Online-Journals.org

iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 21 No. 1 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijet.v21i01.59557

PAPER

Assessing the Adoption of Artificial Intelligence in Higher Education: A Case Study of Hanoi Metropolitan University

Nguyen Nang Hung, Pham Ngoc Son (✉), Nguyen Tra My, Nguyen Thi Mai Anh, Tran Van Anh, Nguyen Thai Minh

Hanoi Metropolitan University, Hanoi, Vietnam

pnson@hnmu.edu.vn

ABSTRACT

This study is set out to examine the current situation of artificial intelligence (AI) application for Hanoi Metropolitan University's faculty members; review challenges and opportunities; and propose a strategic framework of AI integration for teaching and learning. A mixed approach was employed, involving a survey with 156 lecturers across disciplines and sources of qualitative data—institutional documents and in-depth interviews with 20 lecturers. Theoretical background the study is based on the theoretical foundation of the technology acceptance model (TAM). The results suggest that a majority of faculty (67.9%) have tried out AI tools due to the hype of surface-level AI such as generative AI (e.g., ChatGPT) but are not integrating it into their educational practices, with 12.8% using it daily. There were major barriers such as absence of formal training (only 15.4% had any institutional training), lack of infrastructure, and perceived risks to academic integrity and data quality. There was substantial interest in professional development, with a request from 89.1% of faculty members for the AI-related courses. The study, in turn, reveals a real difference between what AI can do and what is used at the Hanoi Metropolitan University (HNMU) for teaching purposes. It argues that a strategic, top-down approach is required to transition from ad hoc use of digital technologies through to meaningful integration. A phased deployment model is recommended, with an emphasis on faculty development, infrastructure support, and well-defined institutional policy. These findings have implications for HNMU and other Vietnamese HEIs that are struggling with the complexities of digital transformation.

KEYWORDS

artificial intelligence (AI), higher education, technology adoption, faculty development, educational technology, Vietnam, technology acceptance model (TAM)

Hung, N. N., Son, P. N., My, N. T., Anh, N. T. M., Anh, T. V., Minh, N. T. (2026). Assessing the Adoption of Artificial Intelligence in Higher Education: A Case Study of Hanoi Metropolitan University. *International Journal of Emerging Technologies in Learning (iJET)*, 21(1), pp. 73–92. https://doi.org/10.3991/ijet.v21i01.59557

Article submitted 2025-10-09. Revision uploaded 2025-11-27. Final acceptance 2025-11-28.

1 INTRODUCTION

The 4th Industrial Revolution has jolted paradigms in every stratum of society, and higher education is the one at a crossroads. Artificial intelligence (AI), as one of the disruptive technologies leading this transformation, is poised to remake terrains of teaching, learning, and research in ways never seen before [1]. AI has a wide range of applications in education, ranging from personalized learning paths that adjust to individual student needs to intelligent tutoring systems and automatic assessment tools that enhance the quality of education, increase efficiency, and support new pedagogical approaches [2], [3], [4], [5]. The global market for AI in the education sector is expected to experience exponential growth, signifying a global shift towards embedding intelligent technologies in the educational ecosystem [6]. While the conversation has primarily been shaped by the institutions of the Global North, it's probably developing countries such as Vietnam that will be impacted more profoundly. For these countries, harnessing AI in ways that can be productive or constructive for education is not just a technical upgrade; it is a development play, a potential vehicle for reducing educational inequality, and an essential step toward participating in the global knowledge economy.

In Vietnam, the central government has acknowledged the critical need for this digital transformation. The National Strategy for Education Development 2021–2030 speaks clearly about the systemic reform of education and training, with decisive use of information and digital technologies. This national agenda puts significant pressure on the academy to innovate and change. Yet, the process of AI adoption in Vietnamese universities is in its infancy, and it is loaded with verbal to practical trials and system challenges [7], [8], [9], [10]. Although there is an increase of international research on AI in education, little literature exists that offers a nuanced and grounded examination of the implementation process from within a Vietnamese HEI.

The case of the Hanoi Metropolitan University (HNMU), a multidisciplinary public university in Vietnam's capital, can illustrate this point accordingly. As an ambitious university aiming at being a center for education, culture, and technology and becoming a smart university in 2045, HNMU officially considers integrating AI as a strategic focus area. The multidisciplinary character of the university, ranging from education and social sciences to economics and engineering, offers a rich environment in which to investigate how technology gets used in different academics. Yet early internal estimates from the university indicate a gap between this strategic vision and what is likely to happen in situ. Faculty uptake is fragmentary, mostly self-driven but without a systemic institutional structure of support and mentoring.

The purpose of this study is to fill the above-mentioned gap in the literature by carrying out an extensive, rich analysis of AI implementation at HNMU. It goes beyond taking a tally of tools used to consider the factors that either enable or block AI integration for pedagogies. To fulfill this, the study will be based on the following specific research questions:

1. How are the levels of AI awareness, knowledge, and application among the lecturers at Hanoi Metropolitan University?
2. What are the general push and pull factors behind faculty's decision to incorporate AI tools in teaching?
3. What are the main obstacles and challenges to incorporating AI effectively and widely in university pedagogy?
4. What are the trends in the adoption of AI and challenges by discipline at different institutions/university?

In response to these questions, in this paper, we seek to begin unpacking a nuanced and data-driven picture of the recently emerging AI adoption scenario in an ordinary Vietnamese public university. The results will also provide practical advice for HNMU's management in and beyond the country to enable them to adopt an effective technology integration strategy and so allow academics elsewhere, as well as policy-makers across the globe, to address this issue through their own national-level activities in a developing nation such as Vietnam [11]. Their study is ultimately relevant, as it may guide the evolution of a sustainable AI and STEAM ecosystem in education to enable teachers, enhance student learning, and be conducive to the country's long-range development. The paper ends with a discussion of evidence-based principles to build an enabling ecosystem for AI in higher education.

2 LITERATURE REVIEW

This section provides a theoretical and empirical foundation for the study by reviewing three key areas of literature: the role and application of AI in higher education, theoretical models of technology acceptance, and the specific context of technology integration in Vietnamese higher education.

2.1 The transformative potential of AI in higher education

The idea of using AI in education is not new; its intellectual roots can be traced as far back as the middle of the 20th century and the early years of computing. The first wave, sometimes described as computer-aided instruction (CAI), was born in the 60s and 70s. Systems such as programmed logic for automatic teaching operations (PLATO) at the University of Illinois were groundbreaking in their day, bringing developments such as plasma screen displays, shared terminals, and primitive online communities. However, their didactic model was essentially that of the behaviorist, and what they for the most part offered were complex 'teaching machines' for drill-and-practice exercises or to supply pre-programmed information with instant response. They worked under a linear or straightforward branching logic and could not comprehend the student's prospective reasoning and misunderstandings.

The second wave was in the 1980s when ITS became fashionable. This represented something of a revolution from behaviorism towards cognitivism. Based on cognitive science and AI concepts, ITS sought to emulate human tutoring through personalized instruction. Guins's classic systems, such as the LISP Tutor and Andes, were built on complex cognitive models. They typically comprised four modules: the expert model (which contained what to teach), the student model (which adapted to how students learned), the pedagogical model (which organized and delivered instructional tasks), and a user interface. Such systems might diagnose student misconceptions, offer personalized nudges through problem solving with a Socratic dialogue [12], or direct students interactively during the process of working out problems. While such 'first-wave' AI-in-education systems have demonstrated efficacy in controlled studies, they were notoriously difficult and expensive to construct. They needed a lot of 'knowledge engineering'—backbreaking work where domain experts and AI folks would spend hundreds of hours encoding expert knowledge and potential student misconceptions into the system for one domain. This made them brittle and hard to scale and limited them largely to wells.

The current third wave of AI in education, which entered the scene in the 2010s and has taken off in a way that is hard to ignore by the 2020s, is a different beast. It is not a result of hand-crafted knowledge engineering but rather of machine learning and data. This new paradigm is driven by a combination of three forces: the increasing availability of very large datasets (Big Data) created by millions of users using online learning platforms and learning management systems (LMS); exponential growth in computing power, especially using parallel processes on graphic processing units (GPUs), which have been particularly effective at training deep neural networks; and significant advances in algorithms for machine learning, especially for deep learning and natural language processing (NLP) [13], [14], including transformer architectures that underpin large language models (LLMs). It has spurred a resurgence in the field, democratizing AI to be more powerful, accessible, and relevant than ever before for mainstream education. The literature points to a number of key areas where the newer generation of data-driven AI is having a particularly strong impact.

Alized and adaptive learning. This is the most applauded use of AI in education. Commercial technologies, such as ITS and ALP, leverage algorithms to represent the knowledge state of a student and personalize content delivery, pacing, and feedback level. Research has established that these systems can be highly effective, often achieving levels of effectiveness comparable to one-on-one human tutoring [12]. Solutions such as Khan Academy's Khanmigo and Carnegie Learning's MATHia are examples of this effort to personalize support at scale.

Automation of administrative and instructional tasks. Artificial intelligence has the potential to greatly reduce overhead on faculty in administration. That's made the auto-moderating of homework more desirable, especially in courses with high enrollments. Tools such as Gradescope leverage AI to match similar solutions and facilitate rubric-based assessment, which results in a substantial reduction in the time required by instructors [15], [16]. Additionally, AI can assist in authoring quizzes, summaries of reading materials, and even initial drafts of lesson plans, thereby allowing faculty to concentrate on more value-added teaching activities.

Smart student support and engagement systems. These AI-driven chatbots and virtual assistants are being used to offer students round-the-clock support. These bots can respond to commonly asked questions about course logistics, deadlines, and university services, offering instant support while also removing some of the email load from faculty inboxes. A landmark example is the well-known "Jill Watson" experiment at the Georgia Institute of Technology, where an AI teaching assistant on the IBM cognitive platform Watson was able to respond with a high level of correctness and human-like style to more than one-third of student inquiries in an online discussion forum without students realizing that they were communicating with a machine [2], [17], [18], [19]. And now universities are making their own custom chatbots for student services, library support, and IT helpdesks on more accessible platforms such as Microsoft's Bot Framework and Google's Dialogflow.

Learning analytics and predictive modeling. Artificial intelligence is great at detecting patterns in massive data sets. In the context of education, this refers to learning analytics (LA), where data from LMS are analyzed to analyze the behavior of students, predict at risk students, and provide feedback about the effectiveness of learning designs [16], [20], [21]. For instance, a model might raise concerns about a student whose level of online activity has dropped dramatically, prompting an intervention by academic advising.

2.2 Theoretical framework: TAM and UTAUT

To understand why faculty members choose to adopt or reject AI tools, this study draws upon established models of technology acceptance. The TAM [22], proposed by Davis (1989), is one of the most influential theories in this field [23]. TAM has been widely validated across numerous contexts and technologies, including recent studies on AI adoption in higher education [24], [25]. TAM posits that two primary factors determine a user's intention to use a new technology:

1. **Perceived Usefulness (PU):** An individual's conviction that utilizing a specific system will improve their professional performance.
2. **Perceived Ease of Use (PEOU):** An individual's perception of how effortless it would be to interact with a particular system.

Technology acceptance model has been widely validated across numerous contexts and technologies. However, it has been criticized for focusing primarily on individual beliefs and not sufficiently accounting for social and organizational factors. To address this, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates elements from TAM and other models. UTAUT identifies four key determinants of user acceptance: Performance Expectancy (similar to PU), Effort Expectancy (similar to PEOU), Social Influence, and Facilitating Conditions [26], [27], [28], [29]. This study will use the core constructs of TAM (PU and PEOU) as its primary theoretical lens, supplemented by the concept of Facilitating Conditions from UTAUT. This integrated approach is justified because while TAM is excellent at explaining individual intention based on personal beliefs, it can sometimes overlook the powerful role of the organizational environment. In a university setting, an instructor might perceive an AI tool as highly useful and easy to use, but if the university provides no license for it, no training on how to use it, and the classroom Wi-Fi is too slow to support it, adoption will not occur. Therefore, Facilitating Conditions act as a critical gateway or bottleneck, moderating the relationship between individual attitudes and actual behavior. This makes the combined TAM + Facilitating Conditions framework particularly well-suited for analyzing technology adoption within an institutional context such as the Hanoi Metropolitan University.

2.3 Technology integration in the Vietnamese higher education context

Vietnam's higher education is going through a phase of quick changes, accelerated by initiatives from the government as part of the National Digital Transformation Program. On the one hand, there is a clear call for universities to be made over in terms of modernization, internationalization, and quality assurance of their teaching and research. But the tech integration, including AI, is fraught with some systematic glitches. Studies have shown that although Vietnamese teachers perceive a positive attitude towards ICT integration, the implementation of it in practice is hindered by an inadequate infrastructure system, a lack of technical assistance, and a shortage of digital pedagogical knowledge [9].

And besides, the teaching culture in a lot of Vietnamese institutions has tended to be more teacher-oriented anyway. Moving toward increasingly student-centered, technology-facilitated pedagogies requires new tools and a global reframing of mindset and practice. The present study is located within this climate of lofty aims and low practice, with a focus on how such trends are apparent at the institutional level in the Hanoi Metropolitan University.

2.4 Ethical considerations and challenges

No conversation about AI in education would be complete without considering the tremendous ethical dilemma it raises. With growing AI systems in the core academic activities, issues of bias, privacy, equity, and AI are probed [30], [31]. AI systems are only as good as the data on which they train, and those data—if indeed, they truly capture some measure of social or human behavior—may reflect existing biases (racial, gender, or socioeconomic) or inequalities in society at large. For instance, an AI-based admissions system that is trained on historical data might pick up how to favor people from privileged groups and perpetuate existing inequalities.

Data privacy is also a big concern. AI-based educational platforms gather huge volumes of sensitive student data, including academic standing and behavioral patterns. But the security surrounding this type of data, who can access it, and how it is used are important questions any institution should be asking. The potential exploitation of such data for commercial purposes, or the development of highly detailed and potentially discriminatory student profiles, carries serious ethical concerns [6]. Finally, the advent of powerful generative AI tools, such as ChatGPT, has spotlighted academic integrity concerns. Meanwhile, the ability for students to create essays, solve problems, and write code with the help of AI is challenging established ideas about authorship and academic evaluation. This has now ignited a global conversation among educators about whether to ban the tools, embrace them, or find some sort of middle ground. It requires a rethink of what assessment might look like, away from things that can easily be automated, to tasks that involve higher-order thinking, creativity, and authentic application of knowledge.

3 METHODOLOGY

A mixed-methods research design was used for this study, utilizing a convergent parallel model [32]. This was opted for owing to the potential to offer a better overall explanation of the complex phenomenon of technology adoption. The quantitative component (a survey distributed to all academic staff) was formulated on the basis of specificity, generalization, and statistical verifiability and took a broad perspective on AI uptake in order to determine typical patterns, frequencies, and correlations throughout a large population. Concurrently, the qualitative portion (depth interviews and document review) was constructed to measure the depth of faculty experience and identify the subtleties, motives, and contextual factors that are driving these figures. Through simultaneously gathering both types of data and subsequently combining them in analysis and interpretation, the study sought to reach 'triangulation'—the confirmation of results from different sources—and 'complementarity'—using qualitative information to account for and elaborate on its quantitative findings. This mixed-method approach is especially appropriate for this study because it enables the researchers to use the statistical results of their survey to reveal what and how much firms are adopting AI and qualitative data from interviews that can show why and how that adoption occurs.

3.1 Research setting and participants

The study was carried out at a public university located in Hanoi, Vietnam (HNMU). As of 2025, HNMU consists of six main faculties and affiliated schools, with a variety of undergraduate programs at graduate programs. Its strategic ambition to become a "smart university" makes it an interesting site for the purpose of this study. The universe of full-time faculty at the university was the target population for the survey. One hundred fifty-six faculty members voluntarily completed the survey, a large proportion of the academic staff across the university. The sample was varied to achieve representation from all major faculties: Faculty of Education (20.5%), Faculty of Social Science and Humanities (17.9%), Faculty of Languages (19.9%), Faculty of Economics and Tourism (18.6%), Faculty of Engineering and the Environment (16.7%) and an associated Thang Long Multilevel School (6.4%). As described in the Results section, those who responded to our questionnaire were generally evenly distributed by age group, departmental rank, and years since their appointment; such balance should better validate our findings.

Using a purposive sampling approach, the qualitative phase sampled 20 faculty members for semi-structured, deep interviews. A maximum variation sample was chosen for the participants: early adopters versus non-users of AI representatives from all faculties, including both junior and senior lecturers.

3.2 Data collection

Data were collected in February and March 2025. Methods: An electronic survey was created and sent to all faculty through the university email system and other media outlets. The survey included the following sections:

1. Demographics: Age, gender, academic rank, school/college, and years of teaching experience.
2. AI Awareness and Knowledge: Subjective sense of knowledge of AI and place for the source of information.
3. AI Usage and Practice: How much AI use, which type of AI-instruments and for teaching purposes.
4. Perceptions and Attitudes (TAM constructs): Using 5-point Likert type scales (1 = Strongly Disagree, 5 = Strongly Agree) measuring PU (e.g., "Using AI tools helps me improve the quality of content for lecturing") and Perceived Ease of Use (e.g., "Learning to use AI tools is easy for me").
5. Barriers and Needs: Query about barriers faced, needed institutional support, and training.

The tool was structured in English and translated into Vietnamese, then back-translated for confirmation. Ten faculty members were invited for a pilot test to assess the clarity and comprehensibility. High internal consistency was evidenced for the final instrument. We performed a reliability test for the Likert-scale items for the TAM constructs, producing a Cronbach's alpha coefficient of 0.847 (far higher than the 0.70 threshold), meaning that the measurement scales for PU and PEOU are highly reliable.

Qualitative Data:

Document Review: The study involved the review of critical institutional documents. These comprised the university's strategic development plan, the official proposal and final report of the internal research project AI in teaching (on which this study is based), and official communications on technology in education. This commentary added context to the university's official policy and approach to artificial intelligence.

Interviews: Twenty-one in-depth interviews (including short interviews as a follow-up after longer ones) of around 45–60 minutes were held. An interview protocol (refer to Table 2) was employed as a guide to help prompt discussion, including queries on their personal experiences and examples of AI application in their course(s), perceived impact on student learning, specific challenges they encountered in such use, and suggestions for the university. Written informed consent was obtained, and all interviews were audio-recorded in Vietnamese and transcribed exactly for analysis.

3.3 Data analysis

Data collected from the questionnaire was analyzed via the Statistical Package for Social Sciences (SPSS) release 28. Frequencies, percentages, means, and standard deviations were computed to describe the demographic profile as well as levels of AI awareness and use. Cross-tabulations (accompanied by chi-square tests) were employed for exploring the cases of associations among faculty characteristics and AI utilization types. The difference between the mean scores of PU and PEOU in AI users and non-users was compared using a T-test.

Qualitative analysis. The qualitative data from the interview transcripts and institutional documents were subjected to a rigorous thematic analysis, following Braun and Clarke's (2006) guidelines. The approach was systematic and iterative. The first three interview transcripts (coded by two researchers working independently) were used to produce a partial coding frame. They got together and compared codes after that point, resolved differences, and cut another set of code lists. This coding scheme became the master file that we used to code the remainder of the transcripts in NVivo. The process was iterative and comprised five separate stages: (1) Familiarizing with the data, achieved by reading and rereading participant material to immerse ourselves in their content; (2) Initial Coding, identifying the main categorical features that typified each source material; (3) Theme Searching, collating coded sections into clusters representing potential themes; (4) Theme Review, a validation step to establish whether they cohered adequately both within themselves and across the whole dataset; and (5) Defining and Naming Themes—an ongoing interpretive activity where we refined theme specifics, as well as downloaded them into a coherent storyline for telling each case's narrative. This systematic approach led to the believability and reliability of the qualitative results, which helped to generate key themes and stories that added explanatory depth to the quantitative survey results.

3.4 Ethical considerations

The study strictly adhered to the ethical protocols of HNMU. All individuals were fully informed of the study objectives, the voluntary basis of their involvement, and the assurance of confidentiality. Following this, informed consent was secured from every survey and interview participant. To safeguard anonymity, the data was processed to remove all personal identifiers from the final dataset and report.

4 RESULTS

This section presents the findings from the quantitative survey and qualitative interviews, organized thematically to provide a comprehensive picture of the AI adoption landscape at the Hanoi Metropolitan University.

4.1 Faculty demographics and profile

The survey sample (N = 156) was broadly representative of the university's faculty. The majority of respondents were female (68.6%). In terms of age, the largest group was the 40–50 age bracket (41.0%), followed by 30–40 years (34.6%) and over 50 years (24.4%). This indicates a mature faculty body, with a significant cohort of mid-career academics. Academically, most participants held a Master's degree (67.3%), while 28.8% held a PhD, and a small fraction (3.9%) were at the rank of Professor or Associate Professor. The distribution across faculties was relatively even, as detailed in the Methodology section.

A chi-square test for independence was performed to examine the relation between academic faculty and AI adoption. The relation between these variables was significant, $\chi^2(5, N = 156) = 12.8$, $p = .025$. As shown in Table 1, the Faculty of Engineering and Environment had the highest adoption rate (84.6%), while the Faculty of Education had the lowest (53.1%). This suggests that disciplinary culture plays a significant role in the propensity to adopt AI tools.

Table 1. AI adoption rate by faculty

Faculty	AI Users (N)	AI Non-Users (N)	Total (N)	Adoption Rate (%)
Engineering & Environment	22	4	26	84.6%
Foreign Languages	23	8	31	74.2%
Economics & Tourism	20	9	29	69.0%
Social Sciences & Humanities	18	10	28	64.3%
Thang Long School	6	4	10	60.0%
Education	17	15	32	53.1%
Total	106	50	156	67.9%

4.2 Awareness, knowledge, and training

The faculty's self-assessed understanding of AI was modest. As shown in Table 2, a combined 71.8% of faculty rated their understanding as "Moderate" or "Limited," with only 23.1% feeling they had a "Good" understanding. A small but notable 5.1% admitted to having no understanding at all.

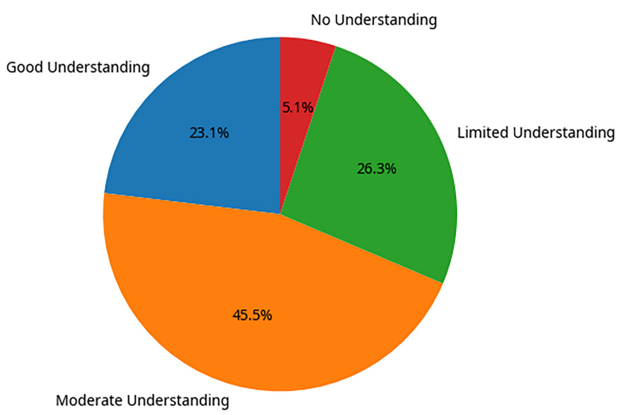

Fig. 1. Self-assessed level of AI understanding

Table 2. Self-assessed level of AI understanding

Level of Understanding	Frequency (N)	Percentage (%)
Good Understanding	36	23.1%
Moderate Understanding	71	45.5%
Limited Understanding	41	26.3%
No Understanding	8	5.1%
Total	156	100.0%

There was a statistically significant difference in understanding across faculties ($\chi^2(12) = 22.54$, $p < .05$). The Faculty of Engineering and Environment reported the highest level of confidence, with 42.3% claiming a "Good" understanding, whereas the Faculty of Education reported the lowest, at just 12.5%. This suggests that disciplinary proximity to technology plays a key role in faculty's knowledge and confidence.

Regarding how faculty acquire this knowledge, the data overwhelmingly points to self-directed learning. The primary source of information was "Internet and specialized websites" (78.2%), followed by "Online courses" (34.6%). In stark contrast, "Formal training from the university" was the least cited source, at only 15.4%. This finding was powerfully echoed in the interviews. A senior lecturer from the Faculty of Social Sciences and Humanities stated, "Everything I know about ChatGPT or other tools, I learned from my children or from searching on Google. The university has not organized any official workshops for us."

4.3 AI usage patterns

Despite the modest level of formal knowledge, a surprising 67.9% (N = 106) of faculty reported having used at least one AI tool in their professional work. This suggests a strong, practitioner-led, bottom-up adoption trend. However, this usage is neither deep nor frequent. As illustrated in Figure 2, only 12.8% of the total faculty are daily users, while nearly a third (32.7%) are only occasional users.

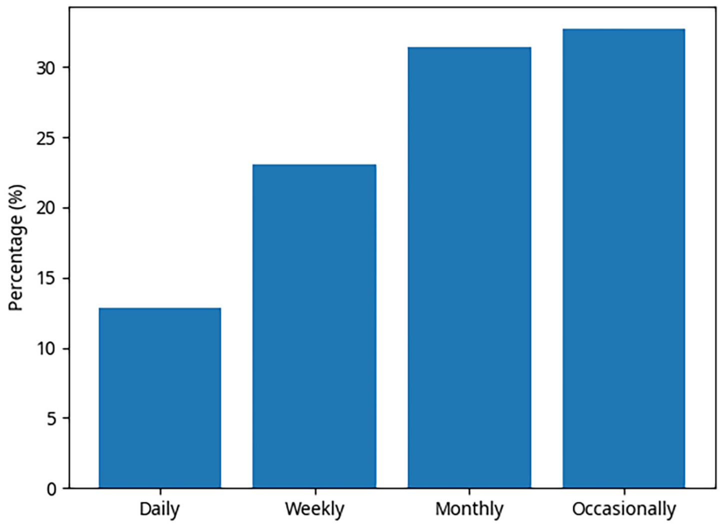

Fig. 2. Frequency of AI use among faculty

The type of tools used is also very specific. Among the 106 faculty members who use AI, generative AI chatbots are dominant. ChatGPT was, by far, the most mentioned tool, with 89.6% of AI users reporting its use. This was followed by translation tools such as Google Translate (67.9%) and grammar-checking tools like Grammarly (45.3%). The use of more pedagogically sophisticated AI, such as adaptive learning platforms or learning analytics dashboards, was virtually non-existent in the survey responses.

Table 3. Most commonly used AI tools (among AI users, N = 106)

Tool Category	Frequency (N)	Percentage of Users (%)
ChatGPT and similar chatbots	95	89.6%
Translation tools (e.g., Google Translate)	72	67.9%
Grammar checkers (e.g., Grammarly)	48	45.3%
AI-integrated design tools (e.g., Canva)	41	38.7%
Automatic quiz generators	25	23.6%

The primary purpose of AI use was for tasks that enhance instructor efficiency rather than directly transform student learning. As detailed in Table 3, "Preparing teaching materials" (78.3%) and "Information search and research" (65.1%) were the top two uses. In contrast, more student-centric applications such as "Student interaction" (19.8%) and "Classroom management" (15.1%) were far less common. This efficiency-focused approach was a recurring theme in the interviews. An interviewee from the Faculty of Economics and Tourism explained, "*I use ChatGPT mainly to brainstorm ideas for case studies and to quickly generate multiple-choice questions. It saves me a lot of time, but I don't use it directly in the classroom with students.*" Another lecturer from the Faculty of Foreign Languages added, "*For me, AI is a powerful assistant. I can create a vocabulary list with example sentences in minutes, a task that used to take an hour. This is its main value right now—giving me back my time.*"

4.4 Perceptions of AI: TAM's usefulness and ease of use

In an effort to understand why the tool was adopted, we reviewed faculty perceptions in the context of the TAM. One-sided t-test results showed a significant PU difference between AI adopters ($M = 4.12$, $SD = 0.68$) and non-adopters ($M = 3.21$, $SD = 0.001$). In the same way, PEOU was significantly different between users ($M = 3.88$; $SD = .75$) and non-users ($M = 2.95$; $SD = .92$); $t(154) = 6.91$, $p < .001$. This is indicative that (for instance) academic staff are significantly more likely to adopt AI technology if they consider it useful and easy to use.

For users of AI, the benefits seemed evident. A substantial majority believe AI enables them to save time (72.6%) and enhance the quality of teaching materials (68.9%). But when it came to direct pedagogical impact, a big "drop-down" was charted. Only 54.7% said AI had made them more creative in teaching, though they were less sure of its impact on students. Only 43.4% believed AI increased student interaction, and even fewer—34.0%—said AI definitely improved the educational outcomes of students. This lack of belief in real learning gains was a major qualitative theme. "*It makes out slides prettier and our work faster, yes*," said a veteran Faculty of Education professor. "*But does it promote more critical thinking among the students?*

I haven't seen the proof of that yet. It's a tool for the teacher rather than necessarily a tool for learning." Another informant from the same faculty echoed this, saying: "*We position ourselves in a skeptical way of our sources and our methods. These AI tools were, in many cases, a black box. I can't, in good faith, teach a tool to my students if I don't know how it's getting to its results. Misinformation could spread too easily*."

4.5 Barriers and needs (Facilitating conditions)

When asked about barriers, faculty identified a range of individual and institutional challenges. The most cited barrier was a "*Lack of knowledge and skills*" (67.3%), followed closely by "*Concerns about the reliability and accuracy of AI-generated information*" (58.3%). The qualitative data richly illustrates this skills gap. A lecturer from the Faculty of Social Sciences and Humanities confessed, "*I feel like I am so far behind. I hear my students talking about these tools, and I just nod along. I downloaded ChatGPT, looked at the blank screen, and had no idea what to type. It's intimidating. Where would I even start to learn?*"

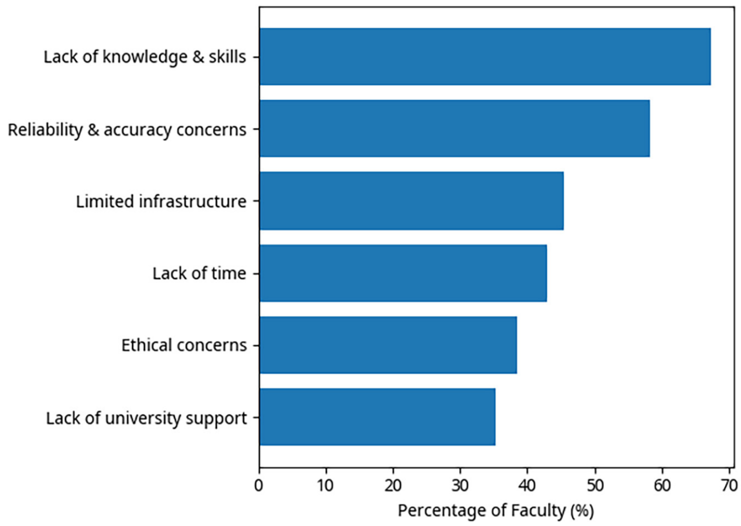

Fig. 3. Major barriers to AI adoption

Table 4. Major barriers to AI adoption

Barrier	Frequency (N)	Percentage (%)
Lack of knowledge and skills	105	67.3%
Concerns about reliability and accuracy	91	58.3%
Limited technological infrastructure	71	45.5%
Lack of time to learn new tools	67	42.9%
Copyright and ethical concerns	60	38.5%
Lack of university support	55	35.3%

These quantitative findings were vividly illustrated in the interviews. A lecturer from the Faculty of Engineering and Environment, despite being in a tech-focused discipline, lamented, "Our Wi-Fi in the lecture halls is often unstable. How can we be expected to use online AI tools in class? The basic infrastructure isn't ready."

This points to a critical lack of "Facilitating Conditions." The desire for these conditions to be improved was overwhelming. A remarkable 89.1% of all faculty members expressed a strong desire to participate in AI-related training workshops. The most requested topics were practical, hands-on guides, such as "Basic AI tool usage" (82.7%) and "Effective prompt engineering techniques" (71.2%). This signals a faculty that is not resistant to change but rather is waiting for adequate support and guidance from the institution.

5 DISCUSSION

The results of this study paint a nuanced and complex picture of AI adoption at HNMU, reflecting a broader narrative of digital transformation in Vietnamese higher education. The findings are best interpreted through the integrated lens of the TAM and the concept of facilitating conditions.

5.1 A bottom-up adoption driven by perceived usefulness

High adoption (67.9%) sounds impressive at first glance. But according to the data, it's a "broad but shallow" adoption. It's not an initiative undertaken top-down by the institutions, but grassroots, bottom-up phenomenon of individual faculty members. The predominantly dominant driving force is PU, evidenced by the robust positive correlation between perceived utility of AI deployment and actual use. Faculty are picking up tools such as ChatGPT for the same reason… It's helping them right now and makes their life easier/how they work smarter, not harder. This is consistent with traditional TAM expectations, which hold that PU is the strongest determinant of adoption and use.

The superficial nature of this adoption becomes apparent in the kind of tools that are being used and for what purposes. Generative AI-based content creation is the overwhelming trend in AI, and the relative neglect of higher-level pedagogical tools indicates that faculty are adopting AI as a kind of personal productivity tool rather than a pedagogical silver bullet. This is a critical distinction. Though there is value and benefit to be had in time saved on administrative work, which can reduce faculty burnout and free up their time for more meaningful endeavors, I'd consider such gains the low-hanging fruit of AI implementation. It in no way alters the teacher-student equation. The relatively limited use of AI for immediate student engagement (19.8%) or educational data mining shows that the more deep-seated potential of AI in education—the capacity to deliver genuinely personalized, adaptive, and informed learning experiences—is not being fully realized yet at HNMU. The university is in the sub and augment phase of AI (such as ChatGPT instead of writing a paragraph, Grammarly for improving the grammar from existing one). They are at the 'Enhancement' stages of the SAMR model (substitution and augmentation), where technology is still a direct tool substitute, however, it has functional improvements. Modification (modifying the task to something significantly different) and, of course, redefinition (makers can create new tasks that were not even able to be accomplished in an analogous way before) levels of 'Transformation' are largely missing. For instance, no evidence indicated instructors' use of AI to develop sophisticated simulations for students (modification) or enable massive collaborative projects with automatic data analysis in real-time (redefinition). This suggests that although faculty are employing AI to make them personally more efficient, they have not yet leaped the vital boundary into applying it to fundamentally reimagining and improving students' learning experiences.

5.2 The critical role of facilitating conditions

Although individual perceptions (PU and PEOU) tell who the AI adopters are, the absence of facilitating conditions tells why adoption is not deeper or more permeating. The study's conclusions deliver a damning verdict on the support network of the institutions. The existence of formal training for the minority (15.4%) of faculty members and an infrastructure that is primarily recognized as a barrier represent major impediments. This is consistent with the UTAUT model, which argues that in the absence of sufficient facilitating conditions, even those technologies that are believed to give high degrees of usefulness will not end up being fully embedded.

Unmet demand for training was the most important finding of this study (89.1%). It pushes back against the idea that faculty are Luddites who ignore new technology. Instead, it is one of a faculty that wishes to engage but believe themselves poorly prepared and unsupported. What they are really doing is signaling to the university leadership, in no uncertain terms, "We are willing to be educated, but you must educate us." There is a demand for tackling practical the practical side (of the RP and digital fabrication) by teaching them through specific tools and operations, which clearly indicates not academic but practical training needs for the development of professionalism [33].

5.3 The discipline divide and ethical apprehension

Another notable discovery is the difference in adoption and understanding across faculties. This greater acceptance at the Faculty of Engineering and Environment and the Faculty of Foreign Languages is not surprising due to their inherent closeness with technology, as well as language analysis. The lower rate in the Faculty of Education, on the other hand, is somewhat ironic but not unexpected, as teacher education programs tend to change more slowly; in particular, they may be taking a more cautious or critical perspective towards technology. But this also is a lost opportunity, as the Faculty of Education should lead the way in demonstrating how to use technology effectively with public school teachers yet to enter our profession.

Second, the high level of concern on reliability (58.3%) and ethical aspects (38.5%), Represent a sound sign of critical engagement. Faculty are not simply embracing AI; rather, they are wrestling with what it means for academic integrity and knowledge itself. An interview subject's anxiety over students misusing AI to cheat is a common one in academia now. One senior lecturer in the Social Sciences mournfully remarked that "How can I get them to do a take-home essay anymore? There is no way to know, if it was a student who wrote it or an AI which did. Neu takes a similar view: "*It's just for me digitally replacing the paper exam,*" she says, "*And it pushes me back to taking an in-class exam that's closed book and that feels like pedagogically one step forward and two steps back*." This underlines the necessity of university-wide clear and accessible AI use guidance that takes into account ethical considerations, whether for students or staff. As such, those policies cannot simply be prohibitive; they must be instructional on what qualifies as appropriate use for both constituencies and how AI-assisted help should be cited appropriately but also used with proper ethical dispositions to foster learning. Lacking such guidance, faculty are left to grapple with an ethical morass in isolation, resulting in widely varying standards, increasing stress, and a possible retreat toward less effective but more "cheat-proof" methods of assessment—none of which will serve the progress of teaching very well.

5.4 Implications for Hanoi metropolitan university's strategy

These findings have profound implications for HNMU's strategic goal of becoming a "smart university." The current bottom-up, laissez-faire approach, while demonstrating faculty initiative, is insufficient to achieve meaningful, equitable, and sustainable transformation. The university is at risk of having pockets of innovation that never coalesce into institutional change, creating a digital divide within its own faculty. To move from this state of sporadic adoption to strategic integration, a deliberate, multi-pronged strategy is required. Based on the study's findings, we propose a three-phase implementation model for HNMU:

Phase 1: Foundational Capacity Building (Year 1)

Goal: To build the floor of AI literacy at our institution and to eliminate as many superficial barriers as possible.

Actions:

- Training: Implement a university-wide, required but adaptable training program. This should involve "AI for all" sessions for all faculty members, with an emphasis on basic concepts as well as common tools (such as the university's preferred generative AI platform) and fundamental ethical principles. These should be complemented by voluntary intermediate-level workshops that are practice oriented (e.g., "Using AI for Assessment," "AI for Language Teaching").
- Infrastructure Audit and Modernization: Do a comprehensive audit of campus Wi-Fi and classroom technology. Develop and implement a plan to provide all rooms in which teaching occurs with dependable high-speed internet as well as the hardware required (e.g., updated computers, projectors).
- Policy: As a first step, we shall form an acceptable use policy for the AI task force right away that involves faculty, students, IT, and the administration. This policy should be considered a living document and disseminated widely.

Phase 2: Pedagogical Integration and Experimentation (Years 2–3)

Objective: To go beyond mere incorporation and urge faculty to incorporate AI into their pedagogical design in a substantive manner.

Actions:

- Faculty Learning Communities (FLCs): Create and support discipline-based FLCs for AI. These groups would collaborate regularly to visit tools, rethink courses, and share results.
- Innovation Grants: Establish a small grants program to support innovative pedagogical projects making use of AI. This would help motivate more faculty to dabble and then give them resources, such as software licenses and student assistants, to do some of that work.
- Create a CTL: If not already available, establish a CTL as the locus of all pedagogical innovation (including AI). Instructional designers, subject matter experts in technology, and other staff members would be located at the CTL to offer faculty one-on-one consultations.

Phase 3: Strategic Transformation and Institutionalization (Years 4–5)

To integrate AI in the core of university processes and its culture (closer to the redefinition level of reflective practice SAMR).

Actions:

- Curriculum Review/Revision: "Facilitate the revision of the department's curriculum to engineer AI literacy as the learning expectation of students.
- Advanced R&D Fund in-house/internal research projects that produce tailor-made AI solutions for specific institutional needs (e.g., An AI-driven student advising chatbot, a learning analytics dashboard for program review) 130.
- Showcase and Dissemination: Organize an annual university-wide symposium on AI in education to showcase successful projects, and disseminate best practices as well as to celebrate innovations and the art of teaching. This will serve to generate momentum and structure the culture of innovation.

This way, HNMU can do enough to establishing facilitating conditions around its faculty and move from a wide gap with the perceived innovativeness towards achieving an actual use of sporadically experimented AI tools in their courses and also towards a deep-rooted and sustainable pedagogically centered integration of AI. This alignment is necessary to help the institution work its way toward the higher end of the SAMR model (Redefinition, Modification) which, put simply, requires that technology transforms activities by replacing old ways or by creating new and unique tasks through the power of tech integration.

6 CONCLUSION AND FUTURE DIRECTIONS

This paper offers an evidence-based and comprehensive study of the status of AI adoption in HNMU. It paints a picture of interests growing up in the grassroots being strangled due to lack of institutional support, training, and infrastructure. A good number of faculty are playing with AI tools, some solitarily, but we're still at a very superficial level of "adoption" on the part of institutions, focused mostly on exerting control rather than innovative pedagogy. The central constructs of TAM (PU and PEOU) emerge as key individual-level predictors of adoption; however, the lack of strong facilitating conditions appears to be a significant bottleneck for greater use.

The take home message is that it's high time the institutions changed strategy from passive to active. The surge in faculty response to the training session signals a readiness for change. HNMU has an opportune moment to leverage this momentum by investing in a comprehensive system of support. This takes the form of continual professional development, improved technology resources, and clear ethical and academic principles.

Limitations of the study. This study has several strengths and limitations that should be addressed despite its originality. First, focusing on one case study (HNMU) can limit the ability to generalize findings for Vietnamese universities, which differ substantially in size, resource allocation, and autonomy as well as in institutional culture. A study at an elite research-intensive university and a smaller, regional college could produce very different findings. Second, the data are based on self-reported survey responses and may be prone to social desirability bias (i.e., faculty dis/willingness to over-report their usage of, or knowledge about, AI) and recall bias. Although steps to minimize this through making the survey anonymous were taken, it cannot be eradicated completely. Third, like all cross-sectional studies, the snapshot in time means that results should be interpreted cautiously in a field that evolves very rapidly. The March 2025 AI landscape might be very different from the March 2026 one. For studying the long-term impacts of AI adoption, a longitudinal study will be essential to examine how it evolved and how its resulting impact emerged.

Future research directions. Following this line of research, many future research directions are possible. Comparisons within a broad sample of Vietnamese universities (e.g., public vs. private, technical vs. social sciences, urban-rural) could reveal systemic factors that go beyond institution-specifics. A longitudinal study of faculty in a cohort graduating from a well-designed and mentor-supported, multi-year AI training program would provide valuable insights into the long-term impact of professional development and instances of pedagogical change over time. In addition, student-centered research remains a glaring miss. How are students using AI, really? (How does it affect their learning behavior, or motivation, or academic honesty, and in turn what is the effect on learning? This should be the subject of an unrelated mixed-methods study. Lastly, it will take more rigorous experimental and quasi-experimental research as the field grows. For instance, educators might compare learning outcomes, engagement levels, and critical thinking ability of students in classes with the full AI experience (e.g., adaptive learning platforms that provide personalized problem-solving tasks and computer generated that concerns interactive feedback) against traditionally taught sections of the same course. Though difficult to design and implement, studies of this sort would be the kind of rigorous, causal research necessary to inform large-scale policy and investment in these transformative technologies.

So, in the end, implementing AI in higher education is a marathon, not a sprint. To HNMU and institutions like it in Vietnam, the way forward is not just about recognizing technology's potential; it's also about making a concerted investment in their most important resource—their teachers. The results of this study are both a diagnosis and a map. The syndrome diagnosis is one of the reasons without backing and will result in broad but not deep cement use. The roadmap itself, however, maps out a comprehensive and institutionally driven approach that tackles infrastructure as well as policy and—most crucially—human capacity. By equipping their educators with the skills, tools, and support they require, universities can help to properly unlock AI's transformative power to deliver the most impactful, accessible, and engaging learning environment for the next generation—fulfilling their mission in the digital era.

Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Competing Interests: The authors declare that they have no competing interests.

Authors' Contributions: All authors contributed equally to the conception and design of the study. The authors have read and agreed to the published version of the manuscript.

7 REFERENCES

[1] R. Luckin, W. Holmes, M. Griffiths, and L. B. Forcier, *Intelligence Unleashed: An Argument for AI in Education*. London, UK: Pearson, 2016.

[2] A. K. Goel and L. Polepeddi, *Jill Watson: A Virtual Teaching Assistant for Online Education*. Atlanta, GA: Georgia Institute of Technology, 2016.

[3] K. T. Huang, C. Ball, J. Francis, R. Ratan, J. Boumis, and J. Fordham, "Augmented versus virtual reality in education: An exploratory study examining science knowledge retention when using augmented reality/virtual reality mobile applications," *Cyberpsychol. Behav. Soc. Netw.*, vol. 22, no. 2, pp. 105–110, 2019. https://doi.org/10.1089/cyber.2018.0150

[4] C. Piech *et al.*, "Deep knowledge tracing," in *Advances in Neural Information Processing Systems*, 2015, pp. 505–513.

[5] E. du Plooy *et al.*, "Personalized adaptive learning in higher education: A scoping review," *BMC Med. Educ.*, vol. 24, pp. 1–15, 2024. https://doi.org/10.1186/s12909-024-06014-9

[6] UNESCO, "A framework for culture and arts education," 2021.

[7] H. T. Nguyen, T. Van Le, H. Le Nguyen, and T. T. C. Tran, "The behavior of students with regard to school culture in high schools," *Academic Journal of Interdisciplinary Studies*, vol. 12, no. 4, p. 267, 2023. https://doi.org/10.36941/ajis-2023-0113

[8] H. L. Nguyen, B. Dang, Y. Hong, and A. Nguyen, "Digital transformation in Vietnamese higher education: An epistemic network analysis of policy documents," *Journal of International Cooperation in Education*, vol. 27, no. 2, pp. 138–156, 2025. https://doi.org/10.1108/JICE-03-2024-0010

[9] H.-H. Pham and T.-T. Ho, "The adoption of ICT in teaching and learning in Vietnamese universities," *Educ. Inf. Technol. (Dordr)*, vol. 25, no. 1, pp. 181–199, 2020. https://doi.org/10.1007/s10639-019-09980-8

[10] T. K. A. Tran, V. T. Nguyen, and M. D. Le, "AI and digital transformation in higher education: Vision and approach of a specific university in Vietnam," *Sustainability*, vol. 15, no. 14, p. 11093, 2023. https://doi.org/10.3390/su151411093

[11] T. P. T. Le and T. M. P. Nguyen, "Digital transformation in higher education from online learning perspective: A comparative study of Singapore and Vietnam," *Journal of Applied Research in Higher Education*, vol. 15, no. 4, pp. 1124–1141, 2023. https://doi.org/10.1177/14782103221124181

[12] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," *Educ. Psychol.*, vol. 46, no. 4, pp. 197–221, 2011. https://doi.org/10.1080/00461520.2011.611369

[13] R. H. Mustofa *et al.*, "The role of subjective norms, ethics, and trust in AI tool adoption among university students," *Social Sciences & Humanities Open*, vol. 11, p. 100190, 2025. https://doi.org/10.1016/j.ssaho.2025.100190

[14] A. Shata *et al.*, "Faculty perceptions and the adoption of generative AI," *International Journal of Educational Technology in Higher Education*, vol. 22, no. 1, pp. 1–24, 2025. https://doi.org/10.1186/s41239-025-00511-7

[15] H. Ghadirian, H. Salehi, and A. F. M. Ayub, "A systematic review of the application of automated writing evaluation in language learning," *Technology, Pedagogy and Education*, vol. 27, no. 2, pp. 241–257, 2018. https://doi.org/10.1080/1475939X.2018.1428410

[16] S. Malik *et al.*, "Advancing educational data mining for enhanced student performance prediction," *Sci. Rep.*, vol. 15, no. 1, p. 1234, 2025. https://doi.org/10.1038/s41598-025-92324-x

[17] W. W. W. Hamzah, I. Ismail, M. K. Yusof, and S. I. M. Saany, "Using learning analytics to explore responses from student conversations with chatbot for education," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 7, pp. 123–130, 2021. https://doi.org/10.14569/IJACSA.2021.0120715

[18] R. Winkler and M. Söllner, "Unleashing the potential of chatbots in education: A state-of-the-art analysis," in *Academy of Management Proceedings*, 2018, p. 15903. https://doi.org/10.5465/AMBPP.2018.15903abstract

[19] L. Yan, L. Zhao, V. Echeverria, Y. Jin, R. Alfredo, and R. Martinez-Maldonado, "VizChat: Enhancing learning analytics dashboards with contextualised explanations using multimodal generative AI chatbots," in *International Conference on Artificial Intelligence in Education*, 2024, pp. 181–196. https://doi.org/10.1007/978-3-031-64299-9_13

[20] G. Siemens and D. Gasevic, "Guest editorial—learning and knowledge analytics," *Educational Technology & Society*, vol. 15, no. 3, pp. 1–2, 2012.

[21] M. Yağc, "Educational data mining: Prediction of students' academic performance using machine learning algorithms," *Smart Learning Environments*, vol. 9, no. 1, pp. 1–19, 2022. https://doi.org/10.1186/s40561-022-00192-z

[22] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989. https://doi.org/10.2307/249008

[23] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly*, vol. 13, no. 3, pp. 319–340, 1989. https://doi.org/10.2307/249008

[24] M. F. Shahzad, S. Xu, and M. Asif, "Factors affecting generative artificial intelligence, such as ChatGPT, use in higher education: An application of technology acceptance model," *Br. Educ. Res. J.*, vol. 51, no. 2, pp. 489–513, 2025. https://doi.org/10.1002/berj.4084

[25] K. Li, "Determinants of college students' actual use of AI-based systems: An extension of the technology acceptance model," *Sustainability*, vol. 15, no. 6, p. 5221, 2023. https://doi.org/10.3390/su15065221

[26] 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, 2003. https://doi.org/10.2307/30036540

[27] A. O. Olaniyan *et al.*, "Leadership's role in facilitating faculty professional development for technology integration," *Journal of Educational Technology Development and Exchange*, vol. 17, no. 1, pp. 45–62, 2024. https://doi.org/10.18785/jetde.1701.03

[28] S. Dysart and C. Weckerle, "Professional development in higher education: A model for meaningful technology integration," *Journal of Information Technology Education: Innovations in Practice*, vol. 14, pp. 255–265, 2015. https://doi.org/10.28945/2232

[29] B. Fishman, C. Dede, and K. A. Lawless, "Designing effective professional development for technology integration in schools," *J Comput. Assist. Learn.*, vol. 36, no. 1, pp. 1–9, 2020. https://doi.org/10.1111/jcal.12394

[30] D. Ferikoğlu and E. Akgün, "An investigation of teachers' artificial intelligence awareness: A scale development study," *Malaysian Online Journal of Educational Technology*, vol. 10, no. 3, pp. 215–231, 2022. https://doi.org/10.52380/mojet.2022.10.3.407

[31] Y. J. J. Alawneh, E. N. Z. Radwan, and F. N. Salman, "Ethical considerations in the use of AI in primary education: Privacy, bias, and inclusivity," in *2024 International Conference on Intelligent Systems and Computer Vision (ISCV)*, 2024, pp. 1–6. https://doi.org/10.1109/ICKECS61492.2024.10616986

[32] J. W. Creswell and V. L. Plano Clark, *Designing and Conducting Mixed Methods Research*, 3rd ed. Thousand Oaks, CA: Sage Publications, 2017.

[33] A. Gulamhussein, "Teaching the teachers: Effective professional development in an era of high stakes accountability," Center for Public Education, Alexandria, VA, 2013.

8 AUTHORS

Nguyen Nang Hung is with the Hanoi Metropolitan University, Hanoi, Vietnam (E-mail: nnhung@hnmu.edu.vn).

Pham Ngoc Son is with the Hanoi Metropolitan University, Hanoi, Vietnam (E-mail: pnson@hnmu.edu.vn).

Nguyen Tra My is with the Hanoi Metropolitan University, Hanoi, Vietnam (E-mail: ntmy@hnmu.edu.vn).

Nguyen Thi Mai Anh is with the Hanoi Metropolitan University, Hanoi, Vietnam (E-mail: ntmanh@hnmu.edu.vn).

Tran Van Anh is with the Hanoi Metropolitan University, Hanoi, Vietnam (E-mail: anhtv@hnmu.edu.vn).

Nguyen Thai Minh is with the Hanoi Metropolitan University, Hanoi, Vietnam (E-mail: minhnt@heuschool.edu.vn).