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Behavioral Intention to Adopt Artificial Intelligence for Teaching in Higher Education: A Case Study in Vietnam

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Abstract: This research paper investigates the behavioral intention of lecturers to embrace Artificial Intelligence (AI) for teaching in higher education settings within Vietnam. As the global education landscape continues to evolve, integrating AI technologies into pedagogical practices has garnered significant attention. Drawing upon the two frameworks of Cognitive Appraisal Theory (CAT) and the Artificially Intelligent Device Use Acceptance (AIDUA) model with adaptations, this study examines the willingness to adopt AI-driven technology in teaching of Vietnamese lecturers. The study has collected 309 valid responses from Vietnamese lecturers and employed structural equation modeling (SEM) for a thorough analysis of data. The research identifies that literacy has the strongest impact on both performance and effort expectancy, though positively and negatively. Furthermore, it establishes that both performance expectancy and effort expectancy serve as antecedents to the generation of positive emotions, which ultimately contribute to the formation of the behavioral intention to adopt AI for teaching among lecturers in higher education. The insights derived from this research hold immense value for policymakers, educational technology developers, as well as researchers and instructors seeking to facilitate the widespread adoption of AI-based teaching methods in Vietnamese higher education. By doing so, this research contributes to enhancing the quality of education, fostering innovative teaching practices, and ultimately advancing the educational landscape in Vietnam.
Keywords: Artificial intelligence, Behavioral intention, Higher Education, AI in higher education

1. Introduction

In recent years, the adoption of Artificial Intelligence (AI) in higher education has emerged as a global trend, reshaping pedagogical practices, and enhancing the learning experience (Jung, 2019). The rapid advancements in AI technologies offer the potential to revolutionize teaching and learning, making education more personalized, efficient, and accessible. Vietnam, a nation with a burgeoning higher education sector characterized by substantial enrollment growth and a strong commitment to technological innovation (Nguyen, 2020), is no exception to this transformative wave.

Vietnam's higher education landscape is marked by a diverse range of institutions, from traditional universities to private institutions (Tran, 2018). As the demand for higher education continues to rise, educators and policymakers face the challenge of ensuring quality education while managing the increasing student population. Integrating AI into the teaching process has the potential to address some of these challenges by offering personalized learning experiences, automating administrative tasks, and facilitating data-driven decision-making (Duong, 2021).

Furthermore, the Vietnamese government has expressed a keen interest in harnessing the power of AI to drive economic growth and development (Gia Linh, 2023). Initiatives like the National Strategy on the Fourth Industrial Revolution and the establishment of AI research centers underscore the country's commitment to advancing AI technologies. In this context, understanding the behavioral intention of educators in Vietnamese higher education institutions to adopt AI for teaching becomes a crucial area of investigation.

In short, the motivation behind this research stems from the convergence of several factors. Firstly, the global trend of AI adoption in higher education calls for a deeper examination of how this technology is being embraced in diverse cultural and educational contexts (Wu et al., 2019). While there is a growing body of literature on AI adoption in Western countries, limited empirical research has focused on the unique challenges and opportunities presented by the Vietnamese higher education landscape. Secondly, the potential implications of AI adoption in Vietnamese higher education are far-reaching, encompassing changes in teaching methodologies, student engagement, and administrative efficiency. Investigating the behavioral intention of educators to adopt AI will provide valuable insights for educational policymakers and institutions seeking to align their strategies with the evolving educational landscape.

The adoption of Artificial Intelligence (AI) in higher education has garnered significant attention from researchers worldwide, leading to a growing body of literature exploring various aspects of this phenomenon. Artificial Intelligence (AI) has opened up exciting possibilities and presents compelling challenges in the context of higher education. The adoption of AI has been recognized as a means to enhance the efficiency and effectiveness of higher education governance (Okebukola, 2019). In the context of applying AI to higher education, AI can be conceptualized as computational systems capable of emulating human-like processes, including adaptation, learning, synthesis, correction, and data utilization for complex tasks (Porayska-Pomsta, 2015). The transformative potential of AI is expected to benefit a wide spectrum of stakeholders, including students, teachers, administrative staff, and researchers (George and Wooden, 2023). This recognition of AI's potential has spurred a need for the motivation and adoption of this modern technology, with the expectation that it will contribute to the overall development of higher education (Kromydas, 2017).

Furthermore, the pursuit of enhancing educational quality is a shared goal across both developed and developing countries. The adoption of modern technologies, such as AI, is viewed as a viable means to achieve this objective (Xu et al., 2021). The integration of AI applications can modernize assessment systems and enable a more comprehensive evaluation of students' capabilities, providing valuable insights for their educational journey (Adiguzel et al., 2023). Governments worldwide have recognized the importance of expanding investments to advance higher education through the application of modern technologies like AI (Elengold, 2019). It is believed that such investments can significantly contribute to the improvement of the quality of higher education (Kromydas, 2017).

Studies have consistently shown that learning with the aid of AI can yield more effective results compared to traditional teacher-centric settings (Grassini, 2023). The key question, however, pertains to aligning the acceptance attitudes of potential users towards AI adoption. User acceptance of modern technology, including AI, is a critical research area in contemporary Information Technology literature (Williams et al., 2009). While several theories and models explain the intention of potential users to adopt innovative technology, the Unified Theory of Acceptance and Use of Technology (UTAUT) has demonstrated its robustness by explaining a substantial variance in behavioral intention (Venkatesh et al., 2003). Consequently, the UTAUT model has been frequently utilized by researchers, sometimes with adaptations and modifications, to interpret the intention of users to adopt modern technology like AI in various contexts (Barrane et al., 2018).

Understanding the factors that influence the behavioral intention of educators to adopt AI in teaching is essential. Several studies have identified key determinants in this context. According to Venkatesh et al. (2003), the Technology Acceptance Model (TAM) provides a useful framework for assessing the adoption of technology, including AI. TAM posits that perceived ease of use and perceived usefulness significantly affect an individual's intention to use technology. Educators' perceptions of AI's ease of integration into their teaching methods and its potential benefits for enhancing pedagogy are thus crucial factors in their adoption decisions. Moreover, the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2007) extends the TAM model by incorporating additional constructs such as social influence and facilitating conditions. In the context of higher education, institutional support and colleagues' influence play significant roles in shaping educators' attitudes toward AI adoption (Chen et al., 2018). These factors highlight the importance of considering both individual and organizational aspects when studying AI adoption in educational settings.

Moreover, research on the impact of AI in teaching and learning has shown promising results. AI-powered tools, such as intelligent tutoring systems, personalized learning platforms, and automated assessment tools, have the potential to enhance student engagement and improve learning outcomes (Wang et al., 2020). For example, AI can adapt content and teaching strategies to individual student needs, offering personalized learning experiences (Wu et al., 2019). Additionally, AI-driven analytics can provide educators with valuable insights into student performance and identify areas where intervention is needed (Baker & Inventado, 2014). This data-driven approach can inform pedagogical decisions, enabling educators to tailor their teaching methods to better meet students' needs.

In conclusion, while the literature on AI adoption in higher education is growing, a noticeable gap exists in the context of Vietnam. Most studies have focused on Western and developed Asian countries, leaving a dearth of empirical evidence on AI adoption in Vietnamese higher education institutions. This research aims to address this gap by conducting a case study in Vietnam, where cultural, institutional, and technological factors may differ significantly from those in Western contexts.

2. Theoretical framework

In the context of higher education, the adoption of AI has emerged as a transformative and promising phenomenon. However, as the adoption of AI technology in this realm is a complex and multifaceted process, it necessitates robust theoretical frameworks to guide the research. While existing studies have primarily relied on established frameworks like the TAM and the UTAUT, it is important to recognize their inherent limitations and consider alternative frameworks that may offer a more nuanced understanding of AI adoption in the unique context of Vietnam. The TAM, initially developed by Davis in 1989, primarily focuses on the perceived ease of use and perceived usefulness of technology as determinants of an individual's intention to use it (Davis, 1989).

While TAM has been influential in understanding technology adoption, it has limitations when applied to the context of AI adoption in higher education. TAM predominantly addresses cognitive aspects and often underestimates the role of societal and emotional factors which can significantly influence AI adoption (Venkatesh & Bala, 2008). Similarly, the UTAUT, though incorporating additional constructs such as social influence and facilitating conditions (Venkatesh et al., 2003), primarily focuses on individual and organizational aspects and may not adequately consider the significance of AI literacy and prior experience with AI-based technology in shaping AI adoption decisions. In the context of higher education, the authors believe that educators' decisions to adopt AI are influenced not only by their individual perceptions but also by societal expectations, institutional support, and the level of their AI literacy and prior experience with AI-based technology.

Considering the limitations of these dominant models, this research proposes the integration of alternative frameworks, specifically Cognitive Appraisal Theory (CAT) and Artificially Intelligent Device Use Acceptance (AIDUA), to provide a more comprehensive understanding of AI adoption by lecturers in Vietnamese higher education.

The CAT delves into the cognitive and emotional aspects of decision-making processes (Lazarus, 1991a, 1991b). In the context of AI adoption, it allows us to explore not just the perceived ease and usefulness of technology but also the emotional and cognitive appraisal of AI adoption, which is critical in understanding how lecturers in Vietnam perceive the challenges, opportunities, and emotional aspects of incorporating AI into their teaching practices.

The AIDUA model, meanwhile, offers a focused perspective on AI devices' acceptance and usage (Gursoy et al., 2019). Given that AI in education often involves specific tools or technologies, AIDUA can provide valuable insights into lecturers' attitudes, beliefs, and their significance to acceptance.

By incorporating CAT and AIDUA alongside TAM and UTAUT, this research seeks to provide a more comprehensive and holistic framework that considers not only the rational factors but also the societal, psychological, and emotional aspects of AI adoption, which may be especially pertinent in the Vietnamese higher education context.

3. Hypotheses development & Proposal of Research model

Building upon Lazarus's well-established framework, this study proposes a three-stage process to explore lecturers' willingness to adopt AI-based technology for teaching in higher education, as depicted in Figure 3.1.

***Primary appraisal**

The primary appraisal stage involves lecturers' assessment of the relevance and significance of incorporating AI technology into their teaching practices. Within this stage, three critical factors come into play: social influence, hedonic motivation, and AI literacy. Two of these factors (social influence and hedonic motivation) align with the principles of AIDUA (Gursoy et al., 2019), emphasizing that individuals initially evaluate the pertinence and importance of integrating AI technology into their teaching methods.

In the realm of higher education, social influence takes on a unique perspective, denoting the extent to which a lecturer's social circles, encompassing family, friends, and colleagues, perceive the integration of AI devices into teaching as pertinent and aligned with communal norms (adapted from Gursoy et al., 2019). This notion resonates with Social Impact Theory (Latané, 1981), which posits that individuals are more inclined to conform to group norms when the group holds significance in their lives. In the context of AI adoption for teaching, the importance of this concept becomes evident. Moreover, adhering to Hogg (2016), the adoption of a group's behavioral norms strengthens the sense of belongingness and attachment that individuals feel toward that particular group. Consequently, if a lecturer's social network expresses favorable opinions and attitudes regarding the use of AI devices in teaching, while also recommending such adoption, it not only benefits the lecturer's personal identity but also fosters a deeper connection to their social circle. One aspect of this attitude formation pertains to the performance expectancy associated with AI devices, reflecting the lecturer's belief in the benefits that can be derived from their utilization (adapted from Gursoy et al., 2019).

Therefore, the authors posit the following hypothesis:

H1: Social Influence is positively related to lecturers' Perceived Performance Expectancy of AI-based technology in teaching

In our investigation of AI adoption among lecturers in higher education, we consider an additional dimension of attitudes, which is "effort expectancy". Effort expectancy, in the study's context, pertains to the perceived level of difficulty associated with using AI devices for teaching. Within the framework inspired by Lazarus, we propose that social influence plays a crucial role in shaping lecturers' perceptions of effort expectancy.

The constructs of social influence, at times referred to as subjective norms, and perceived difficulty have garnered substantial attention in empirical studies across various contexts (Ghalandari, 2012; Escobar-Rodríguez et al., 2014; Chua et al., 2018). Specifically, we posit that if a lecturer's social circles exhibit favorable opinions and believe that AI devices are easy to use for teaching, then the lecturer is less likely to perceive these devices as challenging to employ.

Therefore, the authors posit the following hypothesis:

H2: Social Influence is negatively related to lecturers' Perceived Effort Expectancy of AI-based technology in teaching

The concept of hedonic motivation refers to the perception of enjoyment or pleasure one anticipates experiencing during the adoption of AI devices (Gursoy et al., 2019). In the study's context, it refers to the lecturers' perceived enjoyment or pleasure derived from utilizing AI-based technology in their teaching practices. This construct has been acknowledged as a prominent predictor of technology acceptance behavior, as opined by Ventakesh et al. (2012); Baabdullah et al. (2019). In this essence, the authors deem that when a lecturer possesses a hedonic motivation towards AI devices, using such technology becomes a source of personal gratification, fulfilling their need for novelty and entertainment in the teaching process.

Therefore, the authors posit the following hypothesis:

H3: Hedonic Motivation is positively related to lecturers' Perceived Performance Expectancy of AI-based technology in teaching

Additionally, in line with the research on motivation and task difficulty, which indicates that motivation interacts with the perceived difficulty of a task (Humphreys & Revelle, 1984), we propose that highly motivated lecturers are less likely to perceive the use of AI devices in teaching as a challenging endeavor. Several studies have validated this relationship between motivation and the perceived level of difficulty or effort expectancy associated with a task (Capa et al., 2008; Mazeres et al., 2021).

Therefore, the authors posit the following hypothesis:

H4: Hedonic Motivation is negatively related to lecturers' Perceived Effort Expectancy of AI-based technology in teaching

In the traditional model of AIDUA, the third construct introduced in primary appraisal is anthropomorphism, which refers to the extent to which an object or entity possesses human-like attributes, which may include physical appearance, self-awareness, and emotional qualities (Kim & McGill, 2018). However, in the context of this study focused on AI adoption in higher education, we propose to replace this construct with (AI) literacy due to its strong relevance within the educational context. (AI) Literacy is an essential construct that aligns well with the educational landscape and has been acknowledged in previous studies of technology acceptance in educational settings (Nikou & Aavakare, 2021; Chai et al., 2022). In the context of this study, (AI) literacy is defined as the lecturer's capacity to understand, adapt, and effectively utilize AI-based technology in their teaching practices.

Prior research has emphasized the role of literacy in shaping perceptions of technology performance. Extensive literature in the field of technology adoption underscores that an individual's literacy or proficiency in using a technology is a strong predictor of their belief in its ability to enhance their performance. For instance, Nikou and Aavakare (2021) found that technology literacy significantly influences perceived performance in educational technology adoption. Lecturers with higher (AI) literacy levels are more likely to comprehend the capabilities of AI technology and how it can be applied effectively in their teaching practices, thereby bolstering their perceived performance expectations.

Therefore, the authors posit the following hypothesis:

H5: Literacy is positively related to lecturers' Perceived Performance Expectancy of AI-based technology in teaching

Furthermore, drawn from research highlighting the compensatory nature of motivation and literacy when confronted with increased task difficulty, the authors propose that lecturers who possess a stronger literacy foundation are less likely to perceive the use of AI technology as burdensome and challenging. This is consistent with the findings of Nikou and Aavakare (2021), who revealed that technology literacy can mitigate perceived effort expectancy in educational technology adoption, indicating that proficiency eases the adoption process.

Therefore, the authors posit the following hypothesis:

H6: Literacy is negatively related to lecturers' Perceived Effort Expectancy of AI-based technology in teaching

***Secondary appraisal**

Following this primary appraisal, lecturers who perceive the use of AI technology as relevant and significant proceed to a deliberate evaluation of the benefits and costs associated with AI adoption. This evaluation centers around two key components: their expectations of AI technology's performance (performance expectancy) and the effort they anticipate investing (effort expectancy) in its use. These two factors are identified in this study as the primary constructs guiding customers' assessment of the costs and benefits of the use of AI-based technology. These constructs are instrumental in shaping customers' emotions toward AI devices, echoing the insights provided by Gursoy et al. (2019). As discussed earlier, it's essential to note that these expectations are also subject to influence by a lecturer's pre-existing attitudes concerning AI-based technology. If lecturers initially hold negative perceptions of AI devices during the primary appraisal process, these negative evaluations can be further amplified by higher levels of effort expectancy, which contribute to the reinforcement of their existing negative attitudes. Conversely, higher levels of performance expectancy can mitigate these negative perceptions and attitudes, offering a more positive emotion on AI-based technology adoption in teaching.

Therefore, the authors posit the following hypothesis:

H7: Perceived Performance Expectancy has a positive impact on generation of positive emotion

In the context of utilizing AI-based technology for teaching in higher education, it's essential to acknowledge that such usage may potentially introduce significant communication barriers between lecturers and AI-based technology (adapted from Lu et al., 2019). If lecturers believe that integrating AI-based technology into their teaching will demand a substantial amount of effort, it's likely to generate negative emotions within the framework of CAT. This suggests that the perceived level of effort required in AI-based technology utilization can influence lecturers' emotional responses.

Therefore, the authors posit the following hypothesis:

H8: Perceived Effort Expectancy has a negative impact on generation of positive emotions toward the use of AI-based technology in teaching

***Outcome**

Subsequently, the emotions experienced by lecturers in their interactions with AI technology play a pivotal role in determining their willingness to accept or object to its use in the teaching process. Positive emotions foster greater acceptance, while negative emotions may lead to resistance. This outcome stage reflects the culmination of the three-stage appraisal process and forms the foundation of this study's investigation into lecturers' AI adoption intentions within the higher education context. Consistent with Gursoy et al. (2019), Ribeiro et al. (2021), under the theoretical framework of CAT (in which positive emotions have been proven to impact behaviors) (Lazarus, 1991b), the authors propose the following hypotheses:

H9. Emotion is positively related to lecturers' willingness to accept the use of AI-based technology in teaching

H10: Emotion is negatively related to lecturers' willingness to object the use of AI-based technology in teaching

A synthesis of the above hypotheses shall be presented in Figure 3.1 as follows.

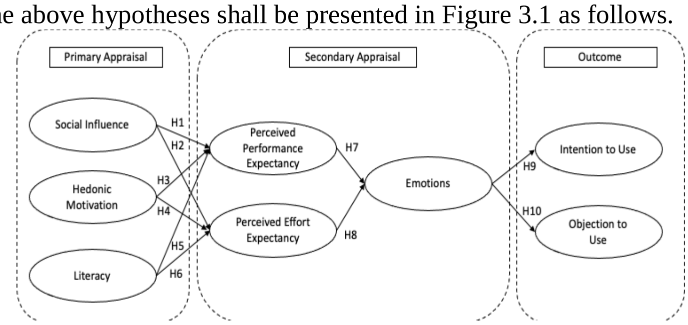

Figure 1: Proposed Research Model(modified from Gursoy et al., 2019)

4. Research methodology

4.1 Research Methodology

In this study, we employ a methodological approach that combines analysis and synthesis to establish our theoretical framework, which is specifically tailored to the context of AI adoption in higher education within Vietnam. We utilize a quantitative research method to gather survey responses from lecturers and educators in

Vietnam who have a specific interest in AI-based technology for teaching. The collected data will undergo thorough statistical analysis using SPSS 20 and AMOS 24 software. Our analysis encompasses a range of statistical procedures, including assessing scale reliability using Cronbach's Alpha coefficient, initial scale validation through exploratory factor analysis (EFA), further scale refinement with confirmatory factor analysis (CFA), and testing the validity of our research model through structural equation modeling (SEM).

4.2 Sampling Methodology

Determining an appropriate sample size is of utmost importance to ensure the study's accuracy and reliability within the educational context of Vietnam. In accordance with recommendations by Hair et al. (1998), we require a minimum sample size of 160 responses due to the 25 observed variables in our study. Additionally, to ensure the effectiveness of our regression analysis, we adhere to Tabachnick et al.'s (1996) suggestion that the sample size should meet the condition: $n \geq 8k + 50$, where n represents the sample size, and k signifies the number of independent variables. Therefore, our study aims to gather a sample size of at least 250.

To obtain this sample, we adopt a convenient sampling technique specifically tailored to select lecturers and educators in Vietnam who are actively engaged in AI-based technology for teaching in higher education. A total of 322 questionnaires are distributed to these educators through online channels. However, we will exclude any questionnaires with unsatisfactory responses, such as identical answers for all questions or nonsensical entries. This meticulous screening process results in a dataset comprising 309 valid questionnaires, forming the basis for our comprehensive data analysis. Data collection is set to commence in July and August 2023, aligning with the unique characteristics of the educational landscape in Vietnam.

4.3 Questionnaire Design

The questionnaire in this study is thoughtfully structured into three distinct sections, aligning with our research focus on AI adoption in higher education within Vietnam.

The initial section is dedicated to gathering crucial demographic data from our survey participants. It covers essential information such as gender, age range, and years of teaching experience. These demographic details are of paramount importance to comprehensively understand the unique characteristics of lecturers and educators actively engaged in the adoption of AI-based technology for teaching.

Moving to the second section, we aim to collect insightful information about the respondents' current knowledge and interest in using AI-based technology in teaching. We have also added questions to screen if respondents have certain past experiences with AI-based technology in teaching.

The third and final section of the questionnaire is designed to encompass 31 crafted questions. These questions directly align with our research model framework, which is tailored to our study's focus on AI adoption in the context of higher education within Vietnam. Respondents are invited to express their levels of agreement using a Likert five-point scale.

The scales employed for our factor analysis have been thoughtfully adapted from previous studies. However, they have undergone significant customization to ensure enhanced compatibility with the unique characteristics of the Vietnamese educational context and the specific nuances related to AI-based technology for teaching. This rigorous adaptation process is aimed at providing a comprehensive and accurate understanding of the attitudes and perceptions of lecturers and educators regarding AI adoption in their teaching practices.

Table1: Measurement scale (authors' compilation)

Construct	Item	Measurement scale	Reference
Social Influence	SI1	"People who influence my behavior would want me to utilize AI-based technology in my teaching profession."	Ventakesh et al. (2012)
	SI2	"People in my social networks who would utilize AI-based technology have a high profile."	Lu et al. (2019)
	SI3	"Using AI-based technology reflects status symbol in my social networks (co-workers, family, friends)"	Lu et al. (2019)
	SI4	"People who are important to me would	Ventakesh et al. (2012)

		encourage me to use AI devices in my teaching profession."	
Hedonic Motivation	HM1	"I presume that using AI-based technology in my teaching profession is fun."	Ventakesh et al. (2012)
	HM2	"I presume that using AI-based technology in my teaching profession is entertaining."	Ventakesh et al. (2012)
	HM3	"I presume that using AI-based technology in my teaching profession is enjoyable."	Ventakesh et al. (2012)
Literacy	LI1	"I can explain how artificial intelligence can be applied effectively in educational settings".	Vatrapu, R., et al., 2018
	LI2	"I am familiar with AI-based tools and technologies that can enhance teaching and learning."	Radu, I., et al., 2018
	LI3	"I have experience integrating AI-based tools into my teaching activities."	Dillenbourg, P., et al., 2018
	LI4	"I can effectively monitor and evaluate the impact of AI-based technology in teaching on student outcomes."	Dillenbourg, P., et al., 2018
	LI5	"I can design and implement pedagogical strategies that leverage AI technology to enhance student learning."	Alpert, S. R., & Haber, J., 2019
Perceived Performance Expectancy	PPE1	"AI-based technology would enhance the accuracy in my teaching activities."	Lu et al. (2019)
	PPE2	"Using AI-based technology would help me to reduce errors in my teaching activities."	Lu et al. (2019)
	PPE3	"Using AI-based technology would help me to provide more consistent teaching activities to my learners."	Lu et al. (2019)
	PPE4	"Information provided by AI-based technology is more consistent."	Lu et al. (2019)
Perceived Effort Expectancy	PEE1	"Using AI-based technology in my teaching profession would take too much of my time."	Lu et al. (2019)
	PEE2	"Working with AI-based technology is so difficult to understand and use in my teaching profession."	Lu et al. (2019)
	PEE3	"It takes me too long to learn how to interact with AI-based technology in my teaching profession."	Lu et al. (2019)

Emotion	EM1	Bored-relaxed	Lu et al. (2019)
	EM2	Melancholic-contented	Lu et al. (2019)
	EM3	Unsatisfied-satisfied	Lu et al. (2019)
	EM4	Annoyed-pleased	Lu et al. (2019)
Intention to Use	IU1	"I would feel happy to interact with AI-based technology in my teaching profession."	Ventakesh et al. (2012)
	IU2	"I am likely to interact with AI-based technology in my teaching profession."	Lu et al. (2019)
	IU3	"I will use AI-based technology in my teaching profession in the near future (less than 1 year)."	Lu et al. (2019)
	IU4	"I will recommend AI-based technology to my colleagues."	Lu et al. (2019)
Objection to Use	OU1	"I believe that using AI-based technology in my teaching activities would reduce the quality of instruction".	Ertmer & Ottenbreit-Leftwich, 2010
	OU2	"I have concerns about the privacy and security of my personal information when AI-based technology is used in my teaching activities".	Huang & Liaw, 2005
	OU3	"I am hesitant to use AI-based technology because I lack the necessary technical skills".	Teo, 2009
	OU4	"I have reservations about the effectiveness of AI-based technology for improving student learning".	Venkatesh et al., 2003

5. Data analysis & Research findings

5.1 Sample characteristics

Table 2 presents information on demographic details of respondents who have participated in the survey questionnaire. Those characteristics hold an implication that the sample size is representative.

Table 2: Demographic information (research result, 2023)

Characteristics		Frequency	Percent
Gender	Male	151	48.9
	Female	156	50.5
	Other	2	0.6
Age range	25 - 44	135	43.7
	45 - 54	126	40.8
	55 - 65	46	14.9
	> 65	2	0.6
Years of teaching experience	< 5	68	22.0
	5 - 10	108	35.0
	10 - 15	96	31.1

Characteristics		**Frequency**	**Percent**
	>15	37	12.0

Table 3 presents information on knowledge and interest of AI-based technology in teaching.

Table 3: Knowledge and Interest of AI-based technology in teaching(research result, 2023)

Contents		Frequency	Percent
Familiarity with AI-based technology in teaching	Not familiar at all	79	25.6
	Somewhat familiar	106	34.3
	Moderately familiar	64	20.7
	Very familiar	60	19.4
Interest in AI-based technology in teaching	Not interested	79	25.6
	Slightly interested	106	34.3
	Moderately interested	64	20.7
	Very interested	60	19.4
Past experiences with AI- based technology in teaching	Yes	61	19.7
	No	248	80.3

5.2 Verification of the proposed model and hypotheses

This study utilized structural equation modeling (SEM) to validate the proposed model and hypotheses, utilizing AMOS 20.0 as the analytical tool. The initial analysis focused on examining the dimensions of components within the research model. Subsequently, a thorough analysis and validation of the research model were conducted. Parameter estimation was carried out using the maximum likelihood method. Model fitness was assessed through both measurement model testing and structural model testing.

b. Testing of the measurement model

The results of Cronbach's alpha reliability analysis and Exploratory Factor Analysis (EFA) are presented in Table 4

Table 4: The results of Cronbach's alpha and EFA analysis(research result, 2023)

Factors	Number of observed variables	Cronbach's Alpha	KMO; Extraction Sums (%)
Social Influence (SI)	4	0.837	0.837; 60.983 %
Hedonic Motivation (HM)	3	0.841	
Literacy (LI)	5	0.874	
Perceived Performance Expectancy (PE)	4	0.806	
Perceived Effort Expectancy (EE)	3	0.868	
Emotions (EM)	4	0.845	
Intention to Use (IU)	4	0.820	
Objection to Use (OU)	4	0.887	

A Confirmatory Factor Analysis (CFA) was performed to assess the quality and appropriateness of the measurement model (Anderson and Gerbing, 1988), aiming to ascertain the reliability, convergent validity, and discriminant validity of the constructs under investigation.

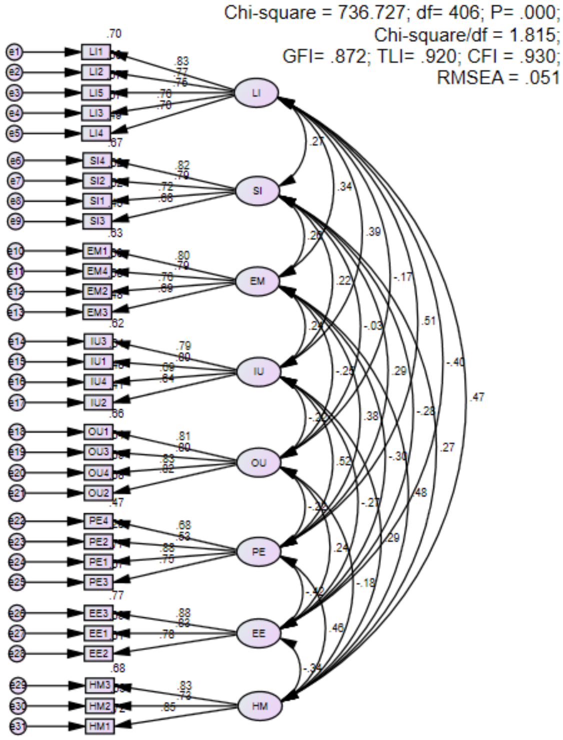

Figure 2: Confirmatory factor analysis(research result, 2023)

The outcomes of the CFA demonstrated the goodness-of-fit indices of the measurement model, which are as follows: the chi-square value for this measurement model was 736.727 with 406 degrees of freedom. The chi-square/df equaled 1.815 and achieved Marsh and Hocevar's (1985) standard that the ratio of chi-square to the degree of freedom ratios should be between 2 and 5; besides, GFI = 0.872, TLI = 0.920, CFI = 0.930, RMSEA= 0.051. According to Marcoulides and Schumacker (1996), the goodness-of-fit model and the overall statistics both achieved the standards of model fitting

Table 5.4 displays the composite reliability (CR) values for the constructs, ranging from 0.807 to 0.888, all surpassing the 0.7 threshold. Additionally, the Average Variance Extracted (AVE) values, ranging from 0.519 to 0.687, all exceed the 0.5 threshold.

Table 5: Composite reliability (CR) and Average Variance Extracted (AVE)(research result, 2023)

	CR	**AVE**
EE	0.868	0.687
LI	0.875	0.584
SI	0.838	0.566
EM	0.846	0.579
IU	0.822	0.539
OU	0.888	0.664
PE	0.807	0.519
HM	0.842	0.641

Next, we will assess the discriminant validity of the constructs. We will evaluate the null hypothesis (H_0) that posits the correlation coefficient between the constructs is equal to 1. The results presented in Table 5.4 indicate that all p-values are less than 0.05, leading to the rejection of the null hypothesis (H_0). Instead, we accept the alternative hypothesis (H_1) that states the correlation coefficient of each construct significantly differs from 1 with 95% confidence. Therefore, these constructs exhibit discriminant validity.

Table 6: Test for discriminant validity(research result, 2023)

	Estimate	r^2	$SE = \sqrt{((1 - r^2)/(n-2))}$	$CR = (1-r)/SE$	$P\_value = TDIST(\lvert CR \rvert, n-2, 2)$
LI<->SI	.268	.071824	.054985222	13.312668	.00000
LI<->EM	.339	.114921	.053693514	12.31061158	.00000
LI<->IU	.39	.1521	.05255368	11.60717962	.00000
LI<->OU	-.173	.029929	.056212458	20.86726056	.00000
LI<->PE	.51	.2601	.049092746	9.981107982	.00000
LI<->EE	-.398	.158404	.052357951	26.70081562	.00000
LI<->HM	.467	.218089	.050467231	10.56130866	.00000
SI<->EM	.256	.065536	.055171158	13.48530694	.00000
SI<->IU	.218	.047524	.055700338	14.03941204	.00000
SI<->OU	-.032	.001024	.057043786	18.09136591	.00000
SI<->PE	.287	.082369	.054671986	13.04141392	.00000
SI<->EE	-.277	.076729	.054839743	23.28603188	.00000
SI<->HM	.271	.073441	.054937305	13.26967165	.00000
EM<->IU	.244	.059536	.055347996	13.65903115	.00000
EM<->OU	-.252	.063504	.055231111	22.6683836	.00000
EM<->PE	.383	.146689	.052721103	11.70309363	.00000
EM<->EE	.302	.091204	.054408157	23.93023528	.00000
EM<->HM	.476	.226576	.050192593	10.43978735	.00000
IU<->OU	-.219	.047961	.055687559	21.88998801	.00000
IU<->PE	.521	.271441	.048715053	9.832689779	.00000
IU<->EE	-.274	.075076	.054888813	23.21055854	.00000
IU<->HM	.286	.081796	.054689053	13.05562927	.00000
OU<->PE	-.216	.046656	.055725713	21.82116554	.00000
OU<->EE	.244	.059536	.055347996	13.65903115	.00000
OU<->HM	-.176	.030976	.056182114	20.93192851	.00000
PE<->EE	-.422	.178084	.051742157	27.48242597	.00000
PE<->HM	.465	.216225	.050527349	10.58832508	.00000
EE<->HM	-.344	.118336	.053589828	25.07938615	.00000

b. Testing of the structural model

We utilized AMOS 20.0 for path analysis to estimate the path coefficients representing relationships between constructs within the research model. The overall goodness-of-fit indices for the structural model are as follows: chi-square value of 845.451 with 421 degrees of freedom, resulting in a chi-square/df ratio of 2.008. Additionally, GFI is 0.856, TLI is 0.901, CFI is 0.910, and RMSEA is 0.057. These values indicate a good fit of the data with the hypothesized structural model.

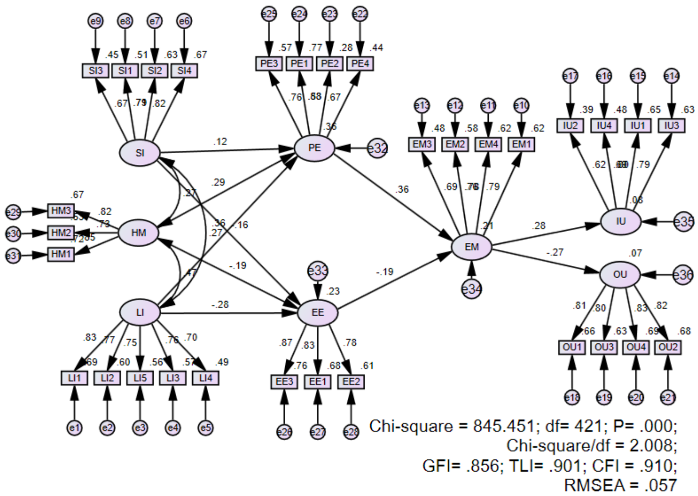

Figure 3: Structural equation modeling(research result, 2023)

Table 7 demonstrates that all paths proposed in the research model are supported (p-value < 0.05)

Table 7: Regression Weights(research result, 2023)

			Estimate	S.E.	C.R.	P
PE	<---	HM	.251	.062	4.025	***
EE	<---	HM	-.248	.095	-2.595	.009
PE	<---	SI	.104	.051	2.039	.041
EE	<---	SI	-.198	.082	-2.433	.015
PE	<---	LI	.305	.062	4.954	***
EE	<---	LI	-.364	.093	-3.926	***
EM	<---	PE	.376	.074	5.091	***
EM	<---	EE	-.134	.045	-2.990	.003

			Estimate	S.E.	C.R.	P
IU	<---	EM	.303	.072	4.190	***
OU	<---	EM	-.326	.079	-4.126	***

Table 8 offers a more comprehensive depiction of the relationships within the model.

Table 8: Standardized Regression Weights (research results, 2023)

			Estimate
PE	<---	HM	.286
EE	<---	HM	-.187
PE	<---	SI	.125
EE	<---	SI	-.157
PE	<---	LI	.355
EE	<---	LI	-.280
EM	<---	PE	.360
EM	<---	EE	-.194
IU	<---	EM	.285
OU	<---	EM	-.271

The results indicate that the following relationships are positive (beta > 0):

Table 9: Positive relationships(research results, 2023)

			Estimate
PE	<---	HM	.286
PE	<---	SI	.125
PE	<---	LI	.355
EM	<---	PE	.360
IU	<---	EM	.285

Meanwhile, the remaining relationships are negative (beta < 0):

Table 10: Negative relationships(research results, 2023)

			Estimate
EE	<---	HM	-.187
EE	<---	SI	-.157
EE	<---	LI	-.280
EM	<---	EE	-.194
OU	<---	EM	-.271

The results also demonstrate the strength of the impact of variables SI, HM, LI on variables PE, EE in descending order as follows: LI > HM > SI.

Derived from the outcomes of the path analysis, the results of hypothesis testing are outlined in Table 11 below:

Table 11: Research Hypotheses Conclusion(research results, 2023)

Hypotheses	Content	Beta	P_value	Result
H_1	Social Influence has a positive impact on Perceived Performance Expectancy	0.125	0.041	Accept
H_2	Social Influence has a negative impact on Perceived Effort Expectancy	-0.157	0.015	Accept
H_3	Hedonic Motivation has a positive impact on Perceived Performance Expectancy	0.286	0.000	Accept
H_4	Hedonic Motivation has a negative impact on Perceived Effort Expectancy	-0.187	0.009	Accept
H_5	Literacy has a positive impact on Perceived Performance Expectancy	0.355	0.000	Accept
H_6	Literacy has a negative impact on Perceived Effort Expectancy	-0.280	0.000	Accept

Hypotheses	Content	Beta	P_value	Result
H_7	Perceived Performance Expectancy has a positive impact on Emotions	0.360	0.000	Accept
H_8	Perceived Effort Expectancy has a negative impact on Emotions	-0.194	0.003	Accept
H_9	Emotions has a positive impact on Intention to Use	0.285	0.000	Accept
H_{10}	Emotions has a negative impact on Objection to Use	-0.271	0.000	Accept

6. Discussion & Implications

The results of our study examining the behavioral intention to adopt Artificial Intelligence (AI) for teaching in higher education in Vietnam have produced significant insights that offer valuable implications for both educational practitioners and policymakers. Our analysis has confirmed several hypotheses, aligning with previous research findings in similar contexts, thus contributing to a broader understanding of AI adoption in education.

Firstly, regarding the impact of Social Influence, Hedonic Motivation, and Literacy, our findings support the positive impact of social influence on perceived performance expectancy (H1). This aligns with previous research that emphasizes the role of peer influence in shaping individuals' attitudes and intentions toward technology adoption (Gursoy et al., 2019). Educators in Vietnam may be more inclined to adopt AI when they perceive that their colleagues or peers endorse its use. This underscores the importance of fostering a collaborative culture to facilitate AI adoption. Similarly, hedonic motivation's positive influence on perceived performance expectancy (H3) corroborates existing literature on the role of motivation in technology adoption (Venkatesh et al., 2003). The idea that educators who derive pleasure from AI-enhanced teaching see higher performance expectations suggests that cultivating a sense of enjoyment and fulfillment in using AI may be a promising strategy. The positive influence of literacy on perceived performance expectancy (H5) underlines the significance of competence in technology use (Al-Gahtani, 2016; Nikou & Aavakare, 2021). Literacy, in the context of our study, appears to empower educators to embrace AI as a tool that enhances their teaching effectiveness. As a practical implication, it is essential for educational institutions to provide training and support to enhance educators' technological literacy.

Secondly, in terms of impacts on Effort Expectancy, our findings also indicate a negative impact of social influence on perceived effort expectancy (H2). While social influence can motivate AI adoption, educators may still perceive it as a potentially effortful process. This underscores the importance of providing training and resources to make AI integration more accessible and user-friendly. Hedonic motivation's negative impact on perceived effort expectancy (H4) may reflect the idea that educators who find pleasure in AI-based teaching may perceive it as less effortful. This suggests that promoting the enjoyable aspects of AI can reduce perceived effort and encourage adoption. The study's findings support (H6) indicating that higher AI literacy among educators leads to a reduced perception of effort in adopting AI-based technology for teaching, aligning with existing research on digital literacy (Nikou & Aavakare, 2021). To facilitate the adoption of AI technology, educational institutions should prioritize AI literacy training for educators and integrate it into the curriculum. Providing resources, technical support, and a conducive environment can further support educators in AI technology adoption. Policymakers can incentivize AI adoption through infrastructure investment and policy measures. These efforts collectively enhance the quality of teaching and learning in higher education.

Thirdly, about the impact on Emotions and Intention to Use, our results show that perceived performance expectancy has a positive influence on emotions (H7), perceived effort expectancy has a negative influence on emotions (H8), and emotions, in turn, positively impact the intention to use (H9). This confirms the importance of the emotional component in technology adoption (Venkatesh et al., 2003 & 2012). When educators perceive AI as enhancing their performance, it is more likely to evoke positive emotions, subsequently strengthening their intention to use AI. Finally, for the Objection to Use, the Emotions also have a negative impact on objection to use (H10). Educators who experience positive emotions in their interactions with AI are less likely to resist its adoption, suggesting that efforts to create a positive emotional experience can mitigate resistance.

The research findings have proposed some implications for Policymakers, Educational Technology Developers, Researchers, and Instructors.

For the Policymakers in Vietnam, they should actively promote policies that encourage collaborative and peer-influenced approaches to AI adoption, at the same time ensure that AI adoption aligns with the national educational objectives in Vietnam, such as improving educational quality, increasing access, and fostering innovation. Besides, it is important to invest in infrastructure and provide financial support to educational institutions to ensure they have access to the necessary technological resources. This will facilitate the implementation of AI technologies in classrooms. Moreover, it is necessary to develop a regulatory framework to govern the ethical use of AI in education with guidelines on data privacy, security, and ethical AI use will instill confidence in educators and students. Finally, the policymakers should develop, and fund teacher training programs specifically aimed at AI integration. These programs should address both technological literacy and emotional preparedness to ensure educators are comfortable with AI tools.

For Educational Technology Developers, researchers and instructors, developers should focus on enhancing the user-friendliness of AI tools, reducing perceived effort, and emphasizing the enjoyable aspects of AI to encourage adoption. Training and support should be tailored to educators' technological literacy levels. Further research should explore the long-term effects of AI adoption and its impact on educational outcomes. Investigating the nuanced emotional experiences of educators in AI adoption can provide insights for designing more emotionally engaging AI technologies. Educators can benefit from professional development programs aimed at enhancing their technological literacy and creating a positive emotional experience in their interactions with AI.

In conclusion, our study provides valuable insights into the behavioral intention to adopt AI for teaching in higher education in Vietnam. These findings emphasize the importance of social influence, hedonic motivation, literacy, and emotions in shaping educators' attitudes toward AI adoption, ultimately contributing to the enhancement of teaching and learning in Vietnamese higher education.

While this study offers valuable insights into the adoption of AI-based technology in higher education in the context of Vietnam, several limitations should be acknowledged. This study's findings are constrained by the exclusive focus on Vietnamese educators, limiting generalizability. The reliance on self-reported data may introduce response bias. Additionally, a more comprehensive range of influencing factors could be considered in future research. Future research should embrace cross-cultural studies to understand AI adoption in diverse educational settings. Long-term effects of AI adoption on student outcomes, pedagogy, and governance warrant further exploration. Investigating AI's impact on pedagogical practices and institutional policies can provide valuable insights to a thorough understanding of the holistic impact of AI in higher education.

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