AI IN HIGHER EDUCATION: NAVIGATING PRACTICAL BENEFITS AND PERCEIVED RISKS FROM STUDENTS' PERSPECTIVES

TRÍ TUỆ NHÂN TẠO TRONG GIÁO DỤC ĐẠI HỌC: GIỮA LỢI ÍCH THỰC TẾ VÀ RỦI RO NHẬN THỨC TỪ GÓC ĐỘ SINH VIÊN

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Abstract - This quantitative study surveyed 435 university students using a 5-point Likert scale to analyze artificial intelligence (AI) adoption. Grounded in an extended Technology Acceptance Model, the research examines perceived usefulness, control ability, perceived risk, intention to use, and learning impact. Results indicate that perceived usefulness is the strongest predictor of intention to use AI ($\beta = 0.498$; $p < 0.001$), followed by the ability to control and use AI responsibly ($\beta = 0.153$; $p < 0.001$). Conversely, perceived risk has a negative effect ($\beta = -0.189$; $p < 0.001$). Notably, the intention to use AI positively influences learning impact ($\beta = 0.347$; $p < 0.001$) and serves as a partial mediator. The model explains 44.5% of the variance in learning impact. Findings suggest that integrating AI into higher education requires clear pedagogical guidance to maximize benefits while mitigating potential risks.

Key words - Artificial intelligence; generative AI; Higher education; Students; Technology acceptance

Tóm tắt - Nghiên cứu khảo sát 435 sinh viên đại học bằng thang Likert 5 mức nhằm phân tích việc chấp nhận trí tuệ nhân tạo (AI) trong học tập. Dựa trên mô hình chấp nhận công nghệ mở rộng, nghiên cứu xem xét tính hữu ích, năng lực kiểm soát AI, nhận thức rủi ro, ý định sử dụng và tác động học tập. Kết quả cho thấy, tính hữu ích dự báo mạnh nhất ý định sử dụng AI ($\beta = 0{,}498$; $p < 0{,}001$), tiếp theo là năng lực kiểm soát AI ($\beta = 0{,}153$; $p < 0{,}001$). Nhận thức rủi ro ảnh hưởng tiêu cực đến ý định sử dụng ($\beta = -0{,}189$; $p < 0{,}001$), còn ý định sử dụng tác động tích cực đến kết quả học tập được cảm nhận ($\beta = 0{,}347$; $p < 0{,}001$). Mô hình giải thích 44,5% phương sai của tác động học tập. Kết quả cho thấy tích hợp AI vào giáo dục đại học cần đi kèm hướng dẫn sư phạm, phát triển năng lực AI và nguyên tắc sử dụng có trách nhiệm để phát huy lợi ích và hạn chế rủi ro.

Từ khóa - Trí tuệ nhân tạo; AI tạo sinh; Giáo dục đại học; Sinh viên; Chấp nhận công nghệ

1. Introduction

The Fourth Industrial Revolution has been driving profound changes across all areas of social life, with higher education among the most strongly affected [1]. Along with the development of digital technology, AI has emerged as a key technology, contributing to changing the way teaching, learning, and educational management are conducted. In higher education, AI is no longer limited to learning management systems or data analysis; it has expanded to include AI-generated tools capable of natural language interaction, text generation, knowledge interpretation, and thinking support [2]. These tools allow students to access knowledge quickly, flexibly, and personally, thereby creating new opportunities for improving the quality of learning. However, the rapid spread of AI in education has also sparked much debate. On the one hand, AI is seen as an intelligent learning assistant that helps students learn more effectively; on the other hand, it raises concerns about technological dependence, a decline in independent thinking, and violations of academic ethics [3]. Therefore, studying how students approach, use, and evaluate AI becomes a pressing issue.

In Vietnam, although university students increasingly use AI, research on the topic from their perspective remains limited, especially studies clarifying the relationships among perception, intention, and the learning impact of AI. This highlights the need for systematic research tailored to the context of Vietnamese higher education.

This study aims to analyze the current state of AI use in university learning among Vietnamese students, identify factors influencing students' intentions to use AI, and assess the impact of AI on university learning from students' perspectives.

Research Questions:

RQ1: How are Vietnamese students using AI in their university studies?

RQ2: What factors promote or hinder students' intentions to use AI?

RQ3: How does AI impact university learning from students' perspectives?

2. Overview

2.1. AI and Generative AI in Higher Education

AI in higher education is the application of computer systems capable of learning, reasoning, and decision-making to support teaching, learning, and educational management activities [4]. In recent years, the

development of generative AI has opened a new phase, allowing learners to interact directly with AI systems through natural language [5]. Studies indicate that generative AI has great potential to help students understand complex knowledge, provide immediate feedback, and personalize learning [6]. Particularly in higher education, where substantial self-study and research are required, AI can act as a personal learning assistant, supporting students outside of class hours [7].

2.2. Proposed influencing factors

The Technology Acceptance Model (TAM) suggests that perceived usefulness and perceived ease of use are key factors influencing the intention and behavior of using technology [8]. Many studies have expanded the TAM to suit the educational context, adding factors such as learning motivation, technological competence, and organizational support. In the context of generative AI, recent studies emphasize the role of AI control competence, risk perception, and academic ethics in explaining students' AI usage behavior [9]. This indicates that the application of AI in education should be approached not only from a technological perspective but also from a pedagogical and ethical perspective.

Despite numerous international studies on AI in higher education, there is a lack of systematic research analyzing the relationship between AI perception, usage intentions, and learning impacts from students' perspectives in the Vietnamese context. This gap forms the basis for the current research.

3. Research methodology

3.1. Research Design

The study employed a quantitative, cross-sectional survey design to collect and analyze students' perceptions, behaviors, and evaluations of the application of AI in university learning [10]. This approach is consistent with the research objective of identifying the relationship between cognitive factors, intention to use, and the learning impact of AI, while also testing the proposed research hypotheses. The research design was built on the foundation of the TAM and recent extended studies in AI in higher education [11]. The study not only focuses on the perceived usefulness of AI but also integrates variables reflecting the specifics of generative AI, including AI control capabilities, perceived risks, and the mediating role of AI usage intentions.

3.2. Research Model and Hypotheses

Based on theoretical foundations and the research overview, the proposed research model includes the following main variable groups:

- Perception of the Necessity of AI (NEC);
- Perception of the Usefulness of AI (PU);
- Competence to Control and Use AI Responsibly (CTRL);
- Perception of Risks When Using AI (RISK);
- Intention to Use AI in Learning (INT);
- Positive Impact of AI on Learning (IMP).

The model assumes that cognitive factors (NEC, PU), personal competence (CTRL) and perceived risk (RISK) directly influence intention to use AI (INT); at the same time, the intention to use AI acts as a mediator in the relationship between perception and IMP (Figure 1).

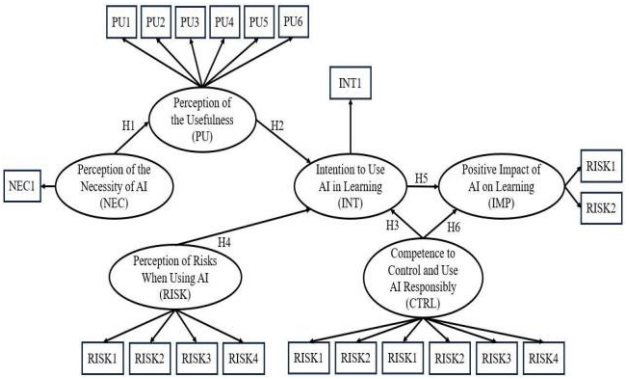


Figure 1. *Research Model*

Based on this, the research hypotheses are constructed as follows:

H1: Perception of the necessity of AI positively influences perception of AI's usefulness.

H2: Perception of AI's usefulness positively influences the intention to use AI in learning.

H3: The ability to control and use AI responsibly positively influences the intention to use AI.

H4: Perception of risks when using AI negatively influences the intention to use AI.

H5: The intention to use AI positively influences the learning impact of AI.

H6: The ability to control AI has a direct and positive influence on the learning impact of AI.

3.3. Research Sample and Survey Subjects

The subjects of this study comprise Vietnamese university students currently enrolled in higher education institutions across various academic fields. To ensure geographical representativeness and capture a nationwide perspective, the sample is distributed across three main regions of Vietnam, consisting of 165 students from the North, 125 from the Central region, and 145 from the South. Due to practical research conditions and the objective of evaluating the proposed conceptual framework, a total of 435 valid survey responses were utilized for final analysis. This sample size of 435 satisfies the minimum statistical requirements for both multiple regression analysis, which typically demands an observation-to-variable ratio of at least 5:1 to 10:1. Consequently, the utilized sample size guarantees the stability, adequacy, and reliability of the statistical estimates, aligning robustly with established empirical methodologies in educational technology research. Data Collection Tools

Data were collected through a structured survey questionnaire, designed based on scales used and validated in international studies on technology and AI adoption in education, and then adapted to the context of Vietnamese students.

The survey questionnaire consisted of three main parts:

- General information section: gender, academic year, field of study, and level of understanding of AI.

- AI usage status section: frequency of use, commonly used AI tools, and purpose of using AI in learning.

- Research scale section: measuring the variables NEC, PU, CTRL, RISK, INT, and IMP.

The scales used a 5-point Likert scale, from 1 (Strongly disagree) to 5 (Strongly agree). The Likert scale captures students' subjective awareness and evaluation levels, making it suitable for behavioral research in education.

3.4. Reliability and Validity of the Scales

The reliability of the scales was assessed using Cronbach's alpha [12]. The results showed that all scales achieved values greater than 0.8, exceeding the commonly accepted threshold in social science and education research. This indicates that the observed variables in each scale have high internal consistency. The convergent validity of the scales was assessed through composite reliability (CR) and average variance extracted (AVE) [13]. The CR values were all greater than 0.7, and the AVE values exceeded 0.5, confirming that the scales accurately reflect the underlying concepts they represent.

3.5. Data Analysis Process and Methods

Survey data were processed and analyzed in the following steps:

(1) Descriptive statistical analysis to characterize the sample and the current state of AI use among students.

(2) Scale reliability testing using Cronbach's Alpha.

(3) Assessment of convergent validity through CR and AVE.

(4) Standardized regression analysis to test hypotheses about the relationship between variables in the model.

(5) Analysis of the mediating role of AI use intention in the relationship between cognition and learning impact.

The analysis was conducted using SPSS and SmartPLS 4.0, which are widely used in educational research, ensuring transparency and reproducibility of the study.

4. Research Results

4.1. Characteristics of the Survey Sample and the Current Status of AI Use Among Students

The research sample consisted of 435 Vietnamese university students, representing various academic disciplines and academic years. Descriptive statistics indicate that students in science and engineering, the social sciences, and economics have relatively high levels of access to and use of AI in their studies. However, a granular examination reveals critical nuances in the adoption pathways and behavior between these academic tracks. Specifically, students in science and engineering exhibit a higher frequency of operational and technical AI integration, predominantly utilizing generative tools for code compilation, algorithmic debugging, and complex data simulation. Their engagement with AI is largely driven by functional efficiency and CTRL. Conversely, students in economics and social sciences leverage AI primarily as a cognitive and communicative catalyst, with major use cases centered on literature synthesis, academic writing support, translation, and structured brainstorming. Interestingly, while engineering students report greater confidence in managing AI outputs, social science and economics students demonstrate a more pronounced sensitivity toward academic integrity and RISK, particularly regarding the potential decline of independent critical thinking. This disciplinary divergence suggests that while PU is a universally potent predictor across the entire sample, pedagogical frameworks must be differentiated: technical disciplines should emphasize ethical boundaries and algorithmic constraints, whereas social and economic tracks require more targeted support in maximizing the advanced analytical capabilities of AI tools. 385 students self-assessed their understanding of AI as average to good, reflecting that AI has become familiar, but that not all students have a deep understanding of its nature and limitations. Regarding usage, 400 students reported having used AI to support their studies, ranging from occasional to frequent. Typical uses of AI include: searching for and explaining knowledge, summarizing study materials, translation, supporting academic writing, outlining, and planning studies. Several students in engineering and information technology fields are also using AI to assist in programming and debugging source code. These results show that AI is gradually becoming a popular learning tool in university environments, no longer limited to technical activities but expanding to many different academic fields.

4.2. Results of Scale Reliability Testing

The reliability of the scales in the research model was assessed using Cronbach's alpha. The analysis results show that all scales achieved high reliability, specifically:

Table 1. *Reliability of the scales in the research model*

No.	Factors	Reliability
1	Awareness of the usefulness of AI (PU)	α = 0.949
2	Competence in controlling and using AI responsibly (CTRL)	α = 0.935
3	Awareness of the risks of using AI (RISK)	α = 0.903
4	Positive impact of AI on learning (IMP)	α = 0.914
5	Need for support from schools (NEC)	α = 0.896

Note: *The variables NEC and INT each have only one observation; Cronbach's Alpha is not reported (NEC, INT N/A).*

All Cronbach's Alpha values exceed 0.8, indicating that the observed variables in each scale have high internal consistency. This confirms that the survey tool used in the study is reliable and suitable for further analysis.

4.3. Assessing the convergent validity of the scale

Based on Table 2, the convergent validity of the scales was assessed through CR and AVE. The results show that all multi-item scales achieved CR > 0.9 and AVE > 0.5. These indicators show that the observed variables can well explain the corresponding latent concepts and confirm that the scales accurately reflect the nature of the theoretical

structures in the research model. Therefore, the measurement model in the study meets the requirements for reliability and convergent validity, providing a solid foundation for testing the structural model.

Table 2. *Reliability and convergent validity of the measurement scales*

Factors	Cronbach's Alpha (α)	CR	AVE
PU – Perceived Usefulness	0.949	0.958	0.741
CTRL – AI Control Ability	0.935	0.946	0.721
RISK – Perceived Risk	0.903	0.918	0.689
IMP – Integrated Learning Impact	0.914	0.928	0.701
SUP – School Support Needs	0.896	0.912	0.674

4.4. Results of Structural Model Testing and Research Hypotheses

4.4.1. Factors Affecting Students' Intention to Use AI

The standardized regression model predicting the INT explains 44.2% of the variance of the dependent variable (R^2 = 0.442). This result shows that the model's independent variables explain students' intention to use AI relatively well. Specifically, PU has the strongest positive influence on INT (β = 0.498; p < 0.001). This indicates that when students perceive AI to bring practical benefits to their learning, they tend to be willing to continue using AI in their studies. Furthermore, the perception of PU also positively impacted the INT (β = 0.139; p = 0.001). This result indicates that students not only use AI out of technological curiosity but also view it as a necessary tool in the current university learning context. In addition, responsible AI control competence (CTRL) positively influenced the intention to use AI (β = 0.153; p < 0.001). This indicates that the more skilled students are at using AI correctly, the more confident and willing they are to integrate AI into their learning process. Conversely, perceived risk (RISK) negatively influenced the intention to use AI (β = –0.189; p < 0.001). Concerns about dependence on AI, a decline in independent thinking, and violations of academic ethics may reduce students' willingness to use AI.

4.4.2. The Impact of AI on University Learning

Table 3. *Variance results of the dependent variable*

No.	Dependent Variable	R^2	Explanation
1	Intention to Use AI (INT)	0.442	Average - Good
2	Positive Impact of AI on Learning (IMP)	0.445	Average - Good

From Table 3, the model predicting positive learning impact (IMP) explains 44.5% of the variance of the dependent variable (R^2 = 0.445). The results show that the INT has a positive, statistically significant effect on learning impact (β = 0.347; p < 0.001). This indicates that AI has a positive impact on learning only when students have a clear, proactive intention to use it. The more frequently and purposefully students use AI, the more aware they become of the benefits it brings to their learning outcomes and processes. Therefore, the analysis of the coefficient of determination (R^2) shows that the research model explains 44.2% of the variance in intention to use AI and 44.5% of the variance in the positive impact of AI on learning. Following established PLS-SEM guidelines [14], these R^2 values indicate moderate explanatory power, reflecting the model's explanatory power in educational behavior research.

4.5. Analysis of the Mediating Role of AI Use Intention

Table 4. *Mediating Role of AI Use Intention*

No.	Intermediate relationship	Direct impact (β)	Indirect impact (β)	Total impact (β)	Conclusion
1	PU → INT → IMP	0.170	0.173	0.343	Partial intermediation

From Table 4, the mediating role analysis indicates that the intention to use AI partially mediates the relationship between the perceived usefulness of AI and the positive impact of AI on learning. Specifically, the indirect effect (β = 0.173) is nearly equivalent to the direct effect (β = 0.170), indicating that the transformation of perception into learning effectiveness depends significantly on students' intention to use AI. This result demonstrates that perception of AI does not automatically translate into learning effectiveness but requires students' actual intention and behavior in using it.

5. Discussion

This study provides clear quantitative evidence on the current state and mechanisms of impact of AI in university learning from the perspective of Vietnamese students. Based on a dataset from 435 students, the analysis results not only reflect the increasing prevalence of AI use but also clarify the role of cognitive factors, personal competence, and perceived risk in shaping the intention to use AI and its impact on learning [15].

The research results show that the PU is the most influential factor on the INT, with a β coefficient of 0.498 (p < 0.001). This is the highest coefficient among all tested relationships, indicating that when students perceive AI as helping them understand lessons faster, saving time, and improving the quality of assignments, they tend to be willing and proactive in using AI in their studies. This result is consistent with the TAM and recent studies on generative AI in higher education, and it also reflects the specific characteristics of Vietnamese students in the context of high academic pressure and significant self-learning requirements [16]. The fact that PU has nearly three times the impact of AI control ability (β = 0.153) shows that the practical pedagogical value of AI is a key factor determining students' acceptance of the technology, rather than purely technical factors [17]. Recent studies published in The University of Danang - Journal of Science and Technology similarly show that perceived usefulness and risk considerations shape university students' acceptance of generative AI [18], while AI use can support learning and self-directed learning when accompanied by critical and responsible engagement [19].

Besides the perception of usefulness, responsible AI control competence (CTRL) also had a statistically significant positive influence on the intention to use AI ($\beta = 0.153; p < 0.001$). Although this impact was lower than PU, the results showed that students not only needed useful AI but also needed to know how to use AI correctly to be ready to integrate AI into their learning. This data indicates that AI is truly accepted by students only when they can control the use process, including formulating appropriate commands, verifying information, and editing the results generated by AI. This helps reduce the risk of dependence and increase learning autonomy. In the context of Vietnamese higher education, where students' AI usage skills remain uneven, these results emphasize the role of AI literacy as an important but not yet strong enough supporting factor to replace the role of perceived usefulness [20].

In contrast, perceived risk (RISK) negatively affected the intention to use AI, with a coefficient $\beta = -0.189$ ($p < 0.001$). This level of impact indicates that perceived risk plays a significant role in deterring students' use of AI. Comparing absolute values, the negative impact of RISK is greater than the positive impact of CTRL ($|-0.189| > 0.153$), suggesting that concerns about declining independent thinking, academic cheating, and dependence on AI may weaken the intention to use AI, even if students perceive AI as useful. This reflects the fact that Vietnamese students are not uncritical in their use of AI but have certain ethical and academic considerations [21].

A key contribution of the study is clarifying the mediating role of INT in the relationship between AI perception and IMP. Analysis results show that INT positively influences IMP ($\beta = 0.347$, $p < 0.001$), and the model explains 44.5% of the variance in learning impact ($R^2 = 0.445$). Notably, the indirect effect of perceived usefulness on learning via intention to use AI is 0.173, nearly equal to the direct effect (0.170). This suggests that AI does not automatically improve learning outcomes; instead, students' intention and willingness to use AI play a decisive role in translating perception into learning outcomes [22]. This result has significant pedagogical implications, confirming that integrating AI into higher education should focus on fostering students' motivation and AI use strategies, rather than simply providing technological tools [23].

The combined results of the analysis show that the research model explains 44.2% of the variance in the intention to use AI and 44.5% of the variance in the learning impact, indicating a moderate to high level of explanation, consistent with behavioral studies in higher education. The statistically significant beta coefficients ($p < 0.001$) confirm the reliability of the proposed relationships. These figures suggest that AI has the potential to impact university learning positively, but its effectiveness depends strongly on how students perceive, control, and proactively use it. Therefore, the application of AI in Vietnamese higher education should be approached in a balanced way, balancing the exploitation of benefits and the management of risks, based on quantitative evidence rather than subjective opinions.

6. Conclusion

This study analyzed the current situation and factors influencing the application of AI in university learning from the perspective of Vietnamese students. The results show that AI is gradually becoming a familiar learning tool, used by students for various purposes. Perception of usefulness is the most important factor driving the intention to use AI. At the same time, the ability to control AI plays a supporting role, and the perception of risk has an inhibitory effect. In particular, the study clarifies that the intention to use AI acts as an intermediary between perception and learning impact. This confirms that AI's effectiveness in higher education depends not only on technology but primarily on how students approach and use it. From the research results, several important implications for Vietnamese higher education can be drawn:

First, universities need to shift from an "allow-or-ban AI" approach to an integrated, directed AI strategy, where AI is considered a legitimate learning support tool.

Second, emphasis should be placed on developing AI literacy skills among students, including understanding AI's capabilities and limitations, responsible AI use, and awareness of academic ethics in the AI era.

Third, lecturers need to innovate in teaching and assessment methods to require higher-order thinking, critical thinking, and creativity, while limiting the misuse of AI and still exploiting its benefits.

The study used data from 435 students. Therefore, to formulate national-level policies, the sample size at each university needs to be increased to fully reflect the practical context of each higher education institution. Further studies should use empirical data, expand the survey sample, and incorporate qualitative methods to deepen understanding of the results.

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