

Factors Influencing the Acceptance and Application of Artificial Intelligence Technologies among University Lecturers in Thailand

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Abstract

Aim/Purpose: The primary objective of this study was to examine the factors that influence the acceptance and practical application of Artificial Intelligence (AI) technologies among university lecturers in Thailand. By adopting the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) as the analytical framework, the study sought to identify how individual perceptions, motivational factors, social influences, and institutional conditions jointly shape lecturers' behavioral intention to use AI and their actual usage behavior. The findings are expected to provide empirical insights that support strategic planning for sustainable AI integration in higher education.

Introduction/Background: Artificial Intelligence has increasingly emerged as a transformative force in higher education, reshaping instructional practices, research processes, and academic administration. AI-driven applications such as adaptive learning systems, intelligent tutoring, automated assessment, and learning analytics have expanded the potential for personalized and data-informed education. In Thailand, national development agendas, particularly Thailand 4.0 and the National Artificial Intelligence Strategy (2022–2027), have emphasized the importance of AI adoption to enhance workforce competencies and educational quality. Within this policy context, university lecturers play a critical role as key agents who translate technological initiatives into classroom practice and institutional outcomes. However, the successful integration of AI in higher education depends not solely on technological availability but primarily on lecturers' acceptance, readiness, and the support structures provided by institutions. Understanding the psychological and organizational factors that influence lecturers' decisions to adopt AI is therefore essential for effective policy implementation and institutional management.

Methodology: In this study, a quantitative research approach was employed using a cross-sectional survey design. The target population consisted of full-time lecturers employed at public and private universities across Thailand. A total of 400 respondents were selected through stratified random sampling to ensure representation across institution types and academic disciplines. Data were collected using a structured online questionnaire developed from established UTAUT2 measurement scales and adapted to the context of AI usage in higher education. The instrument underwent expert validation and reliability testing prior to data collection. Descriptive statistics were used to summarize respondent characteristics and variable levels. In contrast, multiple regression analysis was used to examine the relationships between the independent variables—Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit—and the dependent variables—Behavioral Intention and Use Behavior.

Findings: The results indicated that university lecturers in Thailand generally reported high levels of intention to use AI technologies and moderate to high levels of actual usage. Regression analysis revealed that Performance Expectancy, Hedonic Motivation, Social Influence, and Habit had a statistically significant positive influence on Behavioral Intention to adopt AI. Together, these factors explained 61.2% of the variance in behavioral intention. In contrast, Effort Expectancy and Price Value

did not demonstrate a significant effect on intention in this context. Regarding actual use behavior, Behavioral Intention emerged as the strongest predictor, followed by Facilitating Conditions and Habit. These variables collectively explained 48.7% of the variance in AI use behavior. The findings suggest that lecturers are more likely to adopt AI when they perceive clear professional benefits, derive enjoyment from using AI tools, experience supportive social norms, and have prior experience with digital technologies. At the same time, institutional support plays a crucial role in enabling sustained application.

Contribution/Impact on Society: This study contributes to the academic literature by empirically validating the UTAUT2 model within the context of Thai higher education and AI adoption. It highlights the importance of both utilitarian and intrinsic motivational factors, demonstrating that lecturers value enjoyment and perceived usefulness more strongly than ease of use. The findings have practical implications for policymakers and university administrators by emphasizing that AI adoption strategies should move beyond basic technology provision to foster engaging, supportive, and habit-forming environments that encourage long-term use.

Recommendations: Higher education institutions should prioritize communication strategies that clearly demonstrate the practical benefits of AI for teaching, research, and administrative tasks in order to enhance performance expectancy. In addition, universities should design engaging professional development activities—such as hands-on workshops, innovation labs, and collaborative experimentation—to stimulate hedonic motivation. Adequate technical infrastructure, training opportunities, and ongoing support services should also be ensured to strengthen facilitating conditions and enable lecturers to translate intention into actual use.

Research Limitations: This study was subject to several limitations. The cross-sectional design restricted the ability to capture changes in lecturers' attitudes and behaviors over time. Furthermore, reliance on an online survey may have limited participation by lecturers with lower levels of digital proficiency, potentially affecting the generalizability of the findings.

Future Research: Future studies should adopt longitudinal research designs to examine the evolution of AI adoption behavior over time. Incorporating qualitative methods, such as interviews or focus groups, would also provide deeper insights into lecturers' concerns, expectations, and contextual challenges related to AI usage. Comparative studies across academic disciplines or institutional types are recommended to refine the understanding of AI adoption dynamics in higher education.

Keywords: *Artificial intelligence, technology acceptance, university lecturers, UTAUT2*

Introduction

In the 21st century, Artificial Intelligence (AI) has increasingly become an enabling technology that reshapes how higher education institutions design instruction, manage academic processes, and support decision-making (Popenici & Kerr, 2017). AI holds vast potential to revolutionize teaching methods, learning processes, research activities, and administrative management. AI tools can facilitate personalized learning pathways customized to specific student needs, employ learning analytics to forecast academic performance and offer prompt support, develop Virtual Teaching Assistant systems, and enhance the efficiency of complex research tasks (Zawacki-Richter et al., 2019). Consequently, the integration of AI into higher education is no longer merely an alternative, but a strategic necessity for educational institutions seeking to remain competitive and produce graduates ready for the future (Crompton & Burke, 2023).

In Thailand, national development policies have positioned AI as a strategic tool for strengthening educational quality and workforce readiness. This commitment is evident in the National Artificial Intelligence Strategy (2022–2027), which seeks to build human capacity and encourage AI adoption across various sectors, including education (Ministry of Higher Education, Science, Research and Innovation, 2023). Lecturers in higher education are viewed as pivotal figures in driving this shift. Consequently, their acceptance and utilization of AI are critical determinants for the success of digital

education reform. When lecturers have a positive attitude and are ready to use AI, they can effectively impart essential skills to students, thereby improving the quality of educational management nationwide.

Nevertheless, introducing new technologies into organizations—particularly educational institutions with distinct cultures—often presents obstacles (Fullan, 2007). Lecturers may worry about technological complexity, insufficient digital skills, threats to their traditional roles, or inadequate institutional support (Bao, 2020). Integrating AI into universities relies not only on technological advancement, but also on human and organizational dynamics. Therefore, identifying the factors that shape lecturers' decisions to adopt AI is essential. Such insights allow administrators and policymakers to devise precise and effective promotion strategies (Dwivedi et al., 2023).

In terms of theoretical background, numerous studies have attempted to explain the factors influencing the acceptance of information technology using widely accepted theories and models. For instance, the Technology Acceptance Model (TAM) posits that Perceived Usefulness and Ease of Use are the primary determinants of behavioral intention to use technology (Davis, 1989). Subsequently, Venkatesh et al. (2003) developed a more comprehensive model, the Unified Theory of Acceptance and Use of Technology (UTAUT), integrating concepts from eight prominent theories. UTAUT identified four key factors: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. To explain consumer and user behavior in non-mandatory contexts, Venkatesh et al. (2012) expanded UTAUT into UTAUT2 by adding three factors: Hedonic Motivation, Price Value, and Habit. The UTAUT2 model has been shown to have explanatory power for technology acceptance behavior across various contexts, including education, such as e-learning systems (Al-Gahtani, 2016) and mobile learning applications (Nikolopoulou et al., 2021).

In the context of AI in education, recent research has increasingly applied the UTAUT2 model. For example, Alsharida et al. (2021) found that performance expectancy and facilitating conditions were significant factors in students' acceptance of chatbots in Oman. Meanwhile, a study by Kanont et al. (2024) in Thailand found that performance expectancy, social influence, and habit significantly influenced the intention to use AI-driven tools.

Despite reasonable research on educational technology acceptance in Thailand, studies focusing specifically on the adoption and utilization of AI among university lecturers remain limited. Most existing research has tended to focus on students or on technology in general rather than on AI specifically, which has unique characteristics that may lead to different expectations or anxieties. Furthermore, existing research often uses models that do not account for all relevant factors, particularly personal motivation and habits, which UTAUT2 can better explain. Therefore, a research gap remains, requiring clear and comprehensive answers to the question of which factors within the UTAUT2 framework truly influence the acceptance and utilization of AI technology among university lecturers in the Thai context.

Globally, the adoption of Artificial Intelligence in educational settings is influenced by a complex interplay of various elements. Prior studies indicate that individual factors, such as self-efficacy, AI anxiety, and constructivist pedagogical beliefs, play a crucial role, with educators who hold progressive beliefs adopting AI more readily. Furthermore, technological factors (e.g., perceived usefulness and compatibility with existing teaching methods) and organizational factors (e.g., institutional readiness, proactive policies, and adequate technical support) are critical for overcoming technological reluctance. Additionally, social and ethical influences, including peer encouragement and concerns regarding academic integrity and data privacy, significantly impact decision-making.

Despite a growing body of global literature on educational technology, studies specifically addressing AI adoption among university lecturers in the Thai context remain largely descriptive and fragmented. Existing research often lacks a critical synthesis of how these global trends manifest locally across academic disciplines and demographic groups. Therefore, a distinct theoretical gap exists regarding how a comprehensive framework can encapsulate these multidimensional factors (individual, technological, organizational, and social) to explain AI integration by Thai educators. This

study aimed to fill this gap by providing robust empirical evidence to clarify the academic position on the application of AI in the development of higher education systems.

Based on the reasons mentioned above, the researchers deemed it necessary to conduct a systematic quantitative study on “Factors Influencing the Adoption and Utilization of Artificial Intelligence Technologies among University Lecturers in Thailand.” By utilizing the UTAUT2 theoretical framework, which covers multiple dimensions—including utilitarian, hedonic, and personal factors—this study aimed to gain in-depth knowledge to inform planning policies and strategies to promote AI use in Thai higher education institutions for maximum efficiency.

Research Objectives

1. To assess the acceptance and application of Artificial Intelligence technology among university lecturers in Thailand.
2. To determine the impact of Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit on lecturers’ behavioral intention to adopt AI technologies.
3. To investigate the causal relationships of Behavioral Intention and Facilitating Conditions on the actual use behavior of AI technologies within the lecturer cohort.

Literature Review

This section summarizes documents and research related to AI Technology Adoption and Application by University Lecturers in Thai Higher Education, categorized as follows.

Concepts of Artificial Intelligence in Education (AIEd)

In educational research, Artificial Intelligence is commonly understood as a set of computational techniques designed to support learning, assessment, and academic management rather than as autonomous human-like machines (Russell & Norvig, 2021). In the educational context (AIEd), AI does not necessarily refer to humanoid robots but rather a set of technologies and algorithms applied to support and enhance educational processes (Zawacki-Richter et al., 2019). In higher education, AI applications are most frequently observed in adaptive learning environments, intelligent tutoring systems, learning analytics, and automated assessment tools that assist lecturers in managing instructional workloads (Borenstein & Howard, 2021).

1. Adaptive Learning Systems: Systems capable of adjusting content, teaching methods, and the difficulty level of exercises to align with each learner’s knowledge level and learning style in real-time (Tan et al., 2025).
2. Intelligent Tutoring Systems: Computer programs that simulate the role of an instructor by providing advice, feedback, and personalized learning path suggestions to students.
3. Learning Analytics and Educational Data Mining: The use of AI techniques to analyze large-scale student data (Big Data) to understand learning behaviors, predict dropout risks, and suggest intervention strategies (Baker & Siemens, 2014).
4. Automated Assessment: Using AI to grade essays, programming code, or complex assignments, thereby reducing lecturer workloads and providing faster feedback to students.
5. Chatbots and Virtual Assistants: Conversational programs capable of answering students’ basic questions 24 hours a day, such as inquiries about course syllabi, submission deadlines, or registration procedures (Alsharida et al., 2021; Tlili et al., 2023).

The implementation of these technologies has the potential to transform the role of lecturers from being a “Sage on the Stage” (knowledge transmitter) to a “Guide on the Side” (learning facilitator), allowing them more time to provide in-depth consultation and foster higher-order critical thinking among students.

The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The UTAUT2 theory (Venkatesh et al., 2012) served as the primary conceptual framework for this study. It was further developed from the original UTAUT (Venkatesh et al., 2003) to better technology acceptance behaviors in consumer or voluntary use contexts. The theory consists of seven variables that influence Behavioral Intention and two variables that influence Use Behavior as follows.

1. Performance Expectancy (PE)—the degree to which one perceives that using technology will improve their efficiency or job performance. This study shows that lecturers perceive AI technologies as meaningfully enhancing teaching effectiveness, research productivity, and administrative efficiency within their professional roles.

2. Effort Expectancy (EE)—how easy the system is to use; it implies that AI tools should be user-friendly, understandable, and require minimal effort to master. This research represents lecturers' perceptions of how manageable and learnable AI technologies are within their existing academic routines.

3. Social Influence (SI)—assessing the extent to which an individual feels that significant others (e.g., peers, administrators) believe that they should adopt the new technology. In this study, it is conceptualized as lecturers' perceptions of the expectations and encouragement they receive from colleagues, administrators, or institutional leadership regarding the use of AI.

4. Facilitating Conditions (FC)—lecturers' perceptions of institutional readiness, including access to infrastructure, technical support, training, and organizational resources necessary for AI implementation.

5. Hedonic Motivation (HM)—the pleasure derived from using technology. As an emotional driver, this study refers to lecturers' experiences of enjoyment, curiosity, or intellectual stimulation when experimenting with AI technologies.

6. Price Value (PV)—the cognitive trade-off between the technology's perceived benefits and its cost. In the university context, price value reflects lecturers' evaluations of whether the perceived benefits of AI use justify the time, effort, and learning investment required.

7. Habit (HT)—the extent to which lecturers' prior experience with digital technologies has led AI-related behaviors to become routine and automatic.

8. Behavioral Intention (BI)—the perceived likelihood or degree of an individual's willingness to engage in a specific behavior; in this study, it functions as a critical mediator, bridging the gap between the antecedent determinants and actual use.

9. Use Behavior (UB)—the tangible application or frequency of utilizing the technology within a professional setting. It serves as the final dependent variable, which is primarily driven by the user's intention and established habits.

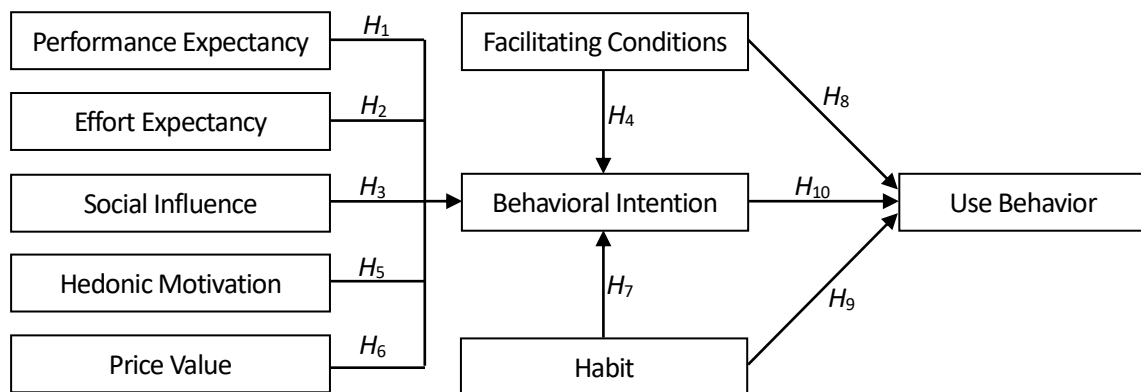
The rationale for selecting the UTAUT2 framework over other established models, such as the Technology Acceptance Model (TAM) or the Technology-Organization-Environment (TOE) framework, was based on its comprehensiveness. While TAM focuses predominantly on perceived usefulness and ease of use, it fails to adequately capture the social and organizational complexities of the academic environment. Conversely, the TOE framework provides a macro-level analysis of institutional adoption but overlooks the micro-level psychological drivers of individual lecturers. UTAUT2 effectively bridged this gap by incorporating critical individual variables such as Hedonic Motivation and Habit. Since university lecturers possess high levels of cognitive capability and autonomy, their intrinsic motivation (enjoyment of technology) and established digital routines were arguably more decisive than mere ease of use; thus, UTAUT2 was identified as the most robust analytical tool for this specific context.

Research Conceptual Framework and Hypotheses

Based on the literature review and UTAUT2 theory, the researchers developed a conceptual framework to study the factors influencing the adoption and utilization of AI among university lecturers in Thailand. The conceptual framework illustrated the relationships between independent variables (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions,

Hedonic Motivation, Price Value, and Habit) and the dependent variables (Behavioral Intention and Use Behavior) as shown in Figure 1.

Figure 1 Research Conceptual Framework



The research hypotheses were established as follows:

- H₁: Performance Expectancy (PE) positively influences Behavioral Intention (BI).
- H₂: Effort Expectancy (EE) positively influences Behavioral Intention (BI).
- H₃: Social Influence (SI) positively influences Behavioral Intention (BI).
- H₄: Facilitating Conditions (FC) positively influences Behavioral Intention (BI).
- H₅: Hedonic Motivation (HM) positively influences Behavioral Intention (BI).
- H₆: Price Value (PV) positively influences Behavioral Intention (BI).
- H₇: Habit (HT) positively influences Behavioral Intention (BI).
- H₈: Facilitating Conditions (FC) positively influences Use Behavior (UB).
- H₉: Habit (HT) positively influences Use Behavior (UB).
- H₁₀: Behavioral Intention (BI) positively influences Use Behavior (UB).

This model enabled analysis of both the determinants of *intent* and those of *actual action* among Thai university lecturers.

Research Methodology

In this study, a quantitative approach was adopted to examine relationships among the determinants of AI adoption among university lecturers. The data collection was conducted as a cross-sectional study, gathering information at a specific point in time.

Population and Sample

Population: The study population comprised approximately 69,645 full-time lecturers at public and private higher education institutions in Thailand.

Sample: Based on Hair et al.'s (2018) recommendations (utilizing a ratio of 20 participants per observed variable), a total of 400 lecturers were selected using stratified random sampling. To ensure the sample accurately represented Thailand as a whole, the data collection was geographically stratified to cover the four major regions: Northern, Northeastern, Central, and Southern Thailand. The sample was further categorized by institution type (Public/Private) and academic discipline (Science and Technology, Health Sciences, Humanities and Social Sciences).

Research Instrument

Data were gathered using a survey instrument that was divided into three parts as follows:

Part 1: Demographic information, including gender, age, education level, academic rank, teaching experience, discipline, and type of institution.

Part 2: Questions regarding factors based on the UTAUT2 framework, totaling nine variables: Performance Expectancy (4 items), Effort Expectancy (4 items), Social Influence (3 items), Facilitating

Conditions (4 items), Hedonic Motivation (3 items), Price Value (3 items), Habit (3 items), Behavioral Intention (3 items), and Use Behavior (4 items). The questions used a 5-point Likert scale.

Part 3: Additional suggestions regarding the promotion of AI technology usage in universities (Open-ended question).

The original UTAUT2 questionnaire items were translated from English into Thai using a back-translation procedure to ensure linguistic and contextual equivalence. Additionally, explicit exclusion criteria were applied during the data screening process; responses exhibiting careless answering patterns (e.g., straight-lining or selecting the same response for all items) or incomplete data were excluded from the final analysis to ensure data integrity.

Instrument Quality Inspection

The researcher proceeded with the quality inspection of the questionnaire as follows.

Content Validity: The draft questionnaire was submitted to three experts in educational technology, social science research, and artificial intelligence to assess accuracy, language appropriateness, and content coverage. The Index of Item-Objective Congruence (IOC) was calculated, with items requiring an IOC of .50 or higher. The evaluation results showed that the IOC value for all items was greater than .60.

Reliability: A pilot test (try-out) was conducted with 30 participants who shared similar characteristics with the target population but were not part of the main study. Internal consistency of the measurement instrument was evaluated using Cronbach's alpha coefficients, with a threshold of .70 for each aspect. The analysis yielded values ranging from .83 to .91, with an overall average of .87, confirming the instrument's reliability.

Data Collection

Data were gathered through a structured online questionnaire distributed to lecturers at public and private universities. The researchers distributed the questionnaire link to the sample group of lecturers via email, academic social networks, and by coordinating with the human resources departments of various universities. The data collection period lasted two months, with periodic follow-up emails to boost response rates.

Data Analysis

Upon receiving complete data, the researchers verified its completeness and analyzed it using statistical software. The statistics used were as follows:

Descriptive Statistics: Used to analyze the general information of respondents using Frequency and Percentage distributions, and to analyze the levels of variables according to the conceptual framework using Means and Standard Deviations.

Inferential Statistics: Multiple regression analysis was used to test the research hypotheses and examine the impact of the independent variables on both behavioral intention and use behavior.

Research Ethics

This research strictly adhered to ethical considerations in human research. The study protocol was reviewed and approved by the Research Ethics Committee of Lampang Rajabhat University. Participants were approached via official online channels. The researchers clearly explained the objectives and details of the research at the beginning of the online questionnaire. Informed consent was obtained prior to participation, ensuring that data was kept strictly confidential, analyzed anonymously, and participation was entirely voluntary.

Results

Demographic Characteristics

A majority of respondents were female (58.8%), aged 31–40 (42.5%) and held a Doctoral degree (65.2%). In terms of academic position, the largest group consisted of Lecturers (48.0%). Regarding

academic discipline, the majority were from the Humanities and Social Sciences (45.0%), and most were affiliated with public universities (70.5%), as shown in Table 1.

Table 1 Demographic Characteristics ($n = 400$)

Demographic Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	165	41.2
	Female	235	58.8
Age	30 years or below	55	13.8
	31–40 years	170	42.5
	41–50 years	120	30.0
	51 years or above	55	13.7
Academic Rank	Lecturer	192	48.0
	Assistant Professor	138	34.5
	Associate Professor	60	15.0
	Professor	10	2.5
Academic Discipline	Science and Technology	130	32.5
	Health Sciences	90	22.5
	Humanities and Social Sciences	180	45.0
Institution Type	Public University	282	70.5
	Private University	118	29.5

Descriptive Statistics Analysis

Overall, all variables were at a “High” level. When considering individual aspects, the variable with the highest mean score was Behavioral Intention (BI) ($M = 4.35$, $SD = .68$), followed by Performance Expectancy (PE) ($M = 4.28$, $SD = .71$), and Habit (HT) ($M = 4.15$, $SD = .80$), respectively. The aspect with the lowest mean was Price Value (PV) ($M = 3.65$, $SD = .95$), as shown in Table 2.

Table 2 Means and Standard Deviations ($n = 400$)

Variables	Mean (M)	Standard Deviation (SD)	Level
Performance Expectancy (PE)	4.28	.71	High
Effort Expectancy (EE)	3.88	.85	High
Social Influence (SI)	3.95	.82	High
Facilitating Conditions (FC)	3.75	.91	High
Hedonic Motivation (HM)	4.05	.75	High
Price Value (PV)	3.65	.95	High
Habit (HT)	4.15	.80	High
Behavioral Intention (BI)	4.35	.68	High
Use Behavior (UB)	3.80	1.02	High

Hypothesis Testing Results

Prior to hypothesis testing, the data were screened for multicollinearity to ensure the robustness of the multiple regression models. Variance Inflation Factor (VIF) and Tolerance values were examined. The VIF values for all independent variables ranged from 1.15 to 2.78, which are well below the strict threshold of 5.00. Furthermore, all Tolerance values were greater than .20. These model fit indicators confirmed the absence of multicollinearity among the predictor variables.

To test the research hypotheses, the researchers conducted a multiple regression analysis, yielding the following results:

Part 1: Hypothesis Testing H_1 to H_7 (Factors Influencing Behavioral Intention)

The regression analysis demonstrated that the seven independent variables collectively predicted Behavioral Intention (BI) with statistical significance ($F(7,392) = 88.45$, $p < .001$). The model yielded a Coefficient of Determination (R^2) of .612, indicating that these variables accounted for 61.2% of the variance in Behavioral Intention.

Regarding individual influences, the results showed that Performance Expectancy ($\beta = .35$, $p < .001$), Social Influence ($\beta = .18$, $p < .01$), Hedonic Motivation ($\beta = .22$, $p < .001$), and Habit ($\beta = .15$, $p < .05$) exerted a positive impact on Behavioral Intention. Consequently, Hypotheses H_1 , H_3 , H_5 , and H_7 were supported. In contrast, Effort Expectancy, Facilitating Conditions, and Price Value did not show a significant effect; thus, Hypotheses H_2 , H_4 , and H_6 were rejected (see Table 3).

Table 3 Multiple Regression Analysis of Factors Influencing Behavioral Intention (BI)

Predictors	B	SE	β	t	p
(Constant)	.85	.21		4.05	<.001
Performance Expectancy (PE)	.33	.05	.35	6.67	<.001**
Effort Expectancy (EE)	.04	.04	.05	1.12	.318
Social Influence (SI)	.15	.05	.18	3.05	.003**
Facilitating Conditions (FC)	.02	.03	.03	.67	.503
Hedonic Motivation (HM)	.20	.04	.22	5.10	<.001**
Price Value (PV)	-.03	.03	-.04	-1.05	.317
Habit (HT)	.13	.05	.15	2.60	.010**
$R^2 = .612$, $F = 88.45$, $p < .001$					

Note. ** $p < .01$

Part 2: Hypothesis Testing H_8 - H_{10} (Factors Influencing Use Behavior)

The analysis indicated that Behavioral Intention (BI), Facilitating Conditions (FC), and Habit (HT) collectively predicted Use Behavior (UB) significantly ($F(3, 396) = 125.67$, $p < .001$). The Coefficient of Determination (R^2) was .487, meaning these three factors explained 48.7% of the variance in Use Behavior. Individual variable analysis revealed that Behavioral Intention ($\beta = .41$, $p < .001$), Facilitating Conditions ($\beta = .25$, $p < .001$), and Habit ($\beta = .19$, $p < .01$) significantly and positively influenced Use Behavior. Hence, Hypotheses H_8 , H_9 , and H_{10} were supported (see Table 4).

Table 4 Multiple Regression Analysis of Factors Influencing Use Behavior (UB)

Predictors	B	SE	β	t	p
(Constant)	.55	.18		3.06	.002
Behavioral Intention (BI)	.61	.07	.41	8.71	<.001**
Facilitating Conditions (FC)	.28	.06	.25	4.67	<.001**
Habit (HT)	.24	.08	.19	3.00	.003**
$R^2 = .487$, $F = 125.67$, $p < .001$					

Note. ** $p < .01$

Discussion

The results can be discussed according to key issues as follows:

Factors Influencing Behavioral Intention

The findings identified Performance Expectancy ($\beta = .35$) as the most potent driver of lecturers' behavioral intention to use AI. This aligned with UTAUT2 theory and prior educational studies (Venkatesh et al., 2012; Kanont et al., 2024), suggesting that Thai lecturers were motivated primarily by functional utility. They were more inclined to adopt AI when they perceived tangible benefits, such as enhanced efficiency in teaching and research or reduced workloads. Thus, their decision-making was grounded in rationality and utility. Promoting the concrete value of AI is therefore essential for fostering positive intention.

The second most influential factor was Hedonic Motivation ($\beta = .22$). This finding was intriguing, as it suggested that, beyond utilitarian reasons, emotional factors and personal satisfaction also played significant roles. Lecturers tended to use AI when it was fun, challenging, or enjoyable to experiment with. This reflected the characteristic that lecturers were lifelong learners who desire to

try new things. This result was consistent with Al-Gahtani's (2016) work, which found that hedonic motivation is a critical factor in the acceptance of E-learning systems.

Social Influence ($\beta = .18$) was another factor with a significant positive effect. This suggested that acceptance by administrators, support from colleagues, or the perception that AI use is an institutional norm can stimulate lecturers' intention. In Thai culture, which is highly collectivist, others' opinions and acceptance carry weight in individual decision-making. This aligned with the research of Ketusiri et al. (2025), which emphasized the importance of administrative support.

Conversely, the research found that Effort Expectancy did not significantly influence behavioral intention. This can be interpreted to mean that, for the lecturer group, which possessed high knowledge and capability, the issue of "ease of use" may not be a primary factor in decision-making. If they perceived clear benefits (Performance Expectancy), they were ready to dedicate effort to learning technologies even if they might be complex. This result differed from some studies of general users, but aligned with research on expert groups, which often prioritize utility over simplicity (Venkatesh et al., 2003).

Factors Influencing Use Behavior

Regarding the actual Use Behavior of AI, the research results confirmed the UTAUT2 theory, which posits that Behavioral Intention is the most potent predictor ($\beta = .41$). This demonstrated that the intention formed internally was the primary driver leading to actual action, reinforcing the importance of building positive intention through the factors mentioned above.

A notable finding was Facilitating Conditions ($\beta = .25$). Although this factor had no direct effect on *intention*, it had a significant positive influence on *actual use behavior*. This means that no matter how firm the lecturers' intention to use AI may be, if there is a lack of essential support from the institution—such as the absence of software, inadequate equipment, or poor training—the intention will not be translated into actual behavior. This result aligned perfectly with the theory and underscores the role of institutional administrators in resource allocation and ecosystem creation (Bao, 2020).

Furthermore, Habit ($\beta = .19$) also had a direct influence on use behavior. This indicated that lecturers who already use digital technologies in their routine work tend to integrate AI into their workflows more smoothly and automatically. Habit helps reduce cognitive load when deciding to use technology each time, leading to continuous use.

Contextual and Demographic Dynamics in AI Adoption

Beyond the primary UTAUT2 variables, the findings revealed crucial dynamics regarding key adoption trends. Firstly, a distinction between academic disciplines is notable. Lecturers in STEM fields (Science and Technology, 32.5%) may adopt AI more rapidly due to stronger existing technological infrastructure and a higher perceived relevance to their disciplines, whereas non-STEM faculties (Humanities and Social Sciences, 45.0%) might require more tailored pedagogical support to effectively integrate AI into their workflows.

Secondly, the recent rise of Generative AI (GenAI) has fundamentally shifted the focus of technological application. For university lecturers, the utility of AI is increasingly dependent on "prompting skills" and a deep understanding of AI-powered efficiency, reinforcing why Performance Expectancy remains the paramount driver. Finally, demographic factors function as critical underlying mechanisms. While this study treated variables collectively, it implied that age and prior digital proficiency can act as mediators; for instance, technology anxiety might affect adoption rates differently across generational cohorts, highlighting the need for age-appropriate training programs.

Theoretical Implications

This research confirms the UTAUT2 model's ability to explain technology adoption in Thai higher education. However, the lack of statistical significance for some factors (such as Effort Expectancy) may indicate the need to consider Moderating Variables, such as age or technological experience,

which might affect the relationships among variables, as suggested by Venkatesh et al. (2012). This serves as a guideline for future research. The finding that Facilitating Conditions affect usage behavior directly but not intention confirms the structural validity of the UTAUT2 model and clarifies the distinct roles of this factor in the adoption process.

Conclusion

The findings indicated that the factors positively influencing Behavioral Intention to use AI, ranked by magnitude of influence, were Performance Expectancy, Hedonic Motivation, Social Influence, and Habit. Collectively, these factors explained 61.2% of the variance in behavioral intention. Regarding Use Behavior, the results revealed that it was influenced by Behavioral Intention, Facilitating Conditions, and Habit, which together accounted for 48.7% of the variance in actual usage.

In summary, the decision to adopt and utilize AI among university lecturers in Thailand is a complex process influenced by a multitude of factors, ranging from utilitarian and emotional aspects to social and personal factors. Crucially, while these motivational factors drive intention, the transition to implementation requires concrete institutional support, coupled with the lecturers' own determination.

New Knowledge

This research has generated significant new knowledge regarding the adoption of educational technology in the Thai context as follows.

1. *Validating and Adapting the UTAUT2 Model for Thai Lecturers:* This research represents an initial attempt to comprehensively apply the UTAUT2 framework to examine AI adoption in the Thai academic context. Specifically, the results provide a clear picture of the hierarchy of factors, showing that "Performance Expectancy" and "Hedonic Motivation" are the top two driving factors. This differs from general organizational contexts that often focus solely on efficiency. This discovery highlights the unique characteristic of the academic group, which values both functional utility and personal satisfaction simultaneously.

2. *Clarifying the Role of Facilitating Conditions:* Empirical evidence from this study confirms that although Facilitating Conditions (such as institutional support) may not directly influence "Intention," they are critical for determining "Actual Use Behavior." This distinction is practically vital; it implies that budgeting solely for technology acquisition fails to generate motivation. Conversely, high motivation without concrete support leads to actual use.

3. *"Ease of Use" (Effort Expectancy) is Not a Deal-Breaker:* The non-significant impact of Effort Expectancy offers a novel insight, challenging the assumption that technology must be "easy" to be accepted. For expert groups like lecturers, "Utility" far outweighs "Ease." They are willing to invest effort in learning complex tools if they are assured of a worthwhile return.

Recommendations

Recommendations for applying the results and guidelines for future research.

Practical Recommendations

For Higher Education Institutional Administrators:

1. *Highlight and Prove Tangible Benefits:* Administrators must focus on communication and activities that showcase how AI elevates teaching efficiency (e.g., automated quizzing) and research capabilities (e.g., data analysis). This strategy targets Performance Expectancy, the most influential factor.

2. *Curate Engaging User Experiences:* Administrators should curate AI tools with intuitive interfaces and host interactive events, such as workshops or hackathons. These activities should encourage lecturers to experiment with AI in creative and enjoyable ways, thereby stimulating Hedonic Motivation.

3. *Build a Supportive Organizational Culture*: Executives should clearly articulate their vision and support for AI use, while fostering a “Community of Practice” where lecturers can exchange experiences and support one another. This will help strengthen positive *Social Influence*.

4. *Provide Adequate Resources and Support Systems*: It is essential to provide necessary infrastructure, such as licensed software and cloud systems. Most importantly, there must be a technical support team ready to provide assistance and ongoing training to ensure that Facilitating Conditions do not become a barrier to actual use.

For Policy-Making Agencies (e.g., Ministry of Higher Education, Science, Research and Innovation)

5. *Formulate National Strategy*: Establish a policy and allocate budgets to support the procurement of AI technology for higher education institutions nationwide to reduce inequality in technology access.

6. *Develop Standard Training Curricula*: Agencies should promote the development of a central curriculum for AI skills training (AI Literacy for Educators) to ensure that lecturers across the country possess the necessary foundational knowledge and understanding.

Recommendations for Future Research

1. *Integration of Qualitative Methods*: Future investigations should complement quantitative findings with qualitative approaches, such as semi-structured interviews or focus groups. These methods are essential for uncovering nuanced psychological barriers, specific anxieties, and underlying motivations regarding AI usage that statistical surveys alone may fail to capture.

2. *Longitudinal Investigation*: Implementing a longitudinal research design is recommended to monitor the trajectory of AI adoption over time. This approach would allow researchers to observe the temporal dynamics of attitudinal shifts and behavioral evolution as AI technology continues to advance.

3. *Comparative Analysis*: Subsequent research should expand to include comparative studies across diverse contexts, such as differing academic disciplines (e.g., Pure Sciences versus Social Sciences) or institutional models (Public versus Private). Such comparisons would yield more granular and context-specific policy recommendations.

4. *Examination of Moderating Effects*: Future studies should explore the impact of potential moderating variables, including age, prior technological experience, and technology anxiety. Investigating these factors could clarify how they strengthen or weaken the relationships between determinants within the UTAUT2 framework.

Author Contributions

Netdao Luangyai: Conceptualization, methodology, writing—original draft; **Suthira Thipwiwatpotjana**: Data curation, formal analysis; **Charuwan Limphaiboon**: Investigation, validation; **Omthong Phattanaphong**: Visualization, writing—review and editing; **Nunta Bootnoi**: Supervision, project administration, resources.

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