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Research on the Factors Influencing the Impact of Artificial Intelligence (AI) Applications on the Learning Process of Students at Selected Universities in Hanoi

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Abstract
In the digital era, when the global student population exceeds 200 million, higher education is facing major challenges arising from expanding enrolment, intensified international competition, and the urgent need to prepare learners with skills for the technological age. According to UNESCO's Global Education Monitoring Report (2021), more than 200 million students worldwide are studying in higher education settings; however, traditional teaching models characterised by large class sizes and a one-size-fits-all pedagogical approach often fail to meet individual learning needs. This may contribute to high dropout rates in some developed countries and to dissatisfaction with educational quality. The objective reason behind this problem is the rapid expansion of digital technology, particularly artificial intelligence (AI), which has transformed learning and work practices and requires higher education to adapt in order to train human resources for the Industry 4.0 labour market.

In Vietnam, this issue has become increasingly urgent because of the country's young population and the rapid development of the digital economy. According to the Ministry of Education and Training (2022), Vietnam has approximately 1.8 million university students, while the higher education system still relies mainly on traditional teaching methods, with average class sizes of 50-80 students at major universities. In Hanoi, where leading higher education institutions are concentrated, such as Vietnam National University, Hanoi University of Science and Technology and Foreign Trade University, the issue is visible in reports on educational quality. Students often experience difficulty accessing learning content that fits their individual interests, which reduces learning effectiveness and contributes to dissatisfaction with educational quality. Relevant contextual factors include shortages of lecturers and facilities, pressure from internationalised curricula, and the growing demand for digital skills in line with Vietnam's national strategy for the Fourth Industrial Revolution.

In higher education, especially in the application of AI technologies to learning, the core issue is closely associated with the trend toward personalised learning. AI has substantial potential to analyse student data and adjust learning content and instructional methods; nevertheless, its implementation remains limited due to inadequate understanding and technological infrastructure. The choice of this research topic also reflects the authors' direct experience as students who have encountered difficulties in university learning in Hanoi, where large classes and insufficiently flexible teaching methods can reduce motivation. At the same time, given the increasing presence of AI in everyday life, including learning-support chatbots, the authors view AI as an opportunity to improve higher education, provided that the factors affecting its adoption and effectiveness are examined systematically.

The importance of studying the factors through which AI applications influence students' learning process has been affirmed in both international and domestic studies. Holmes *et al.* (2019) showed that AI can personalise learning pathways according to students' strengths and weaknesses, improving learning outcomes by 25-30% in experimental models. Similarly, the OECD (2018) emphasised that AI-supported personalised learning can enhance motivation and knowledge acquisition while helping reduce educational inequality, particularly in developing countries. Such findings are persuasive because they are based on practical data from large numbers of students and demonstrate that AI can be a key instrument for addressing large-class teaching and insufficient personalisation in higher education.

In Vietnam, Nguyen *et al.* (2021) indicated that AI-based teaching applications at Vietnam National University could increase course completion rates by approximately 15% while reducing dropout through instant feedback and appropriately tailored content. The Ministry of Information and Communications (2022) also identified AI as an important trend in digital education, with the potential to improve the quality of higher education in Hanoi. These studies show that the topic is not merely theoretical but has practical value for improving learning effectiveness and equipping students with a sound foundation for the digital future.

Despite the growing body of research on AI in education, significant knowledge gaps remain, particularly in the Vietnamese context and in Hanoi specifically. Theoretically, international studies, such as Luckin (2017), often focus on general AI models but do not sufficiently analyse how AI should be integrated into Vietnamese educational culture, which has traditionally emphasised discipline and examinations rather than individual creativity. Tran *et al.* (2020) also identified a gap in theories explaining the influence of culture on the effectiveness of AI adoption in Vietnamese universities.

From a legal perspective, Vietnam has not yet developed a comprehensive regulatory framework for the use of AI in education, including provisions on student-data protection and intellectual property. OECD (2021) noted that several Asian countries, including Vietnam, lack sufficient research on the legal risks of AI, such as privacy violations. Studies conducted in Hanoi have not yet comprehensively examined the legal factors affecting AI implementation in education.

In practical terms, the most significant gap is the lack of comprehensive studies on the factors affecting AI applications in Hanoi's universities. Previous studies have often focused on one institution or a limited set of variables, such as student attitudes, lecturers' digital competencies, technological infrastructure, and learning outcomes. The UNESCO (2022) review suggests that Asian studies have not sufficiently exploited practical data from Hanoi, resulting in a shortage of evidence to guide effective AI implementation. This gap makes the present research necessary, as it aims to provide both theoretical and practical evidence for higher education innovation.

The urgency of the research is heightened by Vietnam's ongoing digital transformation and international integration. As AI becomes increasingly embedded in global education, Hanoi, as Vietnam's largest higher education centre, needs timely evidence in order to avoid falling behind regional leaders such as Singapore. The topic is important because it may provide practical solutions for reducing dropout, improving the quality of training, and ensuring educational equity for students from rural and disadvantaged backgrounds. As students, the authors also expect the study to contribute to the academic community and to the development of research skills for future professional practice.

Accordingly, the study entitled 'Factors influencing the impact of artificial intelligence (AI) applications on the learning process of students at selected universities in Hanoi' is both timely and necessary. The research contributes to filling knowledge gaps, clarifying the role of AI in higher education, and offering practical guidance for the development of Vietnamese higher education in the digital era.

Keywords: Artificial Intelligence, Learning Process, Students, Higher Education, Hanoi

1. Overview of the Research Problem and Research Methodology

1.1 Review of Domestic Studies

1.1.1 Studies Related to Data Quality

Du Thi Chung, Nguyen Cao Minh Thanh, Nguyen Vy Anh Thu, Huynh Diem Trinh and Vu Thi Tuyet Trinh (2024) [2], in the article 'Factors affecting the behaviour of using artificial intelligence in learning among students at universities in Ho Chi Minh City', published in the Journal of Finance-Marketing Research, examined the determinants of students' use of AI tools in learning. The study surveyed 357 university students in Ho Chi Minh City, used PLS-SEM, and combined quantitative analysis with a qualitative group discussion involving ten students to explore and refine the measurement scales. The findings showed that attitude toward AI use, self-regulation, information-system quality and spiritual motivation positively affected students' behaviour in using AI tools for learning. The authors then proposed recommendations to increase AI use in learning-support activities.

Pham Thi Bich Diep and Kieu Linh (2025) [3], in 'Learning and research in the AI era: strengths and challenges', published in the special issue of the Journal of Science of Hanoi Open University, analysed the role of AI and ChatGPT in educational and research development. Using documentary review, analysis and synthesis, the study evaluated the strengths and challenges of AI, particularly ChatGPT, in education and research. The findings indicated that machine learning and neural-network-based systems can generate coherent responses, support personalised and automated learning, improve research efficiency, analyse data and assist literature review. However, the study also warned of AI bias, misinformation, dependence on tools, and challenges to academic integrity, critical thinking and ethics. AI should therefore be used responsibly as a supporting and process-automation tool to limit negative impacts.

1.1.2 Studies Related to AI System Design

Do Van Nhon (2023) [7], in 'Artificial intelligence systems applied in education', published in the Journal of Science of Hong Bang International University, aimed to design AI systems consistent with the trend of digital transformation in higher education. The study used literature review and theoretical analysis to synthesise and examine AI models and applications in education. It emphasised that new AI systems should be designed according to principles of transparency and explainability (XAI) so that teachers and learners can understand the basis for decisions and recommendations, thereby building trust in the system. The study classified AI systems into intelligent tutoring systems, automated assessment systems and learning analytics systems, each requiring distinctive system architectures and algorithms.

Do Van Nhon, Mai Trung Thanh and Hoang Ngoc Long (2023), in 'Design methods for an intelligent system supporting lower-secondary mathematics learning', proposed the design of an intelligent application for mathematics learning. The research followed a design-methodology approach, combining procedural knowledge bases, object-computational knowledge bases and relational databases. It described system modules, architecture, knowledge representation and inference processes.

The findings identified technical issues in implementation, including knowledge representation, data design, links between knowledge and data, and system architecture appropriate for lower-secondary learners.

1.1.3 Studies Related to Student Participation

Bui Hong Dang, Tran Thi Ngoc Lan, Dang Van Tho and Nguyen Huy Duong (2022), in 'Factors affecting online learning effectiveness: a case study of students at Ho Chi Minh City University of Food Industry', examined factors influencing e-learning effectiveness. Based on a quantitative survey of 296 students and statistical tests including Cronbach's Alpha, EFA, Pearson correlation and regression, the study identified five factors positively affecting online learning effectiveness, including student engagement and learning enthusiasm.

Nguyen Vo Anh and Nguyen Chi Hai (2025) [1], in 'Application of artificial intelligence to personalise students' learning activities', published in the Journal of Science of Ho Chi Minh City University of Education, analysed the role of AI in personalised learning and the factors affecting it. The study involved 594 students and five lecturers, using a mixed-methods design including literature synthesis, survey and in-depth interviews. The results showed that AI has potential to enhance motivation and student participation; however, its actual effectiveness depends on multiple factors, including students' own engagement.

1.1.4 Studies Related to Lecturer Competence

Luu Hon Vu (2022) [10], in 'Factors affecting student satisfaction with the quality of online training at the Faculty of Foreign Languages, Banking University of Ho Chi Minh City during COVID-19', aimed to identify determinants of student satisfaction with online education quality. Using a quantitative survey of 205 respondents, the study found three factors that positively affected satisfaction, with the lecturer factor ranking second.

Bui Hong Dang *et al*. (2022), in the previously mentioned study on online learning effectiveness, also demonstrated that the role of the instructor is an important determinant of e-learning effectiveness. The study used 296 survey responses and analysed the data through Cronbach's Alpha, EFA, Pearson correlation and regression, finding that perceived ease of use, system quality, engagement, learning enthusiasm and lecturer guidance contributed to students' online learning effectiveness.

Nguyen Duc Manh and Tran Thi Duyen (2025) [6], in 'Application of information technology and artificial intelligence in teaching at Hanoi University of Natural Resources and Environment', assessed the impact of information technology and AI on teaching quality and changes in lecturers' roles. The study surveyed 50 lecturers and 200 students using a mixed-methods approach. The results showed that lecturers were interested in applying AI to improve lectures, although actual implementation remained limited.

1.1.5 Studies Related to Educational Culture and Policy

Le Anh Vinh and Tran My Ngoc (2024) [5], in 'The impact of artificial intelligence (AI) on the global education system and Vietnamese education', analysed AI's influence on global and Vietnamese education and proposed recommendations for managing and using AI effectively. Using qualitative and quantitative approaches based on secondary data and practical analysis, the study found that AI is becoming an important driver of educational innovation while raising challenges concerning the digital divide, ethics and data security. The authors emphasised the need to build policies, capacities and management strategies for effective, optimal and sustainable AI-integrated education.

Nguyen Nhat Tan (2025) [8], in 'Effects of artificial intelligence (AI) characteristics on university students' perceived learning effectiveness', investigated the effects of AI characteristics, including personalised learning, automatic translation, intelligent information and content generation, on students' perceived learning effectiveness. Data were collected from 130 students and analysed with SPSS and linear regression. The results indicated that AI characteristics have positive and noteworthy effects on students' learning outcomes. The study recommended that educational institutions support and guide students in using AI effectively, while encouraging developers to refine AI applications to fit contemporary learning needs.

1.2 Review of International Studies

1.2.1 Studies Related to Data Quality

Nkechi Patricia-Mary Esomonu (2024), in 'Utilizing AI and Big Data for Predictive Insights on Institutional Performance and Student Success: A Data-Driven Approach to Quality Assurance', published in the academic volume AI and Quality Higher Education, examined the application of AI and big data to predict institutional performance and student success. The study proposed a data-driven quality-assurance framework in higher education and emphasised the integration of academic, financial and operational data to support accurate and timely decisions. The results showed that AI and big data can improve management effectiveness, teaching quality, graduation rates and dropout reduction, while promoting a culture of data-driven decision-making. The author also stressed challenges concerning data quality, AI ethics and information security.

Chung-Jen Fu *et al*. (2024) [14], in 'Assessing ChatGPT's Information Quality Through the Lens of User Information Satisfaction and Information Quality Theory in Higher Education', published in Human Behavior and Emerging Technologies, sought to identify information-quality factors that affect student satisfaction when using ChatGPT in learning. Based on a survey of 508 Indonesian university students and structural equation modelling, the study showed that information format, convenience and timeliness positively affected user satisfaction, whereas accuracy and reliability were not decisive. The study also extended the user information satisfaction-information quality framework in AI-based learning contexts and highlighted the need for students' capacity to evaluate information and understand AI.

1.2.2 Studies Related to AI System Design

Jing Luo, Chunhua Zheng, Jing Yin and colleagues (2025) [19], in 'Design and assessment of AI-based learning tools in higher education: a systematic review', synthesised and analysed the design, development and evaluation of AI-based learning tools in higher education. The review covered 63 scientific reports from January 2014 to April 2024 and discussed AI design elements, including user interfaces and algorithms, while evaluating design effectiveness against criteria such as security and user-algorithm alignment. The study identified three main roles of AI in higher education: assessment and evaluation, personalised feedback and recommendation, and intelligent tutoring. It offered recommendations for optimising the design and implementation of AI in university education.

Chien-Chang Lin, Anna Y. Q. Huang and Owen H. T. Lu (2023) [18], in 'Artificial intelligence in intelligent tutoring systems toward sustainable education: a systematic review', reviewed studies on intelligent tutoring systems combined with AI. Using a systematic literature review, the authors reduced more than 700 initial references to 60 relevant studies. The analysis focused on AI technologies used in intelligent tutoring systems, including machine learning, neural networks and natural language processing, and on how these technologies support learner modelling.

Johannes Schleiss, Matthias Carl Laupichler, Tobias Raupach and Sebastian Stober (2023) [22], in 'AI Course Design Planning Framework: Developing Domain-Specific AI Education Courses', discussed course design for integrating AI into education. Using design and development research, the study examined user experience and usability, leading to the AI Course Design Planning Framework (AI-CDPF), which helps educational organisations design high-quality and sustainable AI courses aligned with labour-market needs.

Lukas Heiland, Marius Hauser and Justus Bogner (2023) [16], in 'Design Patterns for AI-based Systems: A Multivocal Literature Review and Pattern Repository', offered an overview of design patterns for AI-based systems. The study used a multivocal literature review of white and grey literature and identified 70 design patterns, including 36 traditional patterns and 34 patterns newly adapted to the AI context.

1.2.3 Studies Related to Student Participation

Lei Fan *et al*. (2025) [13], in 'Educational impacts of generative artificial intelligence on learning efficiency, initiative, independent thinking and creativity: a survey of Chinese engineering students', examined the potential and challenges of generative AI in engineering education. Based on questionnaire data and a generative-AI impact framework, the study found that 64.19% of participants perceived an increase in learning initiative due to AI, while students also reported more active engagement. However, 39.86% expressed concern about overdependence on AI tools.

Xiaodong Wei *et al*. (2025) [23], in 'The effects of generative AI on collaborative problem-solving and team creativity performance in digital story creation: an experimental study', investigated the effects of generative AI on collaborative problem-solving and team creativity among 60 university students. Using an experimental design based on a PBL + GAI model in digital storytelling, the study found that the group using generative AI significantly outperformed the traditional group in both collaborative problem-solving and team creativity, indicating that AI can promote effective group collaboration.

1.2.4 Studies Related to Lecturer Competence

Hasanein and colleagues (2023) [15], in 'Drivers and Consequences of ChatGPT Use in Higher Education', explored the drivers and positive and negative consequences of ChatGPT use in higher education. The study considered the perspectives of students, lecturers and university leaders using in-depth qualitative interviews and surveys. It recommended that higher education institutions develop clear guidelines and training sessions for both students and lecturers to use ChatGPT responsibly for academic purposes and to reduce ethical concerns.

Sumei Hu (2024) [17], in 'The Effect of Artificial Intelligence-Assisted Personalized Learning on Student Learning Outcomes: A Meta-Analysis Based on 31 Empirical Research Papers', synthesised 36 studies from 31 publications. The meta-analysis showed that educators should select educational-technology applications appropriate to students' needs and subject characteristics. The author emphasised the need for teachers to continue practising and exploring implementation strategies for AI-supported personalised learning.

1.2.5 Studies Related to Educational Culture and Policy

Peter Bannister, Elena Alcalde Peñalver and Alexandra Santamaría Urbieta (2023), in 'Transnational Higher Education Cultures and Generative AI: A Nominal Group Study for Policy Development in English Medium Instruction', aimed to develop a policy framework addressing academic integrity challenges caused by generative AI in transnational higher education and English-medium instruction. Using qualitative consensus from 14 experts and the nominal group technique, the study proposed the GenAI Academic Integrity Policy Development Blueprint as a roadmap for inquiry rather than a mandatory policy.

Yana Samuel *et al*. (2023) [21], in 'Cultivation of human-centered artificial intelligence: culturally adaptive thinking in education (CATE) for AI', conceptualised the Culturally Adaptive Thinking in Education for AI framework. Through conceptual and text-data analysis, the study proposed five principles of CATE-AI to address the risk that AI education without cultural adaptation may generate negative responses and impacts.

Dongmin Ma, Huma Akram and I-Hua Chen (2024) [20], in 'Artificial Intelligence in Higher Education: A Cross-Cultural Examination of Students' Behavioral Intentions and Attitudes', analysed differences in AI-related attitudes and behaviours between Chinese and international students. Using the technology acceptance model, structural equation modelling and confirmatory factor analysis, the study demonstrated the need for training strategies, interface design and learning support that take cultural factors into account to increase students' acceptance and use of AI in higher education globally.

1.3 Research Gaps

1.3.1 Remaining Limitations in Domestic and International Studies

A visible limitation of current research is the narrow scope of research subjects. Many studies focus on one group of students at one or two universities or on one particular city. For example, Du Thi Chung *et al*. (2024) [2] and Nguyen Vo Anh (2025) were conducted in Ho Chi Minh City. Such geographic and institutional limitations make it difficult to generalise findings to the broader Vietnamese student population, particularly to Hanoi, where higher education environments are diverse.

Similarly, Nguyen Duc Manh and Tran Thi Duyen (2025) [6] limited their study to Hanoi University of Natural Resources and Environment, with only 200 students and 50 lecturers surveyed. This restricts the generalisability of the results and cannot fully reflect the broader landscape of Hanoi's universities.

Most studies have not sufficiently examined differences by field of study, type of institution or level of technological access. Engineering students may use AI differently from students in the social sciences and humanities, but comparative analyses remain limited. A study covering multiple universities within Hanoi would therefore improve representativeness and generalisability.

Another limitation is that many studies approach AI in a fragmented way. They often focus on one or two aspects of AI use rather than analysing its multidimensional influence on the learning process. Some studies emphasise technical design, such as algorithms and user interfaces, whereas behavioural studies focus on psychological factors such as attitudes, perceived risks and intrinsic motivation. These perspectives are valuable but have not adequately connected learning motivation, self-study skills, critical thinking, learning outcomes and academic ethics.

Theoretically, domestic studies often adopt technology models such as TAM and UTAUT, which were initially developed for organisational or business environments. These models have not been fully adapted to educational settings. Although Le Anh Vinh and Tran My Ngoc (2024) [5] reviewed the impact of AI on global education, current quantitative studies have not fully operationalised variables related to policy governance and academic ethics in Vietnamese measurement models. As a result, recommendations tend to remain individual-level rather than system-level.

Several important variables, such as misconceptions about AI, learning goals and learner autonomy, remain underexplored in domestic research. This reflects a theoretical gap in developing models suitable for technology-supported contemporary learning behaviour. Without updating international theory and grounding it in Vietnamese higher education, research may lack depth and remain repetitive.

Methodologically, many studies rely primarily on quantitative questionnaires analysed through SPSS or AMOS. While such methods help test relationships among variables, they are less effective in explaining motivations, attitudes and personal contexts. Studies using deep interviews, longitudinal designs or case studies remain relatively rare in Vietnam, although they are necessary to understand why students become dependent on AI or how they negotiate academic-integrity issues.

Furthermore, many studies stop at describing current situations or relationships among variables; there are few experimental, longitudinal or in-depth behavioural studies. Consequently, some conclusions remain statistical inferences rather than sufficiently robust evidence for educational policy or pedagogical innovation. Mixed-methods designs, case studies, longitudinal tracking and group comparisons are needed to address these gaps.

Another significant gap is the weak linkage between theoretical frameworks and the practical realities of Vietnamese education. Imported frameworks such as UTAUT and TAM are often used without sufficient localisation to reflect learning culture, student psychology and patterns of technology use in Vietnam. Emerging behaviours such as superficial learning, chatbot dependence and using AI without understanding knowledge content should be examined through integrated perspectives combining technology studies, educational psychology and teaching practice.

Accordingly, research on AI in education should not merely survey and analyse; it should also propose feasible intervention models and guidelines for institutions, lecturers and students. Practical initiatives such as skill-training programmes, responsible-AI-use protocols and pedagogical redesign remain limited in the Vietnamese context.

1.3.2 Strengths of Previous Domestic and International Studies

Studies conducted between 2022 and 2025 provide a timely and important theoretical foundation for examining the impact of AI on higher education. Works by Pham Thi Bich Diep, Nguyen Vo Anh and Nguyen Nhat Tan (2025) [3] captured the rapid emergence of AI and identified new factors such as personalised learning and challenges related to data accuracy. Studies by Le Anh Vinh and Tran My Ngoc (2024) [5] provided a strategic perspective on global educational transformation in the digital age and positioned AI as an essential factor in improving human-resource quality.

Theoretically, prior studies have developed multidimensional analytical frameworks. Bui Hong Dang (2022) and Luu Hon Vu (2022) [10] applied established models such as TAM and UTAUT to explain students' behavioural motivations, while Do Van Nhon (2023) [7] and Mai Trung Thanh (2023) provided technical insights into intelligent tutoring systems. This combination of behavioural and technical perspectives is valuable for later studies. Du Thi Chung *et al.* (2024) [2] also contributed empirical indicators concerning data quality and human-machine interaction, which can help standardise measurement scales for the Vietnamese educational context.

Another strength is the critical and early-warning orientation of previous studies. Nguyen Duc Manh (2025) identified infrastructure barriers and lecturers' readiness levels, making policy recommendations more realistic. The early recognition of risks concerning academic ethics and algorithmic dependence helps guide students toward responsible AI use and protects academic integrity. Overall, previous studies have effectively explored the current situation and established a scientific foundation for more specialised studies in Hanoi.

1.3.3 Novelty of the Research Topic

Most studies on AI in Vietnam and abroad view AI primarily as a technical support tool. The novelty of this study lies in approaching AI as part of a learning-experience ecosystem. The research does not merely ask what AI can do; it examines how students feel, behave and change when AI is integrated into their learning activities.

The study therefore analyses psychological and behavioural shifts, changes in knowledge-acquisition habits and the way AI redefines the relationship between learners and learning resources. This marks a significant shift from a purely technical approach to a humanistic and educational approach.

Although AI has been widely studied globally, local educational and cultural contexts strongly shape how technology is adopted. Hanoi hosts many leading universities, students face intense academic competition, and family expectations can be substantial. The novelty of this research is to interpret how AI interacts with the learning culture of students at selected universities in Hanoi. Its findings may support digital-education policy in Vietnam in ways that international studies cannot fully capture.

The study also juxtaposes positive factors such as personalisation and efficiency with negative impacts such as dependence on AI and the erosion of independent thinking. It seeks to quantify negative effects that have often been mentioned only as qualitative warnings. By using variables such as data quality and cultural-policy environment, the study aims to identify the threshold at which AI shifts from a supporting tool to a potentially harmful tool. This is an important contribution to digital ethics in higher education.

The research further proposes a coordination framework among data, system design, lecturers, students and policy. Rather than treating these elements separately, the study considers them as interrelated variables. It argues that AI does not operate independently; its effectiveness depends on lecturers' guidance and the institutional policy framework. Integrating macro-level governance factors into a study of students' learning behaviour is a multi-level and relatively novel approach in Vietnam.

Finally, the study provides empirical data from 2026, a time when AI has moved beyond initial curiosity and become deeply embedded in academic life. Using modern analytical tools such as SPSS/AMOS to test hypotheses regarding system quality and learning motivation may produce evaluation criteria for future comparative studies.

1.4 Urgency of the Research Topic

In the context of the Fourth Industrial Revolution, artificial intelligence is no longer a distant concept; it has become a key driver of transformation in many fields, especially higher education. Tools such as ChatGPT, Gemini and domain-specific AI applications have entered academic life, changing how students search for information, analyse data and create content. Studying how AI affects students is therefore not only a matter of updating research trends but also a necessity for institutions that do not wish to fall behind in global digital transformation.

Although AI offers unprecedented opportunities for personalised learning and improved academic efficiency, its development in Vietnam, especially in Hanoi, remains partly spontaneous. A gap persists between the speed of students' AI adoption and the capacity of institutions to respond through policy and teaching methods. Many students use AI without adequate prompt-writing skills, leading to misinformation; lecturers and administrators struggle to balance creativity and academic-integrity control; and empirical studies on students' real experiences, psychology and barriers in Hanoi remain limited.

The urgency of the topic also lies in identifying and mitigating risks. AI overuse may lead to dependence, weaken independent thinking and create digital-ethics problems. This study is needed to determine the influencing factors and provide sound recommendations so that students can use AI responsibly. It serves as a bridge for universities to build a healthy digital culture, transforming AI from a risk into a genuine lever for self-learning and critical thinking.

1.5 Research Methodology

1.5.1 Research Process

Research problem: Factors influencing the impact of artificial intelligence applications on the learning process of students at selected universities in Hanoi.

Scientific foundations: relevant concepts, domestic studies and international studies. Based on these foundations, the preliminary theoretical model and draft scales were developed, followed by the final measurement scales. Quantitative data were then collected, scale reliability was tested, EFA was conducted, the regression model was analysed, hypotheses and group differences were tested, and the findings were discussed with policy recommendations.

Figure 1.1. Research process (Source: Authors' construction).

1.5.2 Data Collection Methods

Primary data collection. In the quantitative phase, the authors collected primary data through an online questionnaire using Google Forms. This method reduced cost, facilitated access to a large number of students across different universities and suited young people's technology-use habits.

The questionnaire link was distributed through Google Forms and social-network channels such as Facebook, Zalo and email to students at Hanoi University of Natural Resources and Environment, Hanoi University of Science and Technology, National Economics University and Hanoi National University of Education. Before the official survey, a pilot test with 30 students was conducted to detect technical issues, assess question clarity and revise wording. The final questionnaire was then distributed for official data collection.

Secondary data collection. Secondary data were obtained through the synthesis and analysis of published academic sources, including monographs, textbooks, research reports, scientific articles in domestic and international journals, theses and dissertations, and electronic sources from reliable academic databases such as Google Scholar, ScienceDirect, SpringerLink and official portals of the Ministry of Education and Training.

Selection criteria focused on studies related to AI applications in education and learning behaviour, with priority given to materials published from 2019 onward. Secondary data helped strengthen the theoretical model, refine measurement scales and ensure the academic and practical relevance of the study.

1.5.3 Data Analysis and Processing

Qualitative method. In the initial phase, a qualitative approach was used to adjust the model and develop measurement scales suitable for the learning environment in Hanoi. The authors conducted semi-structured interviews with lecturers and students at four universities, focusing on purposes of AI use, practical experiences, benefits and risks, and factors affecting usage behaviour. This approach helped identify potential variables not included in the initial theoretical model.

The initial model was built by integrating components from TAM and UTAUT, including perceived usefulness, perceived ease of use, attitude toward technology, social influence and facilitating conditions. Interviews showed that many students had used AI to complete assignments without fully understanding the content, while also expressing concern about violating academic ethics if they copied AI output. Several lecturers emphasised that AI use should be accompanied by guidance on academic responsibility. Accordingly, the variable 'academic ethical awareness' was added to the model.

Some students also reported that they could easily become dependent on AI without learning discipline and information-verification skills. This suggested the need to include 'learning autonomy' to measure control and independent thinking when learning with AI support. The qualitative phase therefore helped connect the theoretical foundation with real learning behaviour in AI-supported higher education.

Quantitative method. The study uses quantitative research as the main method. This approach enables measurement and analysis of relationships among factors influencing students' learning when using AI. Data were collected through a structured questionnaire and processed using SPSS, a widely used tool in social-science research.

The analytical procedure included: Cronbach's Alpha reliability testing to remove unreliable items (alpha < 0.6); exploratory factor analysis (EFA) to identify clusters of related independent variables; Pearson correlation analysis to assess linear relationships; and multiple linear regression to determine the effects of independent factors, such as motivation, digital skills and perceived value, on the dependent variable related to AI-supported learning. All analyses were performed at the common significance level of 5% ($p < 0.05$).

1.5.4 Research Sample Design

The formal study was conducted quantitatively using a questionnaire survey with convenience sampling. The respondents were students at four universities: Hanoi University of Natural Resources and Environment, Hanoi University of Science and Technology, Hanoi National University of Education and National Economics University.

Sample-size selection was informed by several methodological guidelines. Holter (1983) suggested a minimum sample size of 200. Bollen (1989) recommended a sample size equal to the number of observed variables multiplied by 5; with 30 observed variables, the minimum sample would be 150. Tabachnick and Fidell (1996) proposed $N = 8m + 50$, where m is the number of independent variables; for this study, the suggested sample size was 290. For large populations with unknown size, the standard formula n = z^2pq/e^2 can also be applied. Based on these guidelines, with 95% confidence and a 5% allowable error, the authors selected a sample size of 300.

Questionnaire design. Based on the theoretical framework, proposed research model and qualitative findings, the authors developed a survey questionnaire to collect quantitative data for testing hypotheses about the relationship between AI use and students' learning. The questionnaire consists of two main parts: general information, including gender, year of study, university, major and AI-use status; and measurement scales, consisting of 30 observed variables divided into five independent-variable groups (CLDL, TKHT, NLGV, TGTV and VHCS) and one dependent-variable group. Each item is measured on a five-point Likert scale from 1, 'Strongly disagree', to 5, 'Strongly agree'.

Table 1.1: Constructed questionnaire

Factor	Code	Indicator	Reference source
1. Data quality (CLDL) (H1)	CLDL1	Input data of the AI system are diverse and sufficiently reflect learner characteristics.	Siemens & Baker, 2012
	CLDL2	Data used to train the AI system are accurate and reliable.	Ifenthaler & Schumacher, 2022
	CLDL3	Training data of the AI system are regularly updated to ensure relevance.	Ifenthaler & Schumacher, 2022
	CLDL4	Data used for personalised learning are not biased against any learner group.	Ravizza *et al*., 2024
	CLDL5	Data collection and processing comply with security and privacy regulations.	Ravizza *et al*., 2024
2. AI system design (TKHT) (H2)	TKHT1	The AI system is designed in accordance with the specific learning objectives of the course/programme.	Essa *et al*., 2023
	TKHT2	The AI system interface is user-friendly, easy to use and accessible to learners.	Teng *et al*., 2023
	TKHT3	The AI system provides personalised learning content appropriate to each learner’s level and needs.	Essa *et al*., 2023
	TKHT4	The AI system allows learners to interact and collaborate with others during learning.	Teng *et al*., 2023
	TKHT5	The AI system can monitor learners’ progress and provide timely feedback.	Gevorgyan, 2024
3. Lecturer competence (NLGV) (H3)	NLGV1	Lecturers have sufficient knowledge and skills to use AI systems in teaching.	Holmes *et al*., 2019
	NLGV2	Lecturers know how to integrate AI systems effectively into their teaching methods.	Holmes *et al*., 2019
	NLGV3	Lecturers understand the advantages and limitations of applying AI to personalised learning.	Gocen & Aydemir, 2020
	NLGV4	Lecturers can evaluate the effectiveness of AI systems in supporting personalised learning.	Kuleto *et al*., 2021
	NLGV5	Lecturers participate in the design and implementation of AI systems.	Kuleto *et al*., 2021
4. Student participation (TGTV) (H4)	TGTV1	Students provide full and accurate information about their needs, interests and learning styles to the AI system.	Pane *et al*., 2017
	TGTV2	Students regularly provide feedback on the effectiveness of the AI system.	Pane *et al*., 2017
	TGTV3	Students actively use AI systems to support their learning process.	Zawacki-Richter *et al*., 2019
	TGTV4	Students actively interact with the AI system and with peers during learning.	Zawacki-Richter *et al*., 2019
	TGTV5	Students feel comfortable and confident when using AI systems.	Zawacki-Richter *et al*., 2019
5. Educational culture and policy (VHCS) (H5)	VHCS1	There are clear regulations on collecting, using and protecting students’ learning data.	OECD, 2018
	VHCS2	The institution provides sufficient resources, such as finance, facilities and training, to support AI application.	OECD, 2021
	VHCS3	The institution has clear policies on applying AI in personalised learning.	UNESCO, 2023
	VHCS4	The institution encourages lecturers and students to use AI in teaching and learning.	UNESCO, 2023
	VHCS5	The institution has ethical guidelines for applying AI in education.	UNESCO, 2023

1.5.5 Research Implementation

Descriptive statistics were used to summarise and describe the research sample and demographic variables in numerical and graphical forms.

Cronbach's Alpha was used to assess the internal consistency of observed variables within each factor. Following Nunnally (1978) and Peterson (1994), an overall Cronbach's Alpha greater than 0.6 and item-total correlations greater than 0.3 indicate acceptable reliability.

Exploratory factor analysis (EFA) was used to reduce a set of observed variables into meaningful factors. The main criteria included KMO values between 0.5 and 1, Bartlett's Test with Sig. < 0.05, factor loadings of at least 0.5 for practical significance, and total variance extracted greater than 50%.

Multiple linear regression was used with the theoretical model $Y = B0 + B1X1 + B2X2 + ... + BnXn + e$. Model fit was assessed through R2 and adjusted R2, F-test significance below 0.05, beta coefficients, Durbin-Watson statistics and multicollinearity diagnostics using VIF. A VIF greater than 10 indicates multicollinearity.

2. Theoretical and Practical Foundations of Factors Influencing the Impact of AI Applications on Students' Learning Process at Selected Universities in Hanoi

2.1 Theoretical Foundations

2.1.1 Concept of Artificial Intelligence (AI)

Artificial intelligence is a field within computer science and computational science. There are multiple views and definitions of AI. According to John McCarthy, one of the founders of the field, artificial intelligence is 'the science and engineering of making intelligent machines'. This definition emphasises that AI is not merely the programming of rules but also includes the capacity to learn and adapt from experience.

McCarthy *et al*. (1995) described AI as the field of research and development of intelligent computer systems and programmes capable of performing tasks that require intelligence. It focuses on creating computers capable of understanding and performing tasks similar to humans, although AI is not constrained by biological methods.

2.1.2 Concept of Learning

Learning is the most fundamental and important activity for students at universities and colleges. Its effectiveness is strongly enhanced when learning motivation is stimulated. Different scholars define learning in different ways.

According to David Kolb *et al*. (1984) and experiential learning theory, learning is a process that occurs through practical experience. This means that the acquisition of information is not passive but takes place through engagement with real-world experience.

In 'Situated Cognition and the Culture of Learning', Brown, Collins and Duguid (1989) argued that learning is not merely an individual process but occurs within specific cultural and social contexts. Learning is an active process in which learners acquire cultural tools and necessary skills through participation in practical activities and real situations.

The Vietnamese Dictionary of the Institute of Linguistics defines learning as studying and practising in order to gain understanding and skills. Other educational perspectives regard learning as a special human activity aimed at mastering knowledge, skills, techniques and forms of behaviour, with both cognitive and practical significance.

Based on these definitions, this study understands learning as an activity conducted in close relation to teaching, through which learners acquire knowledge, skills, techniques and behavioural methods to develop their personality comprehensively.

2.1.3 Concept of Students

The term student refers to individuals studying at higher education institutions, including universities and colleges, and is used to distinguish them from secondary-school pupils.

Educational dictionaries define students as learners in higher education institutions who may be classified into different categories, such as full-time students, regular students and non-regular students. The concept is widely used to describe a special social group of people preparing professional knowledge to become specialists in economic, cultural and social fields.

Students are generally young people, full of enthusiasm, aspirations and ambitions. In learning activities, they demonstrate independence, activeness, initiative and creativity. In this study, students are understood as young people, mostly between 18 and 25 years old, who are being systematically trained in one or more professional fields in preparation for future work.

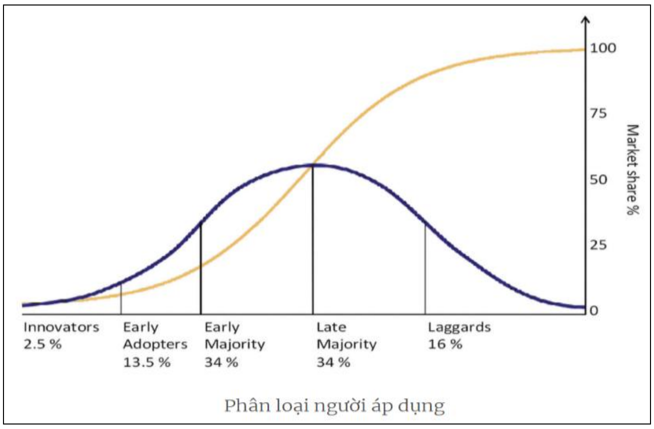
2.2 Foundational theories related to the research problem

2.2.1 Innovation Diffusion Theory (IDT)

Innovation Diffusion Theory, proposed by Everett Rogers in 1962, is a classical framework explaining the diffusion and acceptance of technological innovations, ideas or new practices within a social system. It describes how an innovation is communicated through certain channels over time among members of a social system.

Rogers identified five attributes affecting adoption: relative advantage, compatibility, complexity, trialability and observability. The goal of IDT is to analyse factors that influence the acceptance or rejection of an innovation and to predict its potential diffusion.

IDT is appropriate for analysing factors influencing AI applications in the learning process of students in Hanoi. If AI tools are perceived as more effective than traditional learning methods, simple to use, compatible with students' needs and learning habits, open to trial use and capable of producing observable improvements, students' willingness to adopt and use AI will increase.



Source: Rogers, 2003.

Fig 2.1: Innovation-adoption cycle according to Innovation Diffusion Theory

2.2.2 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action was developed from 1967 by Martin Fishbein and later refined by Fishbein and Icek Ajzen in 1975. It is one of the most widely used theoretical models for explaining and predicting human behaviour.

TRA states that an individual's behaviour is determined by the intention to perform that behaviour. This intention is influenced by two factors: attitude toward the behaviour and subjective norms. Attitude reflects beliefs about and evaluations of behavioural outcomes, while subjective norms reflect perceived social expectations and motivation to comply with them.

Applied to AI-supported learning, TRA explains how AI affects students' attitudes through perceived benefits such as improved learning efficiency, time saving and personalised support. At the same time, AI influences subjective norms through peer diffusion, encouragement from lecturers and wider trends in technology use. These factors help shape intention and actual AI-use behaviour among students.

2.2.3 Theory of Planned Behavior (TPB)

The Theory of Planned Behavior was developed by Icek Ajzen in 1991 as an extension of TRA by adding perceived behavioural control. TPB explains and predicts intentional behaviour across many fields, including health, marketing, consumption and education.

According to TPB, behaviour is guided by behavioural intention, which is affected by attitude, subjective norms and perceived behavioural control. Perceived behavioural control may also directly influence actual behaviour by reflecting how easy or difficult individuals consider the behaviour to be.

In the context of AI-supported learning, TPB suggests that students are more likely to use AI when they believe it has learning benefits, receive support from peers, lecturers and the learning environment, and feel confident in their ability and conditions for use. These factors increase intention and lead to actual AI-use behaviour.

2.2.4 Technology Acceptance Model (TAM)

The Technology Acceptance Model, developed by Fred Davis in 1989, is a theoretical framework for predicting how users accept and use new technologies. TAM is among the most influential models in information-systems and educational technology research.

TAM explains technology acceptance through two core factors: perceived usefulness and perceived ease of use. These factors directly influence attitude, intention and actual use. In this study, students are more likely to use AI when they believe it improves learning outcomes, saves time and supports learning effectively, while also perceiving AI as accessible, user-friendly and not technically demanding.

2.2.5 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was proposed by Venkatesh and colleagues in 2003 by integrating several previous theories of technology acceptance, including TRA, TPB, TAM and IDT. It provides a comprehensive framework for predicting technology-use behaviour.

UTAUT identifies four main determinants of technology use: performance expectancy, effort expectancy, social influence and facilitating conditions. Performance expectancy refers to the belief that technology improves learning or work performance; effort expectancy refers to perceived ease of use; social influence captures the effect of others on adoption decisions; and facilitating conditions reflect available resources, infrastructure and skills.

In AI-supported learning, students are more likely to use AI when they believe it improves academic performance, is easy to use, is encouraged by peers and lecturers, and is supported by adequate devices, skills and learning environments. UTAUT therefore provides an important foundation for the proposed model.

2.3 Research Hypotheses and Model

2.3.1 Research Hypotheses

To clarify the mechanisms through which different factors influence students' AI application in learning, the study formulates hypotheses based on both established theories and empirical observations.

Data quality. In the digital era, data quality is decisive for the value of AI systems in learning. Based on TAM and UTAUT, perceived usefulness and performance expectancy can form usage intention only when technology solves users' problems. For students, AI-provided data must be accurate, reliable and up to date. When data quality is high, students perceive AI as improving learning effectiveness and reducing the time needed to search for and process information. Hypothesis H1: The data quality of AI tools positively affects students' intention and behaviour in using AI for learning.

AI system design. System design reflects technology friendliness and ease of use, which directly influence user experience. According to TAM and IDT, perceived ease of use and system complexity shape innovation adoption. An intuitive and easy-to-use AI interface reduces technical barriers and increases regular and long-term use. Hypothesis H2: AI system design positively affects students' acceptance and use of AI in learning.

Lecturer competence. Lecturers' competence in applying AI to teaching plays an important role in shaping students' behaviour. According to TRA and UTAUT, social influence and subjective norms affect technology-use intention. When lecturers understand AI and integrate it appropriately into teaching, students are more likely to trust and follow their guidance. Hypothesis H3: Lecturer competence positively affects students' intention to use AI in learning.

Student participation. Student participation reflects the extent to which students interact with, test and exploit AI tools. Based on TPB and IDT, it relates to perceived behavioural control and trialability. Active integration of AI into self-learning enhances students' control over technology and improves knowledge acquisition. Hypothesis H4: Student participation positively affects the effectiveness of AI application in learning.

Educational culture and policy. A clear institutional environment and policy orientation influence students' AI-use behaviour. According to UTAUT and IDT, facilitating conditions and compatibility with the institutional environment are essential to adoption. Transparent supportive policies reduce psychological and legal barriers. Hypothesis H5: A positive educational culture and policy environment positively affects the acceptance and diffusion of AI in students' learning.

2.3.2 Research Model

Based on the proposed hypotheses, the research model aims to test relationships among psychological, cognitive and behavioural factors in students' use of AI for learning. The model integrates TAM, TPB and self-regulated learning theory.

The proposed model includes five independent variables: data quality, AI system design, lecturer competence, student participation, and educational culture and policy. In the empirical implementation, educational culture and policy is treated as the dependent variable affected by the other four predictors.

Figure 2.6. Proposed research model (Source: Authors).

3. Current Status of Factors Influencing the Impact of AI Applications on the Learning Process of Students at Selected Universities in Hanoi

3.1 Characteristics of the Research Sample

To collect empirical data for the study, the research team implemented a structured questionnaire survey. A total of 338 questionnaires were distributed and 315 responses were received. After screening and removing invalid questionnaires, 300 valid responses were retained for analysis.

The study used convenience sampling and focused on students at key higher education institutions in Hanoi, including Hanoi University of Science and Technology, National Economics University, Hanoi National University of Education and Hanoi University of Natural Resources and Environment. The sample structure was designed to reflect demographic characteristics, fields of study and actual levels of interaction with AI in academic settings.

Table 3.1: Summary of sample characteristics

S. No	Question	Description	Number	Percentage (%)
1	Gender	Male	161	53.7
		Female	139	46.3
2	Year of study	First year	75	25.0
		Second year	122	40.7
		Third year	63	21.0
		Fourth year	40	13.3
3	University	Hanoi University of Natural Resources and Environment	105	35.0
		Hanoi University of Science and Technology	76	25.3
		Hanoi National University of Education	117	39.0
		National Economics University	2	0.7
4	Field of study	Engineering and Technology	75	25.0
		Economics and Management	139	46.3
		Social Sciences and Humanities	81	27.0
		Other	5	1.7
5	Have you ever used AI for learning purposes?	Yes	210	70.0
		No	90	30.0

Regarding gender, male students accounted for 53.7% and female students for 46.3%. This small difference helps reduce gender bias and supports objectivity in later analyses of technology behaviour.

Regarding year of study, second-year students accounted for 40.7% and first-year students for 25.0%, showing strong digitalisation among new generations of students. These groups tend to actively access and integrate AI tools into their learning pathway from the early stages of university study.

Regarding institutions, students from Hanoi National University of Education represented the largest share, at 39.0%. This reflects an important practical signal: the education sector is shifting from concern to active inquiry and application of AI in future pedagogical practice.

Regarding fields of study, Economics and Management accounted for 46.3%, followed by Social Sciences and Humanities at 27.0% and Engineering and Technology at 25.0%. This structure provides a basis for comparing how students in different disciplines exploit AI.

Regarding experience with AI, 70.0% of students reported having used AI for learning purposes, demonstrating the relatively high prevalence of AI in current higher education. Overall, the sample is diverse and provides a reliable foundation for subsequent quantitative model testing.

3.2 Analysis of Factors Affecting Students' Learning when Using AI

3.2.1 Reliability Testing of Measurement Scales

a. Data Quality scale

Table 3.2: Reliability testing of the Data Quality scale

Observed variable	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
Cronbach Alpha = 0.896				
CLDL1	13.68	9.837	.749	.872
CLDL2	13.92	9.690	.767	.868
CLDL3	13.32	9.917	.747	.873
CLDL4	13.62	10.197	.736	.876
CLDL5	13.86	10.087	.722	.878

The Data Quality scale has a Cronbach's Alpha of 0.896, indicating very good internal consistency. Item-total correlations range from 0.722 to 0.767, all well above the minimum threshold of 0.3. If any item were removed, the overall alpha would decrease, so all five items are retained.

b. AI System Design scale

Table 3.3: Reliability testing of the AI System Design scale

Observed variable	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
Cronbach Alpha = 0.906				
TKHT1	12.84	12.213	.735	.891
TKHT2	12.96	11.363	.776	.882
TKHT3	12.41	11.968	.786	.880
TKHT4	12.88	11.430	.777	.882
TKHT5	12.72	11.868	.745	.888

The AI System Design scale has a Cronbach's Alpha of 0.906, showing excellent reliability. Item-total correlations range from 0.735 to 0.786. Since Cronbach's Alpha would fall if any variable were removed, all five observed variables are retained.

c. Lecturer Competence scale

Table 3.4: Reliability testing of the Lecturer Competence scale

Observed variable	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
Cronbach Alpha = 0.886				
NLGV1	16.35	7.761	.756	.854
NLGV2	16.13	8.370	.708	.865
NLGV3	16.42	7.642	.752	.856
NLGV4	16.22	8.395	.715	.864
NLGV5	16.16	8.465	.699	.868

The Lecturer Competence scale has a Cronbach's Alpha of 0.886. Item-total correlations range from 0.699 to 0.756, confirming that all items are closely associated with the underlying construct. All five variables are retained.

d. Student Participation scale

Table 3.5: Reliability testing of the Student Participation scale

Observed variable	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
Cronbach Alpha = 0.919				
TGTV1	11.95	12.714	.794	.900
TGTV2	11.68	12.767	.779	.903
TGTV3	12.05	12.937	.794	.900
TGTV4	11.77	12.425	.798	.900
TGTV5	11.87	12.731	.791	.901

The Student Participation scale has a Cronbach's Alpha of 0.919, indicating excellent reliability. The item-total correlations are very high and stable, ranging from 0.779 to 0.798. No item should be removed.

e. Educational Culture and Policy scale

Table 3.6: Reliability testing of the Educational Culture and Policy scale

Observed variable	Scale mean if item deleted	Scale variance if item deleted	Corrected item-total correlation	Cronbach's Alpha if item deleted
Cronbach Alpha = 0.872				
VHCS1	14.47	8.163	.699	.845
VHCS2	14.69	8.075	.706	.844
VHCS3	14.30	8.437	.698	.846
VHCS4	14.59	8.255	.704	.844
VHCS5	14.42	8.097	.689	.848

The Educational Culture and Policy scale has a Cronbach's Alpha of 0.872. Item-total correlations range from 0.689 to 0.706, and all alpha-if-item-deleted values are lower than the overall alpha. The full scale is therefore retained.

3.2.2 Exploratory Factor Analysis (EFA)

a. Analysis of independent variables

The study conducted exploratory factor analysis for the scales measuring factors influencing the impact of AI on students' learning process. After reliability testing, the remaining observed variables were analysed using Principal Component extraction and Varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test were used to evaluate the suitability of the data, and the factor-loading threshold was set at 0.5.

The initial EFA results showed that the observed variables converged into meaningful factors. The KMO value of 0.869 exceeded 0.5, indicating sampling adequacy. Bartlett's Test was significant at Sig. = 0.000, showing that observed variables were linearly correlated in the population. The extracted variance reached 72.318%, greater than 50%, indicating that the factors explained a substantial share of the variance.

Table 3.7: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.869
Bartlett's Test of Sphericity: Approx. Chi-Square	3606.499
df	190
Sig.	.000
Total variance extracted	72.318% > 50%
Lowest Eigenvalue	16.190 > 1

Table 3.8: Rotated component matrix

Variable	Factor 1	Factor 2	Factor 3	Factor 4
TGTV4	.872			
TGTV3	.871			
TGTV5	.870			
TGTV1	.870			
TGTV2	.860			
TKHT3		.868		
TKHT4		.862		
TKHT2		.861		
TKHT5		.840		
TKHT1		.831		
CLDL2			.855	
CLDL3			.846	
CLDL1			.844	
CLDL4			.832	
CLDL5			.823	
NLGV3				.847
NLGV1				.847
NLGV4				.823
NLGV2				.817
NLGV5				.810

b. Analysis of the dependent variable

Table 3.9: KMO and Bartlett's Test for the dependent variable

Kaiser-Meyer-Olkin Measure of Sampling Adequacy	0.871
Bartlett's Test of Sphericity: Approx. Chi-Square	679.360
df	10
Sig.	.000

For the dependent variable Educational Culture and Policy, the KMO value was 0.871, which falls within the very good range. Bartlett's Test yielded Chi-Square = 679.360 with Sig. = 0.000, confirming that the variables are sufficiently correlated for EFA.

Table 3.10: EFA results for the Educational Culture and Policy factor

Observed variable code	Coefficient
VHCS2	.670
VHCS4	.670
VHCS1	.662
VHCS3	.662
VHCS5	.650
Variance extracted	66.260% > 50%
Eigenvalue	3.313 > 1

All five observed variables load onto a single factor with coefficients ranging from 0.650 to 0.670, above the standard threshold of 0.5. The Eigenvalue of 3.313 and variance extracted of 66.260% confirm that the scale has good convergent validity and unidimensionality.

3.2.3 Hypothesis Testing of the Model

a. Correlation testing

Before regression analysis, Pearson correlation was used to examine preliminary relationships among variables and to ensure the suitability of input data. The results show that all independent variables are significantly correlated with the dependent variable VHCS at the 0.01 level.

Table 3.11: Correlation matrix

	VHCS	CLDL	TKHT	NLGV	TGTV
VHCS Pearson Correlation	1	.449**	.357**	.359**	.277**
Sig. (2-tailed)		.000	.000	.000	.000
N	300	300	300	300	300
CLDL Pearson Correlation	.449**	1	-.014	-.064	-.004
Sig. (2-tailed)	.000		.808	.271	.947
N	300	300	300	300	300
TKHT Pearson Correlation	.357**	-.014	1	-.008	-.029
Sig. (2-tailed)	.000	.808		.888	.616
N	300	300	300	300	300
NLGV Pearson Correlation	.359**	-.064	-.008	1	-.038
Sig. (2-tailed)	.000	.271	.888		.514
N	300	300	300	300	300
TGTV Pearson Correlation	.277**	-.004	-.029	-.038	1
Sig. (2-tailed)	.000	.947	.616	.514	
N	300	300	300	300	300
** Correlation is significant at the 0.01 level (2-tailed).					

Table 3.12: Regression results

Model	Variable	B	Std. Error	Standardised Beta	t	Sig.	Tolerance	VIF
1	Constant	-1.235	.247		-4.997	.000		
	CLDL	.436	.034	.481	12.725	.000	.996	1.004
	TKHT	.312	.031	.375	9.941	.000	.999	1.001
	NLGV	.405	.038	.404	10.674	.000	.994	1.006
	TGTV	.244	.030	.305	8.070	.000	.998	1.002
Dependent variable: VHCS								

b. Regression model

Regression analysis (See Table 3.12) was performed with four independent variables: Data Quality (CLDL), AI System Design (TKHT), Lecturer Competence (NLGV) and Student Participation (TGTV). The dependent variable was Educational Culture and Policy (VHCS).

The standardised regression equation is: VHCS = 0.481CLDL + 0.404NLGV + 0.375TKHT + 0.305TGTV.

All four predictors have Sig. = 0.000, indicating statistically significant positive effects on Educational Culture and Policy. Based on standardised Beta coefficients, Data Quality has the strongest effect (0.481), followed by Lecturer Competence (0.404), AI System Design (0.375) and Student Participation (0.305).

The VIF values range from 1.001 to 1.006, far below the threshold of 10, and tolerance values are close to 1. These results indicate that the model does not violate multicollinearity assumptions.

Table 3.13: Model summary

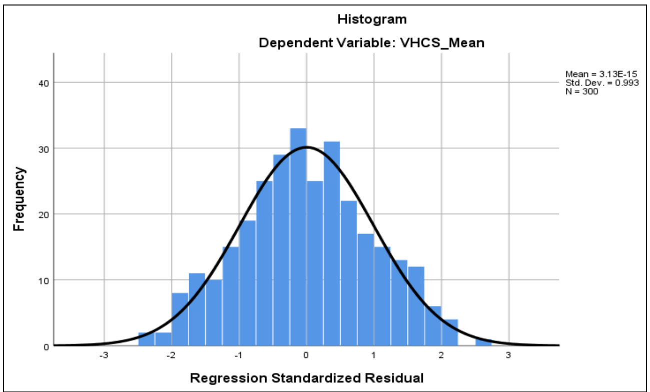
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.761a	.580	.574	.46018	1.978
Predictors: TGTV_Mean, CLDL_Mean, TKHT_Mean, NLGV_Mean					
Dependent variable: VHCS_Mean					

The coefficient R = 0.761 shows a fairly strong positive relationship between the predictors and the dependent variable. R2 = 0.580 and adjusted R2 = 0.574 indicate that the model explains 57.4% of the variance in Educational Culture and Policy. The Durbin-Watson statistic of 1.978 is close to 2, indicating no serious autocorrelation of residuals.

Table 3.14: ANOVA results of the model

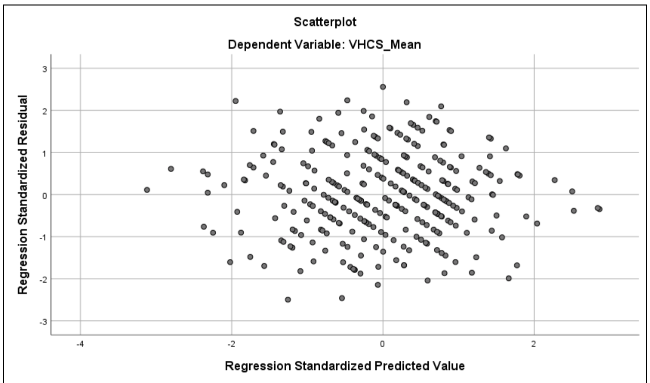
Model	Source	Sum of Squares	df	Mean Square	F	Sig.
1	Regression	86.125	4	21.531	101.672	.000b
	Residual	62.472	295	.212		
	Total	148.597	299			
Dependent variable: VHCS						
Predictors: CLDL, TKHT, NLGV, TGTV						

The ANOVA results show that the model is statistically significant, with F = 101.672 and Sig. = 0.000. This confirms that the independent variables collectively explain a significant portion of the variation in the dependent variable.



Source: Research data processing results.

Fig 3.1: Test of the normal distribution of residuals



Source: Research data processing results.

Fig 3.2: Scatterplot of residuals

The histogram of standardised residuals shows an approximately bell-shaped distribution centred around zero, with a mean close to 0 and standard deviation close to 1. With N = 300, the data provide sufficient support for the assumption of normally distributed residuals.

The scatterplot of standardised residuals and standardised predicted values shows no clear curve, funnel shape or systematic pattern. The residuals are distributed around zero, indicating that the regression model satisfies linearity and homoscedasticity assumptions.

After reliability testing, EFA, regression analysis and assumption checks, the proposed model confirms that the hypotheses H1, H2, H3 and H4 are accepted and no tested hypothesis is rejected.

Table 3.15: Summary of hypothesis testing results

Hypothesis	Content	Testing result
H1	Data quality of AI positively affects educational culture and policy.	Accepted
H2	AI system design positively affects educational culture and policy.	Accepted
H3	Lecturer competence positively affects educational culture and policy.	Accepted
H4	Student participation positively affects educational culture and policy.	Accepted

3.3 Discussion of Research Results

The study shows that all four factors proposed in the theoretical model have statistically significant effects on students' learning when AI is applied. This confirms the suitability of the research model and contributes to the theoretical and practical understanding of higher education under the influence of AI.

First, Data Quality has the strongest effect (beta = 0.481). In the AI era, data are the core input. When data are accurate, updated and transparent, AI systems generate valuable responses, strengthening trust and enabling educational managers to develop effective learning-support policies.

Second, Lecturer Competence also has a substantial positive effect (beta = 0.404). Regardless of technological sophistication, human guidance remains central. Lecturers with strong professional and digital competencies can guide students in using AI properly and help establish cultural norms for responsible technology use.

Third, AI System Design has a positive effect (beta = 0.375). A well-designed, user-friendly and curriculum-aligned AI system promotes broader acceptance of technology. This finding highlights the importance of investing in technical infrastructure and personalised educational technologies.

Fourth, Student Participation has a positive effect (beta = 0.305). Although its coefficient is lower than those of other factors, it remains an indispensable link. Students' initiative, interaction and feedback are essential for improving educational policies and building an active, responsible digital learning community.

Overall, the accepted hypotheses confirm the internal logic of the model. The findings reflect the practical reality that building an educational culture adaptive to AI requires coordination between technological quality, including data and system design, and human capacities, including lecturers and students. This provides an important basis for universities to issue regulations, guidelines and digital-transformation strategies.

4. Solutions to Improve the Effectiveness of AI Use in Students' Learning Activities at Selected Universities in Hanoi

4.1 Solutions Concerning AI System Data Quality

To optimise AI as an effective learning-support tool, ensuring and controlling input data quality is a prerequisite. Students should not passively accept information or use unverified sources; instead, AI use should be linked to the selection and appraisal of credible information sources.

Establishing input-data standards. Students should improve input-data quality through advanced prompt-engineering skills and by providing clear context. Using clean data from official academic sources helps reduce AI hallucination and ensures outputs with greater depth and disciplinary relevance. Learners should maintain iterative interaction and critical thinking to cross-check information, thereby using AI as a genuine lever for logical thinking and scientific research.

Verifying and cross-checking information. AI use in universities requires students to maintain sharp critical thinking. Learners should not become passively dependent on AI output because even advanced AI has limitations in terms of timeliness and absolute accuracy. Students should act as knowledge validators, comparing AI responses with textbooks, scientific documents and practical data. This cross-checking process enhances objectivity, reliability and students' analytical skills.

Building goal-oriented data-use habits. AI use should shift from spontaneous and intuitive use to a strategic process with clear direction. Each interaction with AI should serve a specific research or academic objective. Rather than accepting superficial answers, learners should integrate AI-generated information into their existing knowledge system and transform it into meaningful academic value.

4.2 Solutions Concerning AI System Design

To make AI an effective learning-support tool, educational institutions should develop integrated and modern system infrastructure. System design should prioritise user-friendliness and compatibility with existing learning management systems. A simple and accessible interface reduces technical barriers and allows students to focus on learning content rather than operational complexity.

The real strength of AI systems lies in their capacity to personalise learning pathways. Instead of providing generic information, systems should identify each learner's level, interests and goals and then recommend appropriate learning materials and exercises. Virtual assistants capable of supporting students 24/7 can help resolve learning difficulties without constraints of time or space.

Investment in system infrastructure also demonstrates institutional commitment to modernising education. A well-designed AI system should ensure stability, fast access and strong data security. When students feel supported by a robust technical platform, they become more willing to interact, experiment and create with AI applications.

4.3 Solutions Concerning Lecturers' Digital Competence and Skills

In a digitalised educational environment, lecturers are no longer merely transmitters of knowledge; they must become technology guides and coordinators. Institutions should develop regular and specialised training programmes on AI use in teaching. Mastery of AI is not limited to technical operations; it also requires redesigning lectures to integrate AI effectively and improve interaction.

Assessment methods should also be renewed under the influence of AI. Lecturers should design assignments and tests that require higher-order thinking, analysis, critique and creativity, rather than tasks easily completed through copied prompts. Intelligent assessment mechanisms can naturally encourage students to use AI as a tool for thinking and inquiry rather than as a shortcut for academic misconduct.

Most importantly, lecturers must inspire and guide students in digital ethics. They should teach not only how to use AI but also how to work responsibly in the digital era. Appropriate guidance helps students recognise the value of honesty and personal creativity, transforming AI into a lever for intellectual development rather than a shortcut to laziness.

4.4 Solutions to Promote Student Participation in AI-Supported Learning

Student participation is not simply the use of technology; it is a core link in improving the digital education ecosystem. Universities should create creative spaces such as online forums and specialised AI clubs. In these spaces, students can exchange practical experiences, share effective prompt-engineering methods and jointly solve complex academic problems.

Students' voices should be treated as an important information channel for adjusting and upgrading AI systems. Institutions should establish periodic feedback mechanisms and encourage learners to comment on the usefulness, accuracy and limitations of AI tools. Recognising such contributions helps align AI systems with real learning needs and fosters student responsibility for the educational environment.

4.5 Solutions for Building Digital Culture and Improving Educational Policy

From the institutional perspective, a transparent legal framework and clear policy system are essential for AI to create value in education. Policies should specify rights, responsibilities and 'red lines' in AI use for both lecturers and students. Practical regulations can reduce concerns about academic ethics, protect intellectual property and ensure fairness in student assessment.

Policy objectives should also focus on building a digital culture grounded in academic honesty and self-respect. Universities should strengthen communication on AI ethics, emphasise the value of personal creativity and affirm that machines support but do not replace independent human thinking. A healthy culture in which technology and educational actors collaborate harmoniously will help students develop confidence and resilience.

In the long term, when AI is placed within a humanistic policy framework and a positive learning culture, it can become a strategic lever for improving higher education quality. The alignment between regulatory systems and learner awareness will contribute to developing students with sound digital thinking and readiness for the knowledge economy.

5. Conclusions and Recommendations

5.1 Conclusions

In the context of the Fourth Industrial Revolution and the rapid development of technology platforms and social networks, AI applications are receiving increasing attention in education. AI is not only an important educational tool but is also widely used by students as a learning assistant for writing essays, completing group assignments, practising English, searching for documents and preparing for examinations.

Through surveys and research conducted at universities in Hanoi, especially among students in economics-related fields, the research team identified both positive and negative effects of AI on university students' learning. AI can help students optimise research time, increase access to information and improve learning effectiveness. However,

without proper guidance, students can become dependent on technology, learn passively or copy mechanically, thereby weakening critical thinking and creativity.
Although the data-collection process encountered certain difficulties, the research team sought to complete the study as rigorously as possible. The authors also recognise limitations, particularly the relatively narrow scope of research subjects. The study is expected to provide a foundation for more comprehensive future research.

5.2 Recommendations

AI use has, is having and will continue to have a major impact on the learning process and learning outcomes of students at selected universities in Hanoi and students more broadly. Although AI brings substantial benefits, it also generates negative effects that can directly influence current learning processes. Therefore, the research team proposes several recommendations.
For universities, institutions should organise regular seminars, workshops and expert discussions involving AI specialists, lecturers and students. These events should focus on practical experiences and skills in using AI for learning, as well as on the negative impacts of AI, so as to raise awareness, strengthen effective-use skills and help students shift from passive to active use.
Universities may also integrate AI modules into core courses or open short, application-oriented training programmes on AI. Such programmes should emphasise ethics and critical thinking, turning AI into a reliable assistant while limiting the deterioration of independent thinking and encouraging creativity throughout the learning process.
In addition, lecturers' integration of AI into teaching, including online lessons, interactive support, personalised learning and supervised online question-and-answer activities, can increase flexibility in knowledge access and improve teaching quality in the digital environment.
For students, AI should be positioned as a learning-support tool rather than a replacement for individual thinking. Students need rules to monitor their dependence and adjust use appropriately. AI should supplement self-learning, enabling faster access to knowledge while preserving initiative and creativity.
Students should verify sources, compare AI-generated information with credible documents, and test the accuracy of AI responses. They should also maintain balanced study schedules to avoid exhaustion and ensure that AI remains a support tool rather than a substitute for perseverance and core thinking.
Students should coordinate with universities, lecturers and families by participating in discussion groups about AI's impacts through online platforms. This helps prevent misconceptions about AI, clarifies its nature and practical value, and builds a healthy, responsible AI-use culture that balances learning benefits with the development of social skills.
In conclusion, AI is creating far-reaching effects on students' learning: it accelerates access to diverse knowledge, supports personalisation and enhances self-learning, but it also risks increasing tool dependence, weakening critical thinking, limiting independent creativity, spreading inaccurate information and reducing traditional academic interaction. AI should not replace learning but support it. Strategic intervention by all stakeholders is needed to balance benefits and risks and to build a sustainable learning model for the digital era.

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