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Factors influencing lecturers' adoption of generative artificial intelligence in Vietnamese higher education: An extended theoretical perspective

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Abstract

While universities worldwide are rapidly adopting generative artificial intelligence, empirical evidence from developing nations remains limited. This study explores factors driving Vietnamese university lecturers to integrate these tools. We extended the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating attitude and perceived barriers. Analyzing survey data from 261 academic staff via multiple linear regression, we found a noticeable gap: educators showed high adoption readiness, yet actual usage lagged by 1.19 points on a 5-point scale. Our expanded model explained 43.3% of the variance in adoption intention. Personal attitude was the strongest predictor, followed by performance expectancy and facilitating conditions. Surprisingly, effort expectancy lacked statistical significance. Counterintuitively, perceived barriers positively correlated with adoption intention. Recognizing functional and ethical flaws motivated a critically informed, responsible integration rather than passive rejection among experienced educators. To bridge the intention-practice gap, institutions must provide concrete support, clear governance, and professional development.

Keywords: Behavioral intention, Generative artificial intelligence, Perceived barriers, Unified theory of acceptance and use of technology, Vietnamese higher education, Educational technology, Artificial intelligence adoption.

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Contents

Contribution of this paper to the literature
This study contributes to the technology acceptance literature by extending the UTAUT framework to evaluate generative artificial intelligence within a developing-nation context. It empirically demonstrates the 'Positive Barrier Paradox,' revealing that educators' awareness of technological limitations acts as a catalyst for critically informed adoption rather than a deterrent.

1. Introduction

Generative artificial intelligence and large language models are fundamentally changing higher education across the globe (Kasneci et al., 2023; Lo, 2023). Recent literature shows that these tools can make teaching more efficient and help personalize student learning (Yan et al., 2024). However, empirical evidence coming from developing countries remains relatively scarce (Adarkwah, 2021; Almaiah, Al-Khasawneh, & Althunibat, 2020). Among developing countries, Vietnam represents a particularly relevant context in which further empirical evidence regarding the use of artificial intelligence in education is still needed. As a developing country undergoing rapid integration and robust digital transformation, Vietnam strongly prioritizes digital transformation in higher education, explicitly encouraging the application of artificial intelligence to innovate and elevate teaching quality. To achieve these ambitious national goals, university lecturers must act as pioneers who actively experience, research, and apply these new technologies in their classrooms.

Nevertheless, under conditions of resource constraints and broader system-level barriers in Vietnam, bringing artificial intelligence into universities is not merely a technical problem. It requires a complex negotiation with systemic limits and deep-rooted institutional cultures (Ho et al., 2021; Pham & Ho, 2020). Many contemporary studies rely on the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain why and how people adopt new tools such as artificial intelligence (Habibi et al., 2023; Venkatesh, Thong, & Xu, 2012). Yet, these conventional models often miss the specific realities of university lecturers. Because lecturers possess high academic credentials and a sharp awareness of risks, their decision-making process is unique (Holmes et al., 2022; Nguyen, Ngo, Hong, Dang, & Nguyen, 2023).

When researchers look at the Global South, they usually focus on basic structural hurdles like poor internet connectivity or expensive software licenses (Adarkwah, 2021). What is frequently overlooked, however, is the psychological dimension of adopting and engaging with artificial intelligence. Such perspectives frequently fail to recognize that lecturers' critical awareness of artificial intelligence shortcomings and their risks, especially regarding academic integrity and data security, can serve as a motivating factor for thoughtful engagement and responsible adoption rather than avoidance (Farrokhnia, Banihashem, Noroozi, & Wals, 2024; UNESCO, 2023). To fill this specific research gap, this study was set out to explore what drives 261 university lecturers and academic managers in Vietnam to adopt these tools. In this study, the UTAUT model served as the baseline theoretical framework, which was further extended through the incorporation of two additional core dimensions: attitude (Davis, 1989) and perceived barriers (Rogers, 2003).

Through this expanded model, the study sought to investigate a striking pattern revealed in the primary survey data: a substantial gap of 1.19 points between a strong readiness to adopt and moderate, everyday usage. Previous research usually views barriers purely as roadblocks. In contrast, the present study argues that experienced lecturers often adopt a critically informed stance toward artificial intelligence. From this perspective, recognizing the limits of technology does not trigger passive rejection. Instead, it drives them to demand responsible professional development and proactive governance. Ultimately, this analysis provides vital empirical evidence to help universities design better systemic enablement and institutional policies for lecturers in today's rapidly shifting educational landscape (OECD, 2024; UNESCO, 2023).

2. Literature Review and Hypotheses

2.1. Theoretical Framework: The Extended Unified Theory of Acceptance and Use of Technology

When evaluating how people integrate digital tools, researchers often start with the second iteration of the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2012). While this framework predicts technology uptake exceptionally well in traditional settings (Scherer, Siddiq, & Tondeur, 2019), its application to generative artificial intelligence within the context of a developing country requires a more nuanced and context-sensitive examination.

In the Global South, structural constraints and systemic variables shape technology adoption much more intensely than in well-resourced Western institutions (Almaiah et al., 2020; Tarhini, Hone, & Liu, 2013). Moreover, conventional models tend to treat users as passive consumers. This assumption completely misses the reality of university teaching. Lecturers bring extensive pedagogical expertise and a sharp awareness of potential risks to their classrooms (Holmes et al., 2022).

To capture this complex reality, UTAUT as the baseline model was expanded by integrating two critical psychological constructs: attitude (Davis, 1989) and perceived barriers (Rogers, 2003). This expanded lens enables a more comprehensive evaluation of the nuanced cognitive and emotional negotiations that lecturers go through before bringing these novel pedagogical tools into their practice.

2.2. Hypothesis Development

Attitude and Behavioral Intention: Attitude captures how a person generally evaluates a technology (Ajzen, 1991). For artificial intelligence, a positive attitude means seeing its potential to reduce workload and inspire pedagogical innovation. Conversely, negative attitudes often stem from fears of role displacement and misinformation. For academic professionals, this emotional valuation heavily influences their deliberative choices. Because university lecturers deeply value pedagogical authenticity, their intention to adopt relies fundamentally on their attitudinal stance (Teo, 2011).

Hypothesis 1: A lecturer's attitude toward artificial intelligence significantly and positively predicts their behavioral intention to use it.

Performance Expectancy and Behavioral Intention: Performance expectancy measures whether a user believes the technology will actually improve their job performance (Venkatesh et al., 2012). In our context, this means using artificial intelligence for personalized scaffolding, instant feedback, and content creation (Kasneci et al., 2023). In developing nations, university lecturers frequently face large class sizes and severe instructional time poverty. Therefore, the practical utility of these tools for teaching efficiency becomes a primary driver for adoption (Almaiah et al., 2020).

Hypothesis 2: Performance expectancy significantly and positively predicts behavioral intention.

Effort Expectancy and Behavioral Intention: Effort expectancy is essentially perceived ease of use (Davis, 1989). While usually a strong predictor when a technology is new, its impact often fades for experienced professionals or highly intuitive systems. Today's large language models use conversational interfaces, which drastically lower the technical learning curve compared to older educational software (Wollny et al., 2021). As a result, we expect that basic usability concerns take a backseat to actual instructional value for academic staff.

Hypothesis 3: Effort expectancy significantly and positively predicts behavioral intention.

Facilitating Conditions and Behavioral Intention: This dimension covers the institutional, technical, and social support available to users (Venkatesh et al., 2012). In resource-constrained environments, successful integration heavily depends on external enablement, such as institutional funding for software licenses, clear policies, and peer encouragement. Unlike wealthier contexts where teachers might easily find individual workarounds, lecturers in developing nations need strong organizational backing to move from simply wanting to use a tool to actually applying it (Adarkwah, 2021; Tarhini et al., 2013).

Hypothesis 4: Facilitating conditions significantly and positively predict behavioral intention.

Perceived Barriers and Behavioral Intention: Perceived barriers involve recognizing functional limits, ethical dilemmas, and resource constraints, including academic integrity and data security risks (Farrokhnia et al., 2024). Traditional theoretical models view barriers purely as roadblocks (Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur, & Sendurur, 2012). However, when dealing with highly educated professionals, identifying these boundaries might actually spark a professional commitment to responsible integration. We propose a 'critically informed adoption' logic: being aware of barriers coexists with stronger intentions to adopt, because lecturers understand that mastering these limitations is the only way to apply the technology safely and ethically (Nguyen et al., 2023).

Hypothesis 5: Perceived barriers significantly and positively predict behavioral intention.

Future Trend Assessment and Behavioral Intention: Adoption choices do not happen in a vacuum; they reflect a broader technological worldview. Future trend assessment means believing that generative artificial intelligence represents an unavoidable evolution in modern higher education (Chan, 2023; Lim, Gunasekara, Pallant, Pallant, & Pechenkina, 2023). When lecturers view these tools as a temporary necessity for meeting contemporary learning demands, they naturally become more willing to advocate for and expand their usage.

Hypothesis 6: Behavioral intention is significantly and positively associated with future trend assessment.

3. Methodology

3.1. Research Design and Participants

To understand what exactly drives Vietnamese university lecturers to adopt generative artificial intelligence, a quantitative, cross-sectional survey design was adopted for this study. Rather than relying on a small, localized sample, we distributed a structured digital questionnaire through administrative networks and academic forums, utilizing purposive snowball sampling to reach a wide spectrum of the academic hierarchy.

The final dataset consists of 261 university lecturers and academic managers. Based on the demographic profiles, the participants represent an exceptionally well-credentialed and experienced group considering the context of a developing country, which makes them ideal for evaluating complex educational technologies. For instance, postgraduate degree holders make up the vast majority, as over 93% hold at least a master's degree, including many doctoral scholars and professors. Moreover, teaching experience is extensive; more than 84% have spent over a decade in the classroom, with the majority teaching for over 16 years.

These lecturers come from diverse academic domains, primarily education, engineering, economics, and information technology. While frontline lecturers form the core of our sample, we also captured perspectives from academic leaders like deans and department heads. Because these professionals possess deep pedagogical expertise, they can critically evaluate artificial intelligence beyond just basic usability hurdles.

The participants were recruited from multiple key higher education institutions across Vietnam, ensuring a diverse and representative sample. Specifically, the data were collected from academic staff and educational managers at Hanoi National University of Education (HANUE), Hanoi Pedagogical University 2 (HPU2), National Academy of Education Management (NAEM), Hung Yen University of Technology and Education (UTEHY), Ho Chi Minh City University of Technology and Education (HCMUTE), Vinh University of Technology and Education (VUTE), Nam Dinh University of Technology and Education (NDUTE), and Vinh Long University of Technology and Education (VLUTE). Table 1 presents the demographic characteristics of the participants.

Table 1. Demographic Characteristics of Participants (N = 261).

Characteristic	Category	n	%
Education level	Bachelor's degree	18	6.9
	Master's degree	140	53.6
	Doctoral degree	92	35.2
	Associate Professor	10	3.8
	Full Professor	1	0.4
Academic domain	Education	103	39.5
	Engineering & Technology	47	18.0
	Economics	38	14.6
	Information Technology	34	13.0
	Other	39	14.9
Years of experience	< 1 year	6	2.3
	1-5 years	19	7.3
	6-10 years	15	5.7
	11-15 years	63	24.1
	> 16 years	158	60.5
Job position	Lecturer / Teaching staff	215	82.4
	Head of Department / Dean	20	7.7
	Administrative / Specialist	26	10.0

Note: Percentages may not sum to 100 due to rounding. Job position categories were coded from free-text responses.

3.2. Measurement Instrument and Operationalization

To operationalize the proposed extended theoretical framework (Venkatesh et al., 2012), we designed a comprehensive survey instrument containing 59 analytical items. The instrument was carefully developed and structured to capture eight different psychological and behavioral constructs. For example, to gauge a lecturer's general attitude toward the technology, a 13-item scale was used. Actual usage behavior was measured across 9 practical dimensions. To assess core technological expectancies, we dedicated 10 items to performance expectancy and 4 items to effort expectancy. Contextual support was measured through 5 items on facilitating conditions. To capture risk awareness, we developed 8 items focusing on perceived barriers, specifically targeting functional flaws, ethical dilemmas, and security vulnerabilities. Finally, adoption readiness and technological worldview were measured using 4 items for behavioral intention and 6 items for future trend assessment.

Participants, as university lecturers, were asked to rate each statement using a standard five-point Likert scale. Since the original scales were in English, a rigorous back-translation was conducted to ensure the wording felt natural and contextually appropriate for Vietnamese academia. Before launching the full survey, we pilot-tested the instrument with a small group of academic administrators and educational-technology specialists to refine the phrasing. Table 2 shows the construct operationalization and mean scores.

Table 2. Construct Operationalization and Mean Scores.

Construct	Item (English translation)	M	SD	α	Construct M (SD)
ATT	Attitude			0.908	3.607 (0.661)
	ATT1 AI-Chatbot supports personalised learning	4.08	0.97		
	ATT2 AI-Chatbot reduces lecturer workload	4.09	0.95		
	ATT3 AI-Chatbot improves teaching quality	3.98	0.91		
	ATT4 AI-Chatbot will replace lecturers	2.45	1.00		
	ATT5 AI-Chatbot fosters creativity in teaching	3.85	0.95		
	ATT6 AI-Chatbot reduces lecturer-student interaction	2.91	1.03		
	ATT7 AI-Chatbot helps detect student learning problems early	3.48	0.94		
	ATT8 AI-Chatbot can improve student academic results	3.70	0.92		
	ATT9 AI-Chatbot supports teaching content creation	3.99	0.97		
	ATT10 AI-Chatbot is necessary for higher education	4.00	0.95		
	ATT11 AI-Chatbot may distort instructional content	3.09	1.01		
	ATT12 AI-Chatbot may compromise personal data privacy	3.38	0.93		
	ATT13 AI-Chatbot is effective in answering student FAQs	3.89	0.93		
USE	Actual Use Behaviour			0.930	2.854 (0.862)
	USE1 AI-Chatbot used for daily teaching activities	3.28	0.82		
	USE2 AI-Chatbot updated in course delivery	3.07	0.91		
	USE3 Monitoring student-AI-Chatbot interactions	2.92	1.03		
	USE4 AI-Chatbot for examination support	2.65	1.06		
	USE5 AI-Chatbot to provide reference materials	3.08	1.08		
	USE6 AI-Chatbot for schedule and notification management	2.64	1.20		
	USE7 AI-Chatbot integrated into LMS	2.58	1.20		
	USE8 AI-Chatbot for out-of-class student support	3.07	1.16		
	USE9 AI-Chatbot for student assessment and grading	2.41	1.16		
PE	Performance Expectancy			0.923	3.650 (0.592)
	PE1 increases student engagement in class	3.54	0.77		
	PE2 Improves student self-directed learning	3.69	0.79		
	PE3 saves time in teaching	3.95	0.70		
	PE4 increases student satisfaction	3.67	0.73		
	PE5 improves the quality of feedback to students	3.68	0.78		
	PE6 Timely detection of student learning issues	3.44	0.87		
	PE7 improves student grades	3.50	0.76		

Construct	Item (English translation)	M	SD	α	Construct M (SD)
	PE8 increases student learning motivation	3.58	0.82		
	PE9 Optimises instructional content delivery	3.84	0.69		
	PE10 reduces errors in the teaching process	3.61	0.79		
EE	Effort Expectancy			0.852	3.515 (0.630)
	EE1 has knowledge of AI-Chatbot in teaching	3.72	0.69		
	EE2 has the skills to exploit all AI-Chatbot features	3.43	0.81		
	EE3 can handle AI-Chatbot technical issues independently	3.24	0.83		
	EE4 Comfortable using AI-Chatbot in teaching	3.67	0.69		
FC	Facilitating Conditions			0.805	3.462 (0.653)
	FC1 Financial support from the institution for AI-Chatbot licensing	3.32	1.03		
	FC2 Positive student feedback when using AI-Chatbot	3.60	0.79		
	FC3 Colleague support for AI-Chatbot use	3.69	0.73		
	FC4 No technical difficulties with AI-Chatbot	3.30	0.92		
	FC5 No institutional policy barriers to AI-Chatbot use	3.39	0.86		
BAR	Perceived Barriers			0.919	3.547 (0.654)
	BAR1 AI-Chatbot is inadequate for classroom management	3.46	0.78		
	BAR2 AI-Chatbot is inadequate for student assessment	3.52	0.77		
	BAR3 AI-Chatbot is inadequate for tracking learning progress	3.42	0.85		
	BAR4 AI-Chatbot is inadequate for teacher-student collaboration	3.44	0.81		
	BAR5 AI-Chatbot is inadequate for content accuracy	3.52	0.87		
	BAR6 AI-Chatbot raises academic integrity concerns	3.59	0.85		
	BAR7 AI-Chatbot raises data security concerns	3.62	0.80		
	BAR8 Additional resources needed for effective use	3.81	0.80		
BI	Behavioral Intention			0.903	4.044 (0.613)
	BI1 Expand AI-Chatbot use across multiple subjects	3.95	0.72		
	BI2 Encourage colleagues to adopt AI-Chatbot	4.00	0.67		
	BI3 Participate in AI-Chatbot training programmes	4.10	0.72		
	BI4 Continuously update knowledge about AI-Chatbot	4.12	0.67		
FT	Future Trend Assessment			0.957	4.031 (0.639)
	FT1 AI-Chatbot will be an inevitable educational trend	4.05	0.71		
	FT2 AI-Chatbot is necessary for modern learning needs	4.08	0.69		
	FT3 AI-Chatbot promotes innovation in teaching	4.06	0.65		
	FT4 AI-Chatbot will improve its features continuously	4.07	0.68		
	FT5 AI-Chatbot will meet personalised learning requirements	3.99	0.74		
	FT6 AI-Chatbot will support higher-order thinking strategies	3.92	0.76		

Note: M = mean; SD = standard deviation. ATT, EE, FC, BAR, and FT scales range from 1 = Strongly Disagree to 5 = Strongly Agree. USE scale ranges from 1 = Never to 5 = Very Frequently. PE scale ranges from 1 = Very Ineffective to 5 = Very Effective. BI scale ranges from 1 = Absolutely Not Ready to 5 = Very Ready. α = Cronbach's alpha. Construct M (SD) represents the mean and standard deviation of the construct-level composite score, calculated by averaging the items within each construct.

3.3. Data Analysis Procedure and Computational Pipeline

To ensure full analytical reproducibility, a data processing pipeline was developed and implemented in Python (version 3.12), leveraging scientific libraries like pandas, NumPy, and SciPy. A rigorous multistage analytical procedure was employed to test our expanded model. First, the internal consistency of our survey instrument was assessed. The results were highly reliable; Cronbach's alpha coefficients ranged from 0.805 to 0.957, sitting well above standard empirical thresholds (Nunnally & Bernstein, 1994).

Next, comprehensive descriptive statistical analyses were conducted to uncover basic behavioral trends. At this stage, we first noticed the striking gap between a strong readiness to adopt and a much lower rate of actual classroom use. Therefore, Pearson and Spearman rank-order correlations analyses were subsequently performed to examine the relationships among the latent variables.

For the core predictive modeling, we conducted an ordinary least squares multiple linear regression. Behavioral intention was specified as the dependent variable, driven by our full suite of predictors: attitude, performance expectancy, effort expectancy, facilitating conditions, and perceived barriers. Overall, the model explained a robust 43.3% of the variance, confirming that our theoretical extensions were justified. Finally, we ran a one-way analysis of variance to see if factors like academic rank or years of experience skewed the results. They did not. The statistical uniformity across different demographic subgroups proved that the push to integrate generative artificial intelligence is a systemic and broad phenomenon in Vietnam, not just a trend among younger or technology-focused faculty.

4. Results

4.1. Descriptive Statistics of Adoption Determinants

When examining descriptive statistics, a fascinating paradox immediately stands out in the Vietnamese higher education context: lecturers are psychologically ready, but practically constrained. Out of all the dimensions we measured, behavioral intention and future trend assessment came out on top, both scoring over 4.0 on our five-point scale. Breaking down the individual survey items gives us a clearer picture of this readiness. Lecturers showed a massive appetite for continuous learning and professional development regarding artificial intelligence, with scores hitting above 4.10 for these specific areas. In fact, this finding turns the old stereotype on its head, proving that veteran academics in developing nations are not stubbornly resisting new technologies.

However, the story changes when everyday classroom realities are taken into consideration. Actual-use behavior dropped to a concerningly low aggregate mean of 2.85. This means there is a glaring 1.19-point gap between what lecturers want to do and what they actually do. Digging into the response frequencies, we clearly see the implementation bottleneck. Lecturers are playing around with basic exploratory prompts, but deep pedagogical integration is still rare. For instance, using generative artificial intelligence for complex tasks, such as direct student assessment or systemic integration into learning-management systems, barely scraped a 2.40 average.

To understand why this happens, we further examine how the lecturers perceive performance and barriers. On one hand, they absolutely see the pedagogical value; performance expectancy hit a solid 3.65, mostly because they agree the technology saves precious teaching time. On the other hand, they are highly cautious. The perceived barriers score was notably high, maxing out at 3.81 when we asked about the need for extra institutional resources. Basically, our descriptive data paints a picture of a highly aware academic workforce. They see the benefits of modern digital tools, but they feel structurally handcuffed, unable to turn their positive intentions into regular classroom practice. Table 3 details the construct-level descriptive statistics.

Table 3. Construct-Level descriptive statistics.

Code	Construct	M	SD	Min.	Max.
ATT	Attitude toward AI-Chatbot	3.607	0.661	1.00	5.00
USE	Actual Use Behaviour	2.854	0.862	1.00	5.00
PE	Performance Expectancy	3.650	0.592	1.20	5.00
EE	Effort Expectancy	3.515	0.630	1.00	5.00
FC	Facilitating Conditions	3.462	0.653	1.00	5.00
BAR	Perceived Barriers	3.547	0.654	1.75	5.00
BI	Behavioral Intention	4.044	0.613	1.00	5.00
FT	Future Trend Assessment	4.031	0.639	1.00	5.00

4.2. Correlation Analysis

Next, we ran a Pearson correlation analysis to map out how these different psychological factors connect. The resulting matrix showed us significant positive relationships across the board. The most striking link we found was between behavioral intention and future-trend assessment, showing a massive correlation coefficient of 0.780. What this tells us is that a lecturer's willingness to use generative artificial intelligence is deeply tied to their broader technological worldview. They are not just reacting to a trendy software update; they genuinely believe this represents an unavoidable evolution in higher education.

The core elements of our extended theoretical framework also held up beautifully. Facilitating conditions and performance expectancy proved to be strong correlates, scoring 0.481 and 0.477, respectively. Unsurprisingly, this confirms that when universities provide real institutional backing and the tools actually show pedagogical utility, lecturers are far more likely to jump on board. A lecturer's personal attitude was not far behind at 0.462, proving that the affective dimension is a huge piece of the technology adoption puzzle among academic staff.

But the most exciting takeaway from our correlation matrix was the role of risk awareness. Instead of scaring people away, perceived barriers actually showed a positive correlation of 0.387 with the intention to use the technology. This gives solid mathematical backing to our theoretical extension. For university lecturers, knowing about the functional and ethical limitations does not stop them. Actually, it does the exact opposite. It fuels a critically informed drive to proactively understand and master the technology safely. Table 4 illustrates the Pearson correlations among the study variables. Table 5 presents the results of the multiple linear regression predicting behavioral intention.

Table 4. Pearson correlations among study variables (N = 261).

Variables	1	2	3	4	5	6	7	8
1. ATT	—							
2. USE	0.271***	—						
3. PE	0.344***	0.475***	—					
4. EE	0.256***	0.451***	0.510***	—				
5. FC	0.326***	0.415***	0.535***	0.587***	—			
6. BAR	0.213***	0.060	0.150*	0.195**	0.238***	—		
7. BI	0.462***	0.283***	0.477***	0.399***	0.481***	0.387***	—	
8. FT	0.403***	0.299***	0.531***	0.373***	0.507***	0.273***	0.780***	—

Note: * $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

4.3. Hypothesis Testing and Predictive Modeling

To really test the predictive validity of our extended framework, we built an ordinary least squares multiple linear regression model. We set behavioral intention as the main target and threw our entire suite of cognitive, emotional, and contextual factors in as predictors. The model performed exceptionally well, explaining 43.3% of the variance in adoption readiness, which indicates a significant overall model fit.

First off, our results strongly supported Hypothesis 1. A lecturer's attitude was the undisputed heavyweight champion, serving as the primary positive predictor of their intention to adopt. This essentially means that before any technical features matter, the decision to integrate generative artificial intelligence is anchored in how a lecturer emotionally evaluates its pedagogical value.

Then came the twist that perfectly validated Hypothesis 5. Perceived barriers stepped up as the second-strongest positive predictor. This statistical outcome completely challenges conventional technology acceptance paradigms. Normally, we think of risks, including data-security vulnerabilities and threats to academic integrity, as stop signs. But for our Vietnamese lecturers, this risk awareness acts like a catalyst, encouraging a critically informed intention to master the technology safely.

We also found solid backing for Hypotheses 2 and 4. Performance expectancy and facilitating conditions both delivered significant positive predictive effects. In a resource-constrained environment, this makes perfect sense. Lecturers need to know the tool will make their teaching more efficient, and they desperately rely on robust institutional support structures.

On the flip side, we had to reject Hypothesis 3. Effort expectancy, which represents how easy the tool is to use, completely failed to reach statistical significance. This is actually a huge indicator of how the modern educational technology landscape has shifted. Because today's large language models use highly intuitive conversational interfaces, the old learning curve is gone. Academic professionals simply are not worried about whether the software is too hard to navigate anymore. Finally, current actual-use behavior did not significantly predict future intention, which perfectly mirrors that massive structural divide we observed earlier between current practical application and future adoption readiness.

Table 5. Multiple linear regression model predicting behavioral intention.

Predictor	B	SE	β	t	p	95% CI
Intercept	0.722	0.246		2.940	0.004	[0.238, 1.206]
ATT	0.241	0.048	0.260	5.001	< 0.001	[0.146, 0.336]
PE	0.232	0.064	0.224	3.645	< 0.001	[0.107, 0.357]
EE	0.067	0.061	0.069	1.105	0.270	[−0.053, 0.187]
FC	0.174	0.060	0.186	2.916	0.004	[0.057, 0.292]
BAR	0.226	0.046	0.241	4.871	< 0.001	[0.135, 0.317]
USE	−0.012	0.040	−0.017	−0.294	0.769	[−0.091, 0.068]

Note: B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; CI = confidence interval. Model fit: $R^2 = 0.433$; adjusted $R^2 = 0.419$; $F(6, 254) = 32.26$; $p < 0.001$.

4.4. Analysis of Variance (ANOVA)

We wanted to be sure our predictive modeling was not secretly biased by the demographic stratifications of our sample. To check this, we ran a one-way analysis of variance. First, we looked at academic attainment, comparing everyone from bachelor's degree holders up to established associate professors. We got an F-statistic of 0.872 and a p-value of 0.456, which is not statistically significant. But in this case, finding "nothing" is actually a huge discovery! When we inspected the data, scholars possessing doctoral degrees registered a mean intention score of 4.087, which practically mirrors the 4.046 mean of master's degree holders. This finding shatters the conventional assumption that highly credentialed academics inherently resist novel technological integration.

Next, we evaluated behavioral intention across the spectrum of professional teaching tenure. Again, the analysis showed no significant divide, with an F statistic of 1.660 and a p-value of 0.160, indicating a consistent generational alignment. It turns out that veteran educators with over 16 years of academic experience demonstrated an adoption readiness score of 4.024. That level of readiness statistically equals the intention reported by brand-new, junior faculty members.

Ultimately, this lack of demographic variance is one of our most powerful macro-level findings. The willingness to integrate generative artificial intelligence is not just a young person's game or isolated to specific ranks. It is a consistent, sector-wide phenomenon permeating the entire Vietnamese higher education hierarchy, transcending both academic rank and generational boundaries.

5. Discussion

5.1. The Primacy of Attitude in Professional Artificial Intelligence Adoption

When examining the driving forces behind technological integration, lecturers' personal attitudes emerged as the strongest predictor. Registering the highest predictive weight in our model with a standardized coefficient of 0.260, this emotional and cognitive evaluation easily outpaces purely functional expectancies. This aligns with broader meta-analytical evidence regarding technology acceptance (Scherer et al., 2019) and is strongly corroborated by recent empirical studies indicating that educators' perspectives and affective evaluations are critical for meaningful integration of generative artificial intelligence (Lee et al., 2024). For Vietnamese university lecturers, who are currently acting as pioneers in a massive national digital transformation, the decision to integrate generative artificial intelligence goes far beyond a simple cost-benefit analysis of technical features. Instead, they thoughtfully weigh pedagogical innovation against their own professional integrity.

Looking closely at the attitudinal metrics, which achieved an aggregate mean of 3.607, we see a highly pragmatic academic workforce. These lecturers do not fear technological displacement. They view these digital systems as supportive, cognitive partners rather than institutional replacements. Specifically, they highly value the potential of artificial intelligence to reduce instructional workload and facilitate personalized student learning. Ultimately, this proves that, for experienced pedagogical experts in a developing nation, achieving a cognitive and emotional alignment with the tool's educational value is the absolute prerequisite for any future behavioral commitment.

5.2. Decoding the Positive Barrier Paradox

Perhaps the most fascinating discovery of our research is the positive influence of perceived barriers on adoption readiness. Acting as the second-strongest predictor in our regression model with a standardized coefficient of 0.241, this variable completely challenges classical innovation-diffusion paradigms (Rogers, 2003). Traditionally, theoretical models position structural and ethical hurdles strictly as stop signs for technological acceptance (Ertmer et al., 2012). However, our empirical data reveal a striking paradox within the Vietnamese higher education sector. A heightened awareness of functional limitations actually coexists with a stronger drive to adopt the technology.

The specific barrier metrics provide further insight into the investigated phenomenon. The cohort of Vietnamese lecturers demonstrated significant risk awareness, especially regarding the need for additional operational resources, which hit a peak mean score of 3.81. They also highlighted deep structural concerns about data security and academic integrity vulnerabilities. Yet, rather than scaring them away, these concerns act as a powerful catalyst. This phenomenon may be conceptualized as a critically informed adoption effect. For seasoned pedagogical experts, recognizing the ethical vulnerabilities and functional boundaries of generative artificial intelligence is a fundamental requirement for professional engagement (Nguyen et al., 2023; Yan et al., 2024). Because passive avoidance is no longer a viable option in modern education, identifying where these digital systems fall short actually motivates lecturers to engage more deeply. It compels them to proactively build responsible instructional frameworks and demand necessary institutional resources, a strategic mindset echoed by recent calls for proactive integration of generative artificial intelligence in educational settings (Ng, Chan, & Lo, 2025). This proves that Vietnamese lecturers are proactive academic agents who seek to govern technological integration, rather than passive consumers who run away from inherent risks.

5.3. The Diminishing Salience of Effort Expectancy

The fact that effort expectancy completely failed to predict adoption intention reflects a massive structural shift in modern educational technology. Yielding a standardized coefficient of only 0.069, this dimension simply does not influence the adoption readiness of academic professionals in Vietnam. Unlike legacy electronic learning systems that required extensive technical training, the intuitive conversational interfaces of today's large language models have effectively eliminated traditional ease of use as a primary barrier. This shift supports the emerging concept of teacher-artificial intelligence collaboration, where the focus moves toward hybrid teaching intelligence rather than basic technical operation (Rokkones & Giannakos, 2025).

While the surveyed lecturers in this study reported high levels of general knowledge and operational comfort, their ability to independently resolve technical issues registered much lower at 3.24. However, this specific technical limitation does not hinder lecturers' overall intention to adopt. This finding is particularly significant given that the majority of participants in the sample possessed more than sixteen years of teaching experience. For these experienced lecturers, advanced technical programming mastery is not a prerequisite for pedagogical integration. Consequently, university professional development paradigms need a major update. Rather than wasting time on basic digital literacy training or fundamental software navigation, universities must prioritize cultivating advanced academic competencies. Specifically, training initiatives should focus on designing assessment frameworks that are resilient to generative artificial intelligence and teaching lecturers how to critically evaluate synthetically generated academic outputs.

5.4. Bridging the Gap Between Intention and Usage

Finally, the findings from this empirical study expose a significant structural challenge within the Vietnamese higher education sector. Even though lecturers display a remarkably high psychological readiness to adopt generative artificial intelligence, with a behavioral intention score of 4.04 on a five-point scale, their actual utilization sits at just 2.85. This establishes a glaring 1.19-point gap between professional intention and practical classroom execution.

When examining the specific usage metrics, the nature of this implementation gap becomes more apparent. While lecturers frequently experiment with basic queries, deep pedagogical integrations remain rare. Using these digital tools for complex academic tasks, such as direct student assessment or systemic integration into learning management systems, registered very low average scores. We must emphasize that this challenge does not stem from a lack of personal initiative. It represents a systemic bottleneck. Our regression analysis confirms this by identifying facilitating conditions as a significant predictor of adoption readiness. Lecturers clearly voiced their concerns about the lack of direct financial support for premium software licensing and the absence of clear institutional policy frameworks. This strongly echoes previous observations in Southeast Asia, where high academic aspirations frequently hit a wall due to inadequate institutional infrastructure (Ho et al., 2021; Pham & Ho, 2020). Furthermore, this bottleneck perfectly aligns with the OECD (2024) digital education outlook, which emphasizes that achieving an equitable digital transformation requires moving beyond individual efforts. Right now, the integration of generative artificial intelligence in Vietnam relies far too heavily on isolated individual experimentation. To bridge this divide, educational leaders must transition toward providing systemwide enablement. This means universities must invest in centralized technical infrastructure and establish unified governance frameworks. Only then can they empower their lecturers to safely translate their pioneering intentions into regular academic practice.

6. Conclusion and Implications

6.1. Conclusion

This empirical investigation was conducted to examine the factors driving and influencing Vietnamese university lecturers to integrate generative artificial intelligence into their academic practice. By extending the Unified Theory of Acceptance and Use of Technology (UTAUT), the study evaluated the cognitive and emotional factors behind their adoption decisions. The results reveal a striking paradox within the Vietnamese higher education landscape. While lecturers show an incredibly high psychological readiness to embrace these digital tools, their practical classroom execution remains heavily constrained, leaving a measurable 1.19-point gap between professional intention and practical reality.

The predictive modeling demonstrates that a lecturer's personal attitude acts as the ultimate driver of adoption readiness. Furthermore, the findings of this study challenge traditional innovation diffusion paradigms by revealing that perceived barriers functioned as a positive predictor rather than merely an obstacle to adoption. This suggests that awareness of functional limitations and ethical vulnerabilities does not necessarily discourage lecturers from engaging with generative artificial intelligence. Instead, such awareness may spark a critically informed and responsible adoption process. At the same time, the lack of statistical significance for effort expectancy indicates that intuitive conversational interfaces may have basically eliminated old usability hurdles for experienced academic staff. Overall, the findings challenge the common assumption or stereotype that veteran academics resist technological integration. Vietnamese university lecturers emerge as highly pragmatic and proactive agents of pedagogical innovation. However, to truly unlock this potential, universities must build the systemic infrastructure necessary to close the gap between professional ambition and daily academic practice.

6.2. Implications for Theory and Practice

On a theoretical level, this study significantly expands the technology acceptance literature. It proves that effort expectancy is rapidly losing its relevance when evaluating modern generative artificial intelligence. Because these tools use highly intuitive natural-language interfaces, future theoretical models need to look far beyond basic ease of use. More importantly, our research challenges the traditional assumption that perceived barriers always inhibit adoption. The statistical evidence from our specialized professional cohort indicates that risk awareness actually signifies deep cognitive engagement rather than passive resistance. This means future theoretical frameworks should start treating risk literacy as a powerful catalyst for responsible technological integration.

Translating these theoretical insights into practical execution requires serious institutional backing. The strong predictive power of facilitating conditions shows that university leaders must urgently fix the structural bottlenecks keeping actual usage low. Vietnamese higher education institutions must move beyond relying on isolated individual experimentation. Instead, they must secure subsidized access to premium software platforms and build the centralized technical infrastructure needed to integrate these tools into existing learning management systems. At the same time, professional development initiatives require a major overhaul. Universities need to transition from generic digital literacy seminars toward cultivating discipline-specific competencies. They must focus on teaching lecturers how to design assessment frameworks that are resilient to artificial intelligence and equipping them with the analytical skills to properly evaluate synthetically generated academic outputs. On a macro level, national regulatory bodies, particularly the Ministry of Education and Training, must establish a unified governance framework. Providing clear policy boundaries on student data privacy and academic ethics is essential to empower universities to safely move from cautious exploration to widespread implementation.

6.3. Limitations and Future Research

While this investigation delivers valuable insights into the Vietnamese academic context, we must acknowledge a few methodological boundaries. Because we relied on a cross-sectional survey design and a purposive snowball-sampling strategy, the generalizability of our empirical findings is somewhat restricted. This specific methodological approach also prevents us from definitively establishing long-term causality between the predictive dimensions and adoption readiness.

As institutional governance frameworks and digital educational ecosystems continue to mature across Vietnam, future researchers should definitely utilize longitudinal methodologies. Tracking these trends over time is necessary to see how the gap between professional intention and practical usage evolves as lecturers gradually gain access to better systemic support. Additionally, subsequent investigations would greatly benefit from integrating qualitative approaches. Deploying in-depth interviews and classroom observational methods will allow researchers to deeply explore the pedagogical shifts and the daily lived realities of the critically informed adoption effect. Ultimately, expanding this line of inquiry across diverse academic disciplines will give us a much more comprehensive understanding of how academic professionals integrate generative artificial intelligence into higher education.

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