Adoption of artificial intelligence tools for academic writing

Nguyen Thu Hoai, Lai Thi Thu Thuy
Department of Auditing, Institute of Accounting and Auditing, Thuongmai University, Hanoi, Vietnam

Article Info

Article history:

Received Dec 2, 2025
Revised Feb 23, 2026
Accepted Mar 9, 2026

Keywords:

Academic writing
AI tools
Perceived risk theory
Structural equation modeling
UTAUT

ABSTRACT

The rapid advancement of artificial intelligence (AI) presents both significant opportunities and challenges for academic writing. This study investigates the factors influencing the adoption of AI writing tools among lecturers in Vietnam by proposing an integrated theoretical framework that combines the unified theory of acceptance and use of technology (UTAUT) with perceived risk theory (PRT). The model incorporates performance risk (PR) and ethical risk (ER) as key inhibitors alongside the core UTAUT constructs. Data were collected through a cross-sectional survey of 404 lecturers from public universities across North, Central, and South Vietnam, including both public and private educational institutions, and analyzed using structural equation modeling (SEM). The results show that the proposed model has strong explanatory power, accounting for 77.9% of the variance in behavioral intention (BI) and 75.3% in use behavior (UB). All seven hypotheses were supported. Performance expectancy (PE) was the most potent predictor of intention, while PR was the strongest deterrent. Facilitating conditions (FC) and BI were found to be critical antecedents of actual use. The study contributes by empirically validating an integrated UTAUT–PRT framework in the context of AI writing tool adoption. The findings suggest that universities should prioritize performance-enhancing support mechanisms and risk-mitigation policies to promote responsible AI adoption.

Corresponding Author:

Lai Thi Thu Thuy
Department of Auditing, Institute of Accounting and Auditing, Thuongmai University
No. 79 Ho Tung Mau, Cau Giay, Hanoi, Vietnam
Email: laithuy@tmu.edu.vn

1. INTRODUCTION

Artificial intelligence (AI) is increasingly integrated into the academic ecosystem, offering tools to monitor educational processes, conduct sophisticated analyses, and diagnose academic performance [1]. Technologies such as predictive modeling, intelligent analytics, and automated content analysis are being applied to solve critical educational challenges and enhance quality [2]. Specifically, in the domain of scholarly writing, generative AI tools like ChatGPT have emerged as powerful assets for tasks such as automated draft generation, article summarization, and language translation, promising to make the writing process faster and more efficient [3].

The utility of AI spans the entire research lifecycle. During the literature search phase, AI can assist researchers by identifying relevant papers, summarizing key findings, and highlighting areas of uncertainty, thereby accelerating the comprehension of the current state of knowledge [4]. AI capacity to process vast amounts of information and identify connections between disparate sources surpasses human limitations, enabling researchers to uncover novel insights and pinpoint critical knowledge gaps more effectively [3], [5].

In the manuscript writing process, AI can generate initial drafts, suggest titles, and compose methodology sections based on provided data. Furthermore, it proves exceptionally effective for editing, formatting, clarifying complex sentences, and drafting abstracts. While the output may require human oversight, the time-saving benefits are undeniable [3]. Future applications may even include the automated generation of figures and tables to visualize data.

However, alongside these benefits, the use of AI in academic writing presents significant challenges and ethical concerns. Key issues include the potential for generating inaccurate or biased information, the heightened risk of plagiarism, threats to academic integrity, and data privacy violations [6]. AI-generated text may lack the nuance, style, and originality of human writing, making it detectable by sophisticated software and skeptical reviewers [7]. The ethical dilemma of authorship is particularly acute when AI plays a substantial role in content creation. The practice of using AI to rephrase text to avoid plagiarism detection, while technically possible, raises profound questions about scholarly ethics and is largely considered unacceptable [8]. These multifaceted risks necessitate a regulatory framework to govern the responsible use of AI in scientific writing [3].

Understanding the factors that shape lecturers' adoption of AI writing tools is crucial because these tools influence not only individual productivity but also the ethics and quality of scholarly communication. In particular, educators face dilemmas regarding authorship, originality, and academic integrity when using AI-generated content [9]. Therefore, beyond perceived usefulness and ease of use, perceived risks-such as ethical concerns and the potential for performance inaccuracies-must also be considered when examining adoption behavior.

While the discourse on AI in academia is growing, a significant research gap exists regarding the determinants of its adoption by faculty in developing countries. Most studies are situated in Western contexts [10]–[12], leaving the unique socio-economic, cultural, and institutional dynamics of nations like Vietnam underexplored. To address this lacuna, this study aims to develop and empirically validate a comprehensive model that explains the factors influencing the adoption of AI tools for academic writing among Vietnamese lecturers. The research is guided by an integrated framework combining the unified theory of acceptance and use of technology (UTAUT) with perceived risk theory (PRT) to capture both the drivers and deterrents of this behavior.

Accordingly, the study pursues three main objectives: i) to examine how UTAUT constructs (performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)) influence lecturers' behavioral intention (BI) to use AI tools for academic writing; ii) to investigate the role of perceived risks (performance risk (PR) and ethical risk (ER)) in moderating or directly affecting adoption decisions; and iii) to evaluate the overall explanatory power of the extended UTAUT model in predicting BI and actual usage behavior among Vietnamese lecturers.

This research offers significant theoretical and practical contributions. Theoretically, it extends technology acceptance literature by integrating the utilitarian focus of UTAUT with the crucial barrier-centric perspective of PRT, providing a more balanced model for understanding the adoption of disruptive technologies. Furthermore, it validates this integrated framework within the under-researched context of Vietnamese higher education. Practically, the findings will provide actionable insights for university administrators in designing targeted training and support policies, for policymakers in formulating national strategies for digital literacy, and for AI developers in creating tools that better address the specific needs and concerns of the academic community.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. The unified theory of acceptance and use of technology

When new technologies emerge, user acceptance is a critical prerequisite for successful implementation. The UTAUT model, developed by Venkatesh *et al.* [13] by synthesizing eight prominent technology acceptance theories, has proven highly effective in explaining users' BI and actual usage [14], [15]. The model identifies four core constructs as direct determinants of user behavior.

PE, the degree to which an individual believes that using a technology will enhance their job performance. PE is a crucial determinant of technology adoption [16]. In the academic writing context, lecturers are likely to perceive AI tools as improving writing quality, reducing grammatical errors, and enhancing productivity [17], [18]. When users recognize that AI writing tools help them achieve academic objectives more effectively, they are more inclined to adopt them [19], [20]. Previous studies have consistently found PE to be one of the strongest predictors of BI in technology adoption [11], [21]. In this research, PE refers to the belief among lecturers that AI tools will enhance their academic writing quality and productivity. Therefore, the author hypothesizes: PE positively influences lecturers' BI to use AI tools for academic writing (H1).

EE, the degree of ease associated with the use of a system. EE, or perceived ease of use, is another vital factor [13]. AI-based writing tools that are intuitive, user-friendly, and require minimal technical knowledge tend to foster higher adoption rates [16], [22]. In higher education, lecturers often face time constraints; thus, a system that simplifies the writing process is more likely to be embraced. Prior research has shown that ease of use significantly affects educators' attitudes and intentions toward adopting educational technologies [23], [24]. In this study, EE represents the belief that AI tools are straightforward and require minimal effort to operate. Thus, this research proposes: EE positively influences lecturers' BI to use AI tools for academic writing (H2).

SI, the extent to which an individual perceives that important others believe they should use the new system. SI refers to the extent to which individuals perceive that important others (e.g., colleagues, peers, or administrators) believe they should use a particular technology [13]. In academic environments, lecturers' adoption behaviors are often shaped by institutional culture and peer norms. The opinions and behaviors of colleagues, supervisors, and peers can create a normative pressure that encourages or discourages technology adoption [22]. When senior faculty or administrators endorse AI writing tools as legitimate aids, others are more likely to follow suit. Studies on educational technology adoption have consistently shown that SI significantly predicts BI [20], [25]. This study conceptualizes SI as the extent to which lecturers feel that influential figures in their network endorse the use of AI for research. Accordingly, the author hypothesizes: SI positively influences lecturers' BI to use AI tools for academic writing (H3).

FC, the degree to which an individual believes an organizational and technical infrastructure exists to support the use of the system. FC refer to the availability of necessary resources and support. In the case of AI writing tools, FC may include access to stable internet, institutional guidelines, and availability of training. When universities provide supportive environments and resources for AI tool use, lecturers are more likely to engage with such technologies [24]. Adequate access to technology, institutional subscriptions, training, and technical assistance are critical for successful implementation [26], [27]. Without such support, even the most promising technology may fail to be adopted [28]. This research defines FC as lecturers' perception of having sufficient resources and knowledge to effectively use AI tools. The author hypothesizes: FC positively influence lecturers' actual use of AI tools for academic writing (H4).

2.2. Perceived risk theory

In the context of AI-based writing tools, UTAUT provides a robust lens for understanding why and how educators adopt such tools. However, while UTAUT emphasizes positive motivational factors, it does not explicitly consider potential deterrents such as risk perceptions. This omission is particularly relevant to AI adoption, where ethical and performance concerns are salient. Thus, integrating the PRT [29] enhances explanatory depth by capturing the potential downsides associated with AI tool usage. In the case of AI tools, lecturers may perceive risks related to data accuracy, ethical misconduct, or reputation damage. Incorporating perceived risk into the UTAUT model helps to address the multidimensional nature of decision-making regarding emerging technologies [30]. Two major types of risks are particularly relevant to AI adoption in academia: PR and ER.

PR refers to the possibility that a technology may fail to deliver expected results [30]. PR is heightened by perceptions of algorithmic bias and misinformation. For AI writing tools, lecturers may worry about inaccurate paraphrasing, factual errors, or loss of originality in their academic manuscripts. When users believe a system's output may be discriminatory, unreliable, or untrustworthy, their risk perception increases, leading to resistance [31], [32]. If users believe that AI tools could compromise content quality, they might be hesitant to rely on them. However, when the perceived PR is manageable or outweighed by benefits, users' adoption intentions increase. Prior studies have shown that lower PR enhances technology acceptance [33]. The authenticity of AI-generated content is fundamental to user trust; frequent exposure to flawed outputs erodes this foundation. This research therefore hypothesizes: PR negatively influences lecturers' BI to use AI tools (H5).

ER relates to concerns over moral or ethical issues that may arise from technology use, such as plagiarism, authorship misrepresentation, and violation of academic integrity [9]. When users suspect that AI tools "plagiarize" human creativity or blur creative boundaries, their ethical trust in the system declines [34]. Lecturers may worry that using AI-generated text challenges the originality of their scholarly work or leads to ethical breaches. Trust in AI encompasses not only technical reliability but also ethical reliability-respect for intellectual property, data protection, and clear usage boundaries [35]. An absence of ethical trust can lead users to disengage, even if the tool is functionally effective. Conversely, if users perceive that AI tools can be used responsibly, they are more likely to accept them as legitimate aids. Prior literature highlights ethical concerns as a key determinant of AI acceptance in educational contexts [32]. Consequently, the research hypothesizes: ER negatively influences lecturers' BI to use AI tools (H6).

2.3. Behavioral intention and usage behavior

BI reflects the motivational readiness to use a technology, while UB denotes actual use [13]. The UTAUT model posits that BI directly predicts UB, which has been supported across diverse technologies [11]. Numerous studies have confirmed this relationship, indicating that a strong intention to use a technology is a significant predictor of its eventual usage [16], [36]. In the context of AI writing tools, lecturers' intention to use these systems is expected to lead to actual adoption in teaching, research, and publication activities. Therefore, this research proposes the following hypothesis: BI positively influences lecturers' actual use of AI tools for academic writing (H7).

3. METHOD

3.1. Research design

Based on the UTAUT and PRT, this study proposes a comprehensive model to explain lecturers' adoption of AI tools for academic writing. The model integrates six exogenous constructs: PE, EE, SI, FC, PR, and ER to predict BI and UB. In this model: PE, EE, SI, PR, and ER directly influence BI; FC and BI directly influence UB. All constructs are conceptualized as latent variables measured through multiple observed indicators. This integrated framework enables a simultaneous examination of both positive motivational and negative risk factors, providing a balanced understanding of AI adoption among lecturers.

The target population for this research comprised full-time lecturers currently employed at 27 public universities across Vietnam. As a definitive sampling frame was inaccessible, a non-probability sampling method was utilized, combining convenience and snowballing techniques. Initial survey invitations were distributed to personal and institutional contacts at major universities in key academic hubs, including Hanoi, Ho Chi Minh City, and Da Nang. Participants were then encouraged to forward the survey to their colleagues to broaden the sample's reach. The study successfully achieved a final sample of 404 respondents.

3.2. Data collection and instrument

Data collection was administered using an online survey hosted on Google Forms. To guarantee linguistic and conceptual equivalence, a rigorous forward-backward translation protocol was employed. The instrument was first translated from English to Vietnamese by a bilingual academic and then back-translated by an independent expert. The final instrument comprised two distinct parts. Section 1 gathered demographic profiles, including gender, age, academic discipline, and research experience. Section 2 assessed the eight latent constructs of the research model.

To ensure content validity, measurement items were adapted from established literature, as detailed in Table 1 (covering PE, EE, SI, FC, PR, ER, BI, and UB). All items were contextualized to reflect the usage of AI tools in academic writing and were evaluated using a 5-point Likert scale ranging from 1 to 5 (1=strongly disagree; 2=disagree; 3=neutral; 4=agree; 5=strongly agree). Before the main survey, a pilot study was conducted with 30 lecturers. Feedback from this pilot phase led to minor refinements in wording to improve clarity and relevance, ensuring the instrument's final validity.

3.3. Data analysis

The collected data were analyzed using a two-stage process employing IBM SPSS Statistics 26 and AMOS 24. Preliminary analysis: the dataset was initially screened for missing values, outliers, and normality. Descriptive statistics were generated in SPSS to summarize the demographic profile of the sample. The internal consistency and reliability of each measurement scale were assessed using Cronbach's alpha. Structural equation modeling (SEM) was the primary analytical technique used to test the hypothesized model. This was conducted in two sequential steps.

3.3.1. Measurement model analysis

Confirmatory factor analysis (CFA) was performed to evaluate the measurement model's psychometric properties. Convergent validity was assessed using the average variance extracted (AVE>0.5), and discriminant validity was established using the Fornell-Larcker criterion. Composite reliability (CR>0.7) was also calculated to confirm scale reliability.

3.3.2. Structural model analysis

Following the validation of the measurement model, the structural model was analyzed to test the hypothesized relationships between the constructs. The overall goodness-of-fit of the model was evaluated using a battery of indices, including the Chi-square/degrees of freedom ratio ($\chi^2/df<3$), comparative fit index (CFI>0.9), Tucker-Lewis index (TLI>0.9), root mean square error of approximation (RMSEA<0.08).

Table 1. Construct measurement items and sources

Factors	Items	Item	Source
PE	PE1	I think using AI tools is useful for my academic writing	[11], [13], [17], [37], [38]
	PE2	I think using AI tools make my academic writing tasks easier to complete	
	PE3	I think using AI tools increases my productivity in academic writing	
EE	EE1	I think my interaction with AI tools for academic writing is clear and understandable	[13], [17], [38]
	EE2	I think learning how to operate AI tools for academic writing is easy for me	
	EE3	I think AI tools for academic writing are easy to use	
	EE4	I think it is easy for me to become skillful at using AI tools for academic writing	
SI	SI1	My friends and family think that I should use AI tools for academic writing	[17], [39], [40]
	SI2	My colleagues think that I should use AI tools for academic writing	
	SI3	Influential people in my field, or experts recommend the use of AI tools for academic writing	
	SI4	My research adviser thinks I should use AI tools for academic writing	
FC	FC1	I have the necessary technology (e.g., computer, internet access) to use AI tools for academic writing	[11], [24], [41]
	FC2	Resources that teach me how to use AI tools for academic writing (e.g., tutorials, guides) are available to me	
	FC3	My university supports and encourages the use of AI tools for academic writing	
	FC4	Technical support is available to help me if I experience difficulties with AI tools for academic writing	
PR	PR1	I am concerned that content generated by AI tools for academic writing may be inaccurate or untruthful	[30], [35], [42]–[44]
	PR2	I am concerned that using AI tools for academic writing could result in producing misleading or deceptively false information	
	PR3	I am concerned that content generated by AI tools for academic writing might contain or reinforce harmful biases and stereotypes	
	PR4	I find it is difficult to verify the factual accuracy of content generated by AI tools for my academic writing	
ER	ER1	I am concerned that using AI tools for academic writing could lead to infringing on the intellectual property of others	[9], [35], [44], [45]
	ER2	I find it is difficult to determine if content generated by an AI tool for academic writing constitutes plagiarism	
	ER3	I am concerned about the privacy and confidentiality of the information and data I input into AI writing platforms	
BI	BI1	I intend to use AI tools for my academic writing tasks in the near future	[17], [46]
	BI2	I predict I will use AI tools regularly for my academic writing over the next few months	
	BI3	I plan to integrate AI tools into my regular academic writing process	
UB	UB1	I frequently use AI tools for my academic writing tasks	[35], [47]
	UB2	I regularly use AI tools as part of my academic writing process	
	UB3	Using AI tools has become a habitual part of how I approach my academic writing	

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Respondent demographics

Of the total 412 responses collected, 404 were complete and valid and were used for the final analysis. The detailed demographic characteristics of the study sample are presented in Table 2. The analysis showed that the sample was relatively balanced and diverse. In terms of gender, the proportion of women was in the majority (55.94%). The predominant age group was 35-44 years old (48.27%), indicating that the majority of participants were researchers and scholars who had a solid position in their careers. The study sample also had diversity in professional fields, in which the social sciences and humanities group accounted for the largest proportion (35.4%). In particular, the majority of participants had extensive research experience, with 48.26% having more than 10 years of experience. The demographic diversity and breadth of experience of the sample ensures that the data collected is highly representative, providing a solid foundation for testing the model on AI tool acceptance in academic writing.

4.1.2. Measurement model assessment

Internal consistency was evaluated using Cronbach's alpha and CR. Table 3 details the reliability and validity assessment of the measurement model. In terms of reliability, both Cronbach's alpha (ranging from 0.762 to 0.966) and CR values (ranging from 0.765 to 0.968) surpassed the recommended threshold of 0.70 [48]. These figures indicate a high level of internal consistency across all constructs. Regarding convergent validity, the model was evaluated based on factor loadings and AVE. All standardized factor loadings were statistically significant, falling between 0.778 and 0.971, which is well above the 0.70 cutoff. Additionally, AVE values ranged from 0.521 to 0.910, exceeding the 0.50 benchmark. This confirms that each construct accounts for more than 50% of the variance in its indicators. Collectively, these findings provide strong evidence for the model's reliability and validity, justifying the subsequent structural analysis.

Table 2. Demographic profile of respondents (N=404)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	178	44.06
	Female	226	55.94
Age group	25-34 years	102	25.25
	35-44 years	195	48.27
	45-54 years	86	21.29
	55 years and above	21	5.1
Discipline	STEM	117	28.96
	Social sciences and humanities	143	35.4
	Economics and business	120	29.7
	Other	24	5.94
Research experience	Less than 5 years	62	15.35
	5-10 years	147	36.39
	More than 10 years	195	48.26

Table 3. Factors loading, Cronbach's alpha, reliability, and convergent validity

Factors	Items	Cronbach's alpha	Factor loadings	CR	AVE
PE	PE1	0.933	0.950	0.933	0.824
	PE2		0.940		
	PE3		0.927		
EE	EE1	0.853	0.825	0.855	0.596
	EE2		0.832		
	EE3		0.875		
	EE4		0.800		
SI	SI1	0.905	0.871	0.906	0.706
	SI2		0.892		
	SI3		0.900		
	SI4		0.865		
FC	FC1	0.937	0.906	0.937	0.788
	FC2		0.922		
	FC3		0.933		
	FC4		0.908		
PR	PR1	0.886	0.778	0.889	0.670
	PR2		0.887		
	PR3		0.898		
	PR4		0.889		
ER	ER1	0.762	0.823	0.765	0.521
	ER2		0.795		
	ER3		0.851		
BI	BI1	0.966	0.970	0.968	0.910
	BI2		0.969		
	BI3		0.971		
UB	UB1	0.953	0.949	0.955	0.875
	UB2		0.971		
	UB3		0.950		

4.1.3. Correlation and discriminant validity analysis

After confirming the reliability and convergent validity of the measurement model, a Pearson correlation analysis was conducted to examine the relationships between the core constructs. Furthermore, discriminant validity-which ensures that the constructs in the model are empirically distinct from one another-was assessed using the Fornell-Larcker criterion. The results are presented in Table 4.

Table 4. Correlation coefficient among core variables

EE	SI	PE	ER	PR	FC	BI	UB
0.772							
0.225***	0.840						
0.183**	0.378***	0.908					
-0.004	-0.009	-0.044	0.722				
0.468***	0.448***	0.563***	-0.090	0.818			
0.211***	0.482***	0.424***	-0.054	0.475***	0.888		
0.496***	0.614***	0.663***	-0.199***	0.436***	0.399***	0.954	
0.414***	0.638***	0.594***	-0.125*	0.520***	0.698***	0.743***	0.936

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

As shown in Table 4, most of the core variables are positively and significantly correlated. For instance, BI shows a strong positive correlation with UB ($r=0.743$, $p<0.001$) and PE ($r=0.663$, $p<0.001$). Notably, ER was found to be negatively correlated with BI ($r=-0.199$, $p<0.001$) and UB ($r=-0.125$, $p<0.05$). To establish discriminant validity, the Fornell-Larcker criterion is met if the square root of the AVE for a given construct is greater than its correlations with all other constructs. The results in the table confirm that this condition was satisfied for all variables. Therefore, the analysis confirms that all constructs in the study possess adequate discriminant validity, indicating that they measure distinct concepts.

4.1.4. Structural model and hypothesis testing

The structural model fit was assessed using χ^2/df, CFI, TLI, and RMSEA. The assessment of the structural model, as detailed in Table 5 and Figure 1, revealed a high degree of compatibility between the model and the observed data. Key goodness-of-fit indices fell within the recommended ranges. Specifically, the ratio of χ^2/df was 1.804, satisfying the requirement of being less than 3. Other comparative indices also demonstrated strong fit, with CFI (0.973) and TLI (0.969) surpassing the 0.90 benchmark, while GFI reached 0.904 (exceeding the 0.80 threshold). Furthermore, the RMSEA value of 0.045 was well within the acceptable limit of <0.08. These results confirm the model's robustness, justifying the subsequent hypothesis testing. Based on the 404 valid responses, the proposed relationships were examined by analyzing standardized path coefficients (β), critical ratios, and p-values. The results, as detailed in Table 6, show that all seven proposed hypotheses were statistically significant and supported.

Table 5. Model fitting results

Fit index	Recommended threshold	Observed value	Evaluation result
CMIN/DF	<3	1.804	Good fit
GFI	>0.8	0.904	Good fit
CFI	>0.9	0.973	Good fit
TLI	>0.9	0.969	Good fit
RMSEA	<0.08	0.045	Good fit

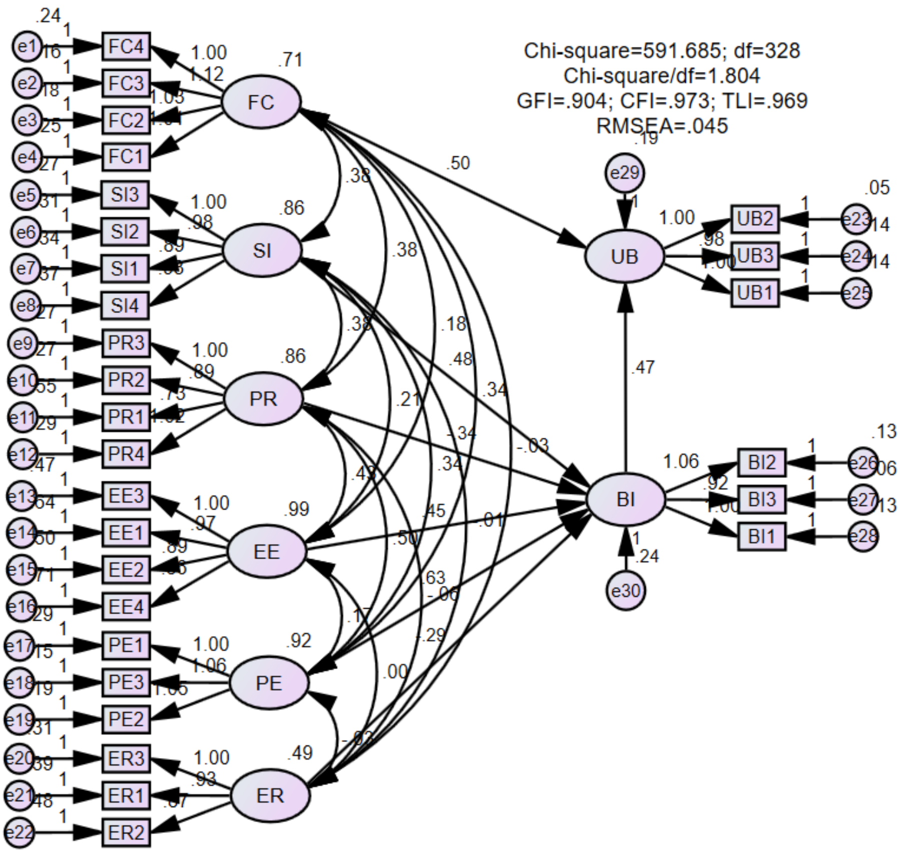

Figure 1. Results of the SEM analysis

Table 6. Results of hypothesis testing

Hypothesis	Path	Std. Beta (β)	Critical Ratio	p-value	Result
H1	PE→BI	0.585	13.575	0.000	Supported
H2	EE→BI	0.438	10.597	0.000	Supported
H3	SI→BI	0.434	11.385	0.000	Supported
H4	FC→UB	0.477	13.456	0.000	Supported
H5	PR→BI	-0.308	-6.328	0.000	Supported
H6	ER→BI	-0.194	-5.497	0.000	Supported
H7	BI→UB	0.544	16.273	0.000	Supported

a. Factors influencing behavioral intention

Regarding the antecedents of academics' intention to use AI writing tools, the structural model explained a significant 77.9% of the variance in BI (R^2=0.779). The results validated all five proposed hypotheses. Specifically, PE emerged as the strongest driver, exerting a substantial positive impact on BI (β=0.585, p<0.001), thereby supporting H1. Similarly, EE (β=0.438, p<0.001) and SI (β=0.434, p<0.001) demonstrated strong positive associations with intention, confirming H2 and H3. In contrast, risk factors acted as barriers; both PR (β=-0.308, p<0.001) and ER (β=-0.194, p<0.001) had significant negative effects on BI, supporting H5 and H6. These findings are particularly insightful when viewed in the context of the respondent demographics. The paramount importance of PE (H1) suggests that this sample of predominantly experienced academics (48% with >10 years of experience) is highly pragmatic. Their decision to adopt AI is driven primarily by the tangible improvements it can bring to their work. Furthermore, the strong negative influence of PR (H5) underscores that for established researchers, the fear that an AI tool might compromise the quality or integrity of their output is a major deterrent.

b. Factors influencing use behavior

Next, the model evaluated the predictors of the actual use of AI writing tools. The model was highly effective, accounting for 75.3% of the variance in UB (R^2=0.753). BI was the strongest predictor of UB, with a standardized path coefficient of β=0.544 (p<0.001). This confirms H7, highlighting that a strong intention is the most critical driver of actual adoption. FC also had a significant and strong direct positive effect on UB (β=0.477, p<0.001), supporting H4. This highlights that for the academics surveyed, translating intention into action is heavily reliant on having the necessary resources and support (FC). Even with strong intent, practical barriers can impede the actual use of AI tools in their academic writing process. In summary, all seven hypotheses were supported, and the high R^2 values confirm the model's robust ability to explain the factors driving the adoption of AI writing tools among the surveyed academic population.

4.2. Discussion

The proliferation of AI is fundamentally reshaping the landscape of academic research, heralding a new phase within the broader "era of transformation" driven by digitalization and hyperconnectivity [46]. The finding that PE is the most powerful predictor of adoption intention (β=0.585) provides robust empirical support for the arguments of Grassini *et al.* [19] and Wang [20]. As they suggest, academics are fundamentally pragmatic users; their willingness to adopt a new tool is primarily driven by the belief that it will enhance their research productivity and writing quality. This result confirms that the promise of AI to make the writing process "faster and more efficient" is the central value proposition for this demographic [3].

Similarly, the strong positive influence of EE (β=0.438) aligns perfectly with the conclusions of Budhathoki *et al.* [16] and Guggemos *et al.* [22]. Even for a highly educated user group, the perceived ease of use is a critical factor. The intuitive and user-friendly nature of modern generative AI tools lowers the barrier to entry for busy academics, making them more likely to experiment with and integrate these systems into their workflow.

SI was found to be a significant driver of intention (β=0.434), confirming the arguments of Guggemos *et al.* [22] regarding the normative pressures within professional environments. This suggests that as more scholars and research teams begin to use AI tools, a network effect is created, encouraging non-users to adopt the technology to maintain a competitive edge and align with evolving academic norms. Crucially, this study found a strong, direct link between FC and UB (β=0.477). This empirically validates the assertions of Hsu [26], Alanzi and Ratten [27] that organizational and technical infrastructure are not merely helpful but essential. It underscores that even when lecturers possess a strong intention to use AI, this intention cannot be converted into actual use without institutional support, such as access to premium tool subscriptions, official guidelines, and adequate training.

A key contribution of this study is its quantification of perceived risks as significant barriers to adoption. The powerful negative influence of PR (β=-0.308) on intention resonates strongly with the concerns raised by several studies [31], [32] regarding algorithmic bias and the potential for unreliable outputs. Our findings show that for academics, whose careers are built on intellectual rigor, the fear of AI producing flawed or inaccurate content is the single greatest deterrent.

Furthermore, the significant negative impact of ER (β=-0.194) aligns with the wide-ranging concerns about academic integrity, plagiarism, and authorship [6], [8]. This result empirically supports the notion proposed by Jia *et al.* [34] that when users perceive an ethical misalignment-such as the potential for unintentional plagiarism or data privacy violations-their trust in the system erodes, leading to resistance. Finally, the strong predictive power of BI on UB (β=0.544) confirms the foundational relationship established in the UTAUT model and supported by numerous studies [16], [36], cementing its role as the primary antecedent of actual technology use.

5. CONCLUSION

The adoption of AI tools for academic research by Vietnamese lecturers is a complex process driven by a rational evaluation of benefits and usability, but significantly tempered by perceptions of risk. This study successfully integrated the UTAUT model and PRT to demonstrate that PE and EE are key drivers of intention, while perceived risk is a formidable barrier. To translate intention into actual use, both individual motivation and strong institutional support in the form of FC are indispensable. As AI continues to evolve, fostering an environment of informed, critical, and ethical adoption will be paramount for the advancement of academic research in Vietnam.

This research makes two primary theoretical contributions. First, it validates the core UTAUT model within the novel context of AI tool adoption in a developing nation's higher education system, confirming its cross-cultural applicability. Second, and more importantly, it demonstrates the value of augmenting UTAUT with PRT. For emerging and potentially disruptive technologies like AI, where user trust is not yet established and the outcomes are uncertain, risk perception is a crucial inhibitor. Our findings advocate for the inclusion of perceived risk as a standard construct when studying the adoption of AI and other autonomous systems.

The findings of this study yield several practical recommendations for stakeholders and for university administrators: i) promote value: focus communication and demonstrations on how specific AI tools can directly improve research outcomes (e.g., publication rates, grant acquisition); ii) provide robust support: invest in institutional licenses for reputable AI tools, organize hands-on training workshops, and establish clear, university-wide guidelines on the ethical use of AI to mitigate risk perceptions; and iii) address risks: proactively address lecturers' concerns about ethics and accuracy by fostering open dialogue and providing resources on how to use AI responsibly and critically. For AI tool developers: i) prioritize usability: design tools with intuitive interfaces and provide clear tutorials and ii) build trust: be transparent about data privacy policies, algorithmic limitations, and how the tool should be cited. Features that help users check for source accuracy can directly combat PR. For lecturers: develop a critical form of "AI literacy" that involves not only using the tools but also understanding their limitations and evaluating their output with scholarly rigor.

This study is subject to several limitations. First, this study utilized non-probability sampling techniques, including convenience and snowball sampling. Therefore, the sample may not be fully representative of the entire population of Vietnamese lecturers, which limits the generalizability of the findings. Second, the cross-sectional design provides only a static snapshot of AI adoption; a longitudinal study would be beneficial for capturing the dynamic nature of technology acceptance over time. Third, the data is based on self-reports, which may be subject to common method bias or social desirability bias.

Future research could build on this study in several ways. Qualitative studies, such as in-depth interviews, could provide richer insights into the specific nature of lecturers' perceived risks and their strategies for mitigating them. Comparative studies could explore how adoption factors differ across academic disciplines. Finally, future models could incorporate other potentially relevant variables such as personal innovativeness, trust in AI, or the moderating effect of prior AI experience.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Nguyen Thu Hoai	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Lai Thi Thu Thuy	✓	✓			✓	✓	✓	✓	✓	✓	✓			✓

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

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [LTTT] on request.

REFERENCES

[1] X. Zhai *et al.*, "A review of artificial intelligence (AI) in education from 2010 to 2020," *Complexity*, vol. 2021, no. 1, p. 8812542, Jan. 2021, doi: 10.1155/2021/8812542.
[2] S. Z. Salas-Pilco and Y. Yang, "Artificial intelligence applications in Latin American higher education: a systematic review," *International Journal of Educational Technology in Higher Education*, vol. 19, no. 1, p. 21, Dec. 2022, doi: 10.1186/s41239-022-00326-w.
[3] M. Salvagno, F. S. Taccone, and A. G. Gerli, "Can artificial intelligence help for scientific writing?" *Critical Care*, vol. 27, no. 1, p. 75, Feb. 2023, doi: 10.1186/s13054-023-04380-2.
[4] M. M. Suverein *et al.*, "Early extracorporeal CPR for refractory out-of-hospital cardiac arrest," *New England Journal of Medicine*, vol. 388, no. 4, pp. 299–309, Jan. 2023, doi: 10.1056/NEJMoa2204511.
[5] S. B. Patel and K. Lam, "ChatGPT: the future of discharge summaries?" *The Lancet Digital Health*, vol. 5, no. 3, pp. 107–108, Mar. 2023, doi: 10.1016/S2589-7500(23)00021-3.
[6] A. Tlili *et al.*, "What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education," *Smart Learning Environments*, vol. 10, no. 1, p. 15, Feb. 2023, doi: 10.1186/s40561-023-00237-x.
[7] C. A. Gao *et al.*, "Comparing scientific abstracts generated by ChatGPT to real abstracts with detectors and blinded human reviewers," *NPJ Digital Medicine*, vol. 6, no. 1, p. 75, Apr. 2023, doi: 10.1038/s41746-023-00819-6.
[8] M. Hammad, "The impact of artificial intelligence (AI) programs on writing scientific research," *Annals of Biomedical Engineering*, vol. 51, no. 3, pp. 459–460, Mar. 2023, doi: 10.1007/s10439-023-03140-1.
[9] D. R. E. Cotton, P. A. Cotton, and J. R. Shipway, "Chatting and cheating: ensuring academic integrity in the era of ChatGPT," *Innovations in Education and Teaching International*, vol. 61, no. 2, pp. 228–239, Mar. 2024, doi: 10.1080/14703297.2023.2190148.
[10] M. Bearman and R. Ajjawi, "Learning to work with the black box: pedagogy for a world with artificial intelligence," *British Journal of Educational Technology*, vol. 54, no. 5, pp. 1160–1173, Sep. 2023, doi: 10.1111/bjet.13337.
[11] Y. K. Dwivedi, N. P. Rana, A. Jeyaraj, M. Clement, and M. D. Williams, "Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): towards a revised theoretical model," *Information Systems Frontiers*, vol. 21, no. 3, pp. 719–734, Jun. 2019, doi: 10.1007/s10796-017-9774-y.
[12] M. Perkins, "Academic integrity considerations of AI large language models in the post-pandemic era: ChatGPT and beyond," *Journal of University Teaching and Learning Practice*, vol. 20, no. 2, pp. 1–24, Jan. 2023, doi: 10.53761/1.20.02.07.
[13] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: toward a unified view," *MIS Quarterly*, vol. 27, no. 3, pp. 425–478, Sep. 2003, doi: 10.2307/30036540.
[14] W. Wu, B. Zhang, S. Li, and H. Liu, "Exploring factors of the willingness to accept AI-assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory," *Frontiers in Psychology*, vol. 13, p. 870777, Jun. 2022, doi: 10.3389/fpsyg.2022.870777.
[15] K. Wong, S. Russo, and J. McDowall, "Understanding early childhood student teachers' acceptance and use of interactive whiteboard," *Campus-Wide Information Systems*, vol. 30, no. 1, pp. 4–16, Dec. 2012, doi: 10.1108/10650741311288788.
[16] T. Budhathoki, A. Zirar, E. T. Njoya, and A. Timsina, "ChatGPT adoption and anxiety: a cross-country analysis utilising the Unified Theory of Acceptance and Use of Technology (UTAUT)," *Studies in Higher Education*, vol. 49, no. 5, pp. 831–846, May 2024, doi: 10.1080/03075079.2024.2333937.
[17] G. Chen, J. Fan, and M. Azam, "Exploring artificial intelligence (AI) chatbots adoption among research scholars using Unified Theory of Acceptance and Use of Technology (UTAUT)," *Journal of Librarianship and Information Science*, vol. 57, no. 4, pp. 1205–1223, Dec. 2025, doi: 10.1177/09610006241269189.
[18] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, p. 102274, Apr. 2023, doi: 10.1016/j.lindif.2023.102274.
[19] S. Grassini, M. L. Aasen, and A. Møgelvang, "Understanding university students' acceptance of ChatGPT: insights from the UTAUT2 model," *Applied Artificial Intelligence*, vol. 38, no. 1, p. 2371168, Dec. 2024, doi: 10.1080/08839514.2024.2371168.
[20] Q. Wang, "EFL learners' motivation and acceptance of using large language models in English academic writing: an extension of the UTAUT model," *Frontiers in Psychology*, vol. 15, p. 1514545, Jan. 2025, doi: 10.3389/fpsyg.2024.1514545.

[21] M. Al-Emran, V. Mezhuyev, and A. Kamaludin, "Technology acceptance model in m-learning context: a systematic review," *Computers & Education*, vol. 125, pp. 389–412, Oct. 2018, doi: 10.1016/j.compedu.2018.06.008.

[22] J. Guggemos, S. Seufert, and S. Sonderegger, "Humanoid robots in higher education: evaluating the acceptance of pepper in the context of an academic writing course using the UTAUT," *British Journal of Educational Technology*, vol. 51, no. 5, pp. 1864–1883, Sep. 2020, doi: 10.1111/bjet.13006.

[23] D. Al-Fraihat, M. Joy, R. Masa'deh, and J. Sinclair, "Evaluating e-learning systems success: an empirical study," *Computers in Human Behavior*, vol. 102, pp. 67–86, Jan. 2020, doi: 10.1016/j.chb.2019.08.004.

[24] C. Y. Lai, K. Y. Cheung, C. S. Chan, and K. K. Law, "Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: a survey with students," *Computers and Education: Artificial Intelligence*, vol. 6, p. 100246, Jun. 2024, doi: 10.1016/j.caeai.2024.100246.

[25] C.-M. Chao, "Factors determining the behavioral intention to use mobile learning: an application and extension of the UTAUT model," *Frontiers in Psychology*, vol. 10, p. 1652, Jul. 2019, doi: 10.3389/fpsyg.2019.01652.

[26] L. Hsu, "EFL learners' self-determination and acceptance of LMOOCs: The UTAUT model," *Computer Assisted Language Learning*, vol. 36, no. 7, pp. 1177–1205, Sep. 2023, doi: 10.1080/09588221.2021.1976210.

[27] S. Alanzi and V. Ratten, "The use of technology in facing the COVID-19 negative consequences and the associated opportunity for digital entrepreneurship in KSA," *Journal of Trade Science*, vol. 11, no. 2/3, pp. 31–44, Dec. 2023, doi: 10.1108/JTS-06-2023-0002.

[28] D. Menon and K. Shilpa, "'Chatting with ChatGPT': analyzing the factors influencing users' intention to use the open AI's ChatGPT using the utaut model," *Heliyon*, vol. 9, no. 11, p. e20962, Nov. 2023, doi: 10.1016/j.heliyon.2023.e20962.

[29] R. Bauer, "Consumer behavior as risk taking," in *Dynamic Marketing for A Changing World*, R. S. Hancock, Ed., Chicago, IL: American Marketing Association, 1960, pp. 389–398.

[30] M. S. Featherman and P. A. Pavlou, "Predicting e-services adoption: a perceived risk facets perspective," *International Journal of Human-Computer Studies*, vol. 59, no. 4, pp. 451–474, Oct. 2003, doi: 10.1016/S1071-5819(03)00111-3.

[31] P. Brauner, A. Hick, R. Philipsen, and M. Ziefle, "What does the public think about artificial intelligence?—A criticality map to understand bias in the public perception of AI," *Frontiers in Computer Science*, vol. 5, p. 1113903, Mar. 2023, doi: 10.3389/fcomp.2023.1113903.

[32] T. Zhou and H. Lu, "The effect of trust on user adoption of AI-generated content," *The Electronic Library*, vol. 43, no. 1, pp. 61–76, Jan. 2025, doi: 10.1108/EL-08-2024-0244.

[33] M. Chang and W. Wu, "Revisiting perceived risk in the context of online shopping: an alternative perspective of decision-making styles," *Psychology and Marketing*, vol. 29, no. 5, pp. 378–400, May 2012, doi: 10.1002/mar.20528.

[34] H. Jia, A. Appelman, M. Wu, and S. Bien-Aimé, "News bylines and perceived AI authorship: effects on source and message credibility," *Computers in Human Behavior: Artificial Humans*, vol. 2, no. 2, p. 100093, Aug. 2024, doi: 10.1016/j.chbah.2024.100093.

[35] T. Yu, Y. Tian, Y. Chen, Y. Huang, Y. Pan, and W. Jang, "How do ethical factors affect user trust and adoption intentions of AI-generated content tools? Evidence from a risk-trust perspective," *Systems*, vol. 13, no. 6, p. 461, Jun. 2025, doi: 10.3390/systems13060461.

[36] M. N. Yakubu and S. I. Dasuki, "Factors affecting the adoption of e-learning technologies among higher education students in Nigeria," *Information Development*, vol. 35, no. 3, pp. 492–502, Jun. 2019, doi: 10.1177/0266666918765907.

[37] A. Alaiad, M. Alsharo, and Y. Alnsour, "The determinants of m-health adoption in developing countries: an empirical investigation," *Applied Clinical Informatics*, vol. 10, no. 5, pp. 820–840, Oct. 2019, doi: 10.1055/s-0039-1697906.

[38] J. Balakrishnan, S. S. Abed, and P. Jones, "The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services?" *Technological Forecasting and Social Change*, vol. 180, p. 121692, Jul. 2022, doi: 10.1016/j.techfore.2022.121692.

[39] F. Abdullah and R. Ward, "Developing a general extended technology acceptance model for e-learning (GETAMEL) by analysing commonly used external factors," *Computers in Human Behavior*, vol. 56, pp. 238–256, Mar. 2016, doi: 10.1016/j.chb.2015.11.036.

[40] W. Zhang, "A study on the user acceptance model of artificial intelligence music based on UTAUT," *Journal of the Korea Society of Computer and Information*, vol. 25, no. 6, pp. 25–33, 2020.

[41] A. Mosunmola, A. Mayowa, S. Okuboyejo, and C. Adeniji, "Adoption and use of mobile learning in higher education," in *Proceedings of the 9th International Conference on E-Education, E-Business, E-Management and E-Learning*, Jan. 2018, pp. 20–25, doi: 10.1145/3183586.3183595.

[42] A. S. Doyal, D. Sender, M. Nanda, and R. A. Serrano, "Chat GPT and artificial intelligence in medical writing: concerns and ethical considerations," *Cureus*, vol. 15, no. 8, p. e43292, Aug. 2023, doi: 10.7759/cureus.43292.

[43] M. Ozanne, A. Bhandari, N. N. Bazarova, and D. DiFranzo, "Shall AI moderators be made visible? Perception of accountability and trust in moderation systems on social media platforms," *Big Data and Society*, vol. 9, no. 2, pp. 1–13, Jul. 2022, doi: 10.1177/20539517221115666.

[44] I. I. Ishmuradova, S. P. Zhdanov, S. V. Kondrashev, N. S. Erokhova, E. E. Grishnova, and N. Y. Volosova, "Pre-service science teachers' perception on using generative artificial intelligence in science education," *Contemporary Educational Technology*, vol. 17, no. 3, p. ep579, Jul. 2025, doi: 10.30935/cedtech/16207.

[45] F. Li and Y. Yang, "Impact of artificial intelligence–generated content labels on perceived accuracy, message credibility, and sharing intentions for misinformation: web-based, randomized, controlled experiment," *JMIR Formative Research*, vol. 8, no. 1, p. e60024, Dec. 2024, doi: 10.2196/60024.

[46] L. Li, W. Peng, and M. M. J. Rheu, "Factors predicting intentions of adoption and continued use of artificial intelligence chatbots for mental health: examining the role of UTAUT model, stigma, privacy concerns, and artificial intelligence hesitancy," *Telemedicine and e-Health*, vol. 30, no. 3, pp. 722–730, Mar. 2024, doi: 10.1089/tmj.2023.0313.

[47] A. Biloš and B. Budimir, "Understanding the adoption dynamics of ChatGPT among generation Z: insights from a modified UTAUT2 model," *Journal of Theoretical and Applied Electronic Commerce Research*, vol. 19, no. 2, pp. 863–879, Apr. 2024, doi: 10.3390/jtaer19020045.

[48] J. F. Hair, W. Black, B. J. Babin, and R. E. Anderson, *Multivariate data analysis: a global perspective*, 7th ed. Upper Saddle River, NJ: Pearson, 2010.

BIOGRAPHIES OF AUTHORS

Nguyen Thu Hoai received her Ph.D. at Thuongmai University, Vietnam and is currently a senior lecturer and educational researcher at this institution. She has taken part in various professional development activities for teachers and published several articles on qualified international journals and conferences. Her research field includes accounting, auditing, higher education, teacher training, and mentoring. She can be contacted at email: nguyenhoai@tmu.edu.vn.

Lai Thi Thu Thuy received her Ph.D. at Thuongmai University, Vietnam and is currently a senior lecturer and educational researcher at this institution. She has taken part in various professional development activities for teachers and published several articles on qualified national and international journals and conferences. Her research field includes accounting, auditing, higher education, teacher training, and mentoring. She can be contacted at email: laithuy@tmu.edu.vn.