing AI anxiety and GAI adoption. Incorporating additional behavioral, psychological, or contextual variables in future models would strengthen explanatory power. Finally, because perceptions of AI may vary across demographic groups and educational environments, further comparative studies are needed to better understand AI anxiety and adoption intentions. Such research would provide more robust evidence to guide policymakers and stakeholders in developing effective AI integration strategies across diverse educational contexts.

5.2. Research novelty contribution

This study advances the literature on GAI adoption in higher education by uncovering a set of counterintuitive relationships that challenge dominant acceptance models. While prior research frequently identifies social influence, subjective norms, and institutional support as primary drivers of students' technology adoption [22], [29], the present findings demonstrate that these supportive environmental factors do not significantly predict Thai university students' intention to use GAI. Instead, the study reveals that AI related anxiety—particularly fears of sociotechnical blindness and job replacement—emerges as the strongest determinant of adoption intention, marking a clear departure from conventional assumptions embedded in technology acceptance model (TAM), unified theory of acceptance and use of technology (UTAUT), and AI in education frameworks.

A further novel contribution lies in the negative association between both perceived usefulness and self-efficacy with intention to adopt GAI. This contradicts the foundational premise of major adoption models, which typically position perceived usefulness and self-efficacy as positive and robust antecedents of behavioral intention. The findings suggest that increased knowledge of AI and heightened awareness of its societal and labor market implications may amplify anxiety and suppress adoption intention, a phenomenon rarely documented in prior studies and insufficiently theorized in existing frameworks. Additionally, the study distinguishes between direct and indirect effects of supportive environmental factors. Although social influence and facilitating conditions do not directly predict intention, they significantly shape perceived usefulness and self-efficacy, indicating an important, previously underexplored mediating role. This nuance contributes to theoretical refinement by demonstrating that supportive environments matter, but not in the straightforward manner traditionally assumed.

Taken together, these contributions provide new empirical evidence from the underrepresented Thai higher education context, challenge long standing assumptions in technology adoption theory, and highlight the central role of AI related anxiety as a psychological barrier to GAI adoption. The findings call for a reconsideration of existing theoretical models and underscore the need to integrate emotional and sociocognitive dimensions—particularly AI anxiety—into future frameworks explaining student engagement with emerging AI technologies. Therefore, we recommend that, a targeted initiative—such as integrating AI-focused learning activities, ethical discussions, and skill-building modules into the curriculum—can enhance students' awareness of AI's capabilities and limitations and foster more positive attitudes toward GAI. By addressing anxieties and improving perceived usefulness, educational institutions can better support responsible and effective AI adoption. As educators play a central role in shaping future generations, developing clear pedagogical strategies and supportive policies is essential for preparing students to engage with AI-driven learning environments.

6. CONCLUSION

Conclusively, this study advances the understanding of GAI adoption in higher education by providing empirical evidence that challenges core assumptions of dominant technology acceptance models. Based on the findings of this study, which shows a different viewpoint from the Thai university students' context, the results show that social influence, subjective norms, and institutional support do not directly predict students' intention to use GAI, contradicting earlier research grounded in TAM, UTAUT, and related frameworks. Instead, AI-related anxiety—particularly concerns about sociotechnical blindness and job displacement—emerges as the strongest determinant of adoption intention, while the unexpected negative effects of perceived usefulness and self-efficacy suggest that increased awareness and competence may intensify critical reflection and anxiety rather than encourage use. At the same time, the study refines existing theories by demonstrating that supportive environmental factors exert indirect effects through perceived usefulness and self-efficacy, underscoring a more nuanced and mediated adoption process. Collectively, these findings move the literature forward by repositioning emotional and sociocognitive factors, especially AI anxiety, at the center of GAI adoption research and highlighting the need to reconceptualize acceptance frameworks to better reflect the complexities of emerging, socially disruptive technologies in higher education.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

INFORMED CONSENT

We obtained informed consent from all individuals for the study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [SNA].

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