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# Determinants of AI Use among Gen-Z Students: Evidence from Ho Chi Minh City, Vietnam

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## ABSTRACT

Background: AI supports learning through personalized content, resource access, and task automation, but concerns about privacy, ethics, and overreliance may impede adoption. This study uses the Technology Acceptance Model (TAM) to examine factors influencing AI adoption in education. Purpose: This study examines how perceived risks, digital literacy, and self-efficacy influence university students' intentions to adopt AI in education within Vietnam's evolving educational landscape. Methodology: A survey of 305 students in Ho Chi Minh City, Vietnam, was conducted using a structured questionnaire, validated through Cronbach's alpha and exploratory factor analysis. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data. Findings: Digital literacy enhances perceived ease of use and self-efficacy, both driving AI adoption. Perceived usefulness strongly predicts acceptance, while risks like accuracy and privacy concerns hinder it. Self-efficacy mediates digital literacy's impact on acceptance. Students prioritized AI's functionality over accessibility. Implications and Recommendations: The findings advocate enhancing digital literacy and addressing risks to promote responsible AI use in education. Limited to one university, future research should explore diverse contexts. Contribution: This study underscores digital literacy and self-efficacy as key to AI adoption in Vietnam's educational landscape.

**Keywords:** Artificial Intelligent, Technology Acceptance Model (TAM), Education, Digital literacy

## INTRODUCTION

The application of Artificial Intelligence (AI) into higher education has changed how things are taught and run, which offers oppoturnities to personalize learning, improve administrative automation and make students more engaged in their learning (Luckin & Holmes, 2016; *OECD Digital Education Outlook*, 2023). This change is obvious to Generation Z (born 1997 - 2012), a group of "digital natives" who are closedly accustomed to technology (Dimock, 2019). With 97% of adolescents using the internet daily, this generation is predicted to become the primary driver and consumer of AI-enhanced education as they attend universities worldwide (Monica et al., 2023). In Vietnam, where this population group marks a remarkably part of the population, understanding their adoption of AI is critical to national educational development (Fritz & Le, 2023).

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However, in the context of Vietnam, the potential for AI in education encounters issues of unequal preparedness and systemic constraints. Studies show that AI could boost learning results by around 40% (EdTech Magazine, 2024), but Vietnam's digital setup has noticeable differences. The country ranks 51st worldwide in digital readiness with an urban-rural divide: 25% of rural students have regular access to devices that work with AI, compared to 80% in cities (Economist Intelligence Unit, 2022; *Vietnam Internet Network Information Center*, 2023). Simultaneously, university students' digital literacy is average and schools' IT infrastructure is often not good enough to integrate AI well (Nguyen & Habók, 2022).

Additionally, psychological, social, and moral obstacles, as well as structural problems, have an impact on how people accept new things. According to recent studies, many educators in Vietnam have moral problems with data privacy, algorithmic bias and keeping learning standards as big reasons not to use artificial intelligence (Quy et al., 2023). Students also share the same concerns, stating that AI tools are hard to understand and seem to be a threat to academic honesty and personal data security (Bui et al., 2025). Therefore, it is important to consider ease of use along with computer skills, confidence in using Al, and perceptions of possible dangers.

In Vietnam's higher education, where digital skills are lacking, academic culture is collectivist, and ethical concerns are strong, these factors are very important. But, there isn't a combined model that looks at all these things that help or stop Vietnamese students from using technology.

This study uses the Technology Acceptance Model (TAM) to study this inter-action. TAM posits that perceived usefulness and ease of use influence technology adoption (Davis, 1989). However, the classical TAM has its own limit in explaining adoption in new areas such as AI because it often ignores human capacity and barrier factors (Al-Adwan et al., 2022). Therefore, researchers have extended TAM by integrating concepts such as digital literacy, self-efficacy and risk perception to significantly enhance its explanatory ability (Alowayr & Al-Azawei, 2021; Vázquez-Madrigal et al., 2024). In Vietnam's higher education, these factors are crucial because digital skills are not common, academic culture is collectivist, and there are considerable ethical considerations. However, prior studies have failed to integrate these variables into a combined model.

This study aims to fill this gap by suggesting and testing an expanded Technology Acceptance Model (TAM). It looks at: (1) how digital literacy and AI self-efficacy predict acceptance; (2) how digital literacy shapes the perceived ease of use of AI tools; and (3) how perceived risks affect usage intentions. The research, which focuses on university students in Ho Chi Minh City, is guided by three questions:

1. **What is the influence of Digital Literacy and Self-Efficacy on Vietnamese students' adoption of AI?**
2. **What is the impact of Digital Literacy on the Perceived Ease of Use of AI tools?**
3. **What is the effect of perceived risks on students' Intentions to Use AI?**

This research uses a quantitative survey with Partial Least Squares Structural Equation Modeling (PLS-SEM) to study the adoption of artificial intelligence. The aim is to build a specific model for AI acceptance. This study should help in two ways: 1) It validates a Technology Acceptance Model (TAM) within an emerging country. 2) It gives Vietnamese educators and policy-makers useful data to advance digital skills, address ethical issues, and encourage AI adoption in higher education.

## LITERATURE REVIEW

### Artificial Intelligence in Education

Artificial Intelligence (AI) in education can be defined as the use of computational systems that simulate human cognitive functions, such as learning, reasoning and problem-solving to enhance instructional effectiveness and administrative efficiency (Alsheibani et al., 2018). The transformative potential of AI-enabled systems has been widely recognized, particularly in their ability to support personalized learning paths, automate routine academic processes and provide scalable real-time feedback, thereby enhancing learning engagement and performance (Belfer et al., 2022; Luckin & Holmes, 2016).

However, successful adoption of AI in higher education depends not only on the technological availability also on reliable digital infrastructure heavily, adequate user abilily and organizational readiness to manage the accompanying ethical and governance challenges (Bozkurt et al., 2021; Holmes & Tuomi, 2022). In the Vietnamese context, these prerequisites pose significant barriers. Despite increasing policy emphasis on digital transformation, AI implementation remains constrained by infrastructural limitations, uneven digital literacy among students and limited teaching preparation (Le et al., 2024; Nguyen & Habók, 2022). Furthermore, ethical concerns - particularly related to data privacy, algorithmic bias, and academic integrity - are consistently identified by a majority of educators as primary obstacles to adoption (Quy et al., 2023). This context highlights the need for a theoretical model that can systematically explain these human capacity and cognitive determinants of the adoption.

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Theoretical Foundation

The Technology Acceptance Model (TAM), introduced by Davis (1989), provides a foundational framework for understanding the adoption of technology. According to TAM , an individual's behavioral intention to use a technology is primarily determined by two core beliefs: **Perceived Usefulness (PU)** and **Perceived Ease of Use (PEOU)**. Meta-analytic evidence supports the robustness of the model, indicating that it accounts for approximately 40 - 60% of the variance in intentions to adopt educational technologies(Granić & Marangunić, 2019).

Nevertheless, TAM has been criticized for primarily focusing on facilitating trust, while underrepresenting capability-based enablers and risk-related barriers that are important for new and complex technologies (Al-Adwan et al., 2022; Cenfetelli, 2004). This limitation is especially pronouced in the context of AI in education, where adoption depend not only on the features of the technology but also on users' digital skills, confidence in their abilities, and perceived risks (Akgun & Greenhow, 2022). To address this, researchers have extended the TAM framework by incoporating constructs such as digital literacy, self-efficacy, and perceived risk, significantly enhancing its explanatory capacity (Alowayr & Al-Azawei, 2021; Vázquez-Madrigal et al., 2024).

Building on this established research direction, the present study proposes an integrated model that **Digital Literacy (DL)** serves as a foundational competency, **Self-Efficacy in AI (SEAI)** acts as a key motivator, and **Perceived Risk and Concern (PRC)** functions as a main inhibitory influence to explain AI adoption intentions among Vietnamese university students.

**Digital Literacy**

Digital Literacy (DL) is defined as an individual's ability to effectively and critically access, evaluate, and utilize digital information and technologies (Demir et al., 2022). In AI-supported learning environment, DL is believed to provide the essential cognitive and technical foundation for interacting with tools, such as intelligent tutoring systems and generative AI (Getenet et al., 2024). Higher level of DL reduces perceived technical complexity and promotes a stronger sense of control.

Empirical evidence identifies DL is a significant direct predictor of individuals's intentions to adopt technology (Yuan et al., 2024). Furthermore, DL positively enhances **Perceived Ease of Use (PEOU)** by increasing users' familiarity with digital systems and lowering the cognitive effort required for interaction (Kabakus et al., 2023). Aligned with Social Cognitive Theory (Bandura, 1997), higher digital competencies also strengthen **task-specific self-efficacy in using AI(SEAI)** through accumulated mastery experiences (González-Prida et al., 2024). In the context of Vietnam, where digital skill varies considerably, the influence of DL is expected to be particularly prominent. Therefore, we hypothesize:

**H1:** Digital Literacy (DL) positively influences Intention to Adopt AI (INTA).

**H2:** Digital Literacy (DL) positively influences Perceived Ease of Use (PEOU).

**H3:** Digital Literacy (DL) positively influences Self-Efficacy in AI (SEAI).

**Self-Efficacy in AI**

Self-efficacy is defined as individuals' belief in their capability to successfully perform specific tasks (Bandura, 1986)**. Self-Efficacy in AI (SEAI)** reflects students' confidence in their ability to use AI-based tools to support in their learning. Higher self-efficacy is connected with greater motivation, sustained effort and stronger engagement with emerging technologies (Zimmerman, 2000).

In AI adoption, SEAI enables students to overcome initial challenges and actively explore new technological tools. Students with higher SEAI are more likely to obtain a significantly higher adoption and persistent use of emerging educational technologies (Arpaci, 2017; Bui et al., 2025). Thus, we hypothesize:

**H4:** Self-Efficacy in AI (SEAI) positively influences Intention to Adopt AI (INTA).

**Perceived Ease of Use**

**Perceived Ease of Use (PEOU)** is the extent to which an individual believes using a technology would be effortless (Davis, 1989). In AI-supported learning, PEOU is reflected in the intuitiveness and transparency of interfaces for tools, such as chatbots and adaptive platforms. According to (Musyaffi et al., 2022), higher PEOU indicates a consistently strong predictor of higher adoption intentions and sustained useage behavior.

The positive relationship between PEOU and behavioral Intention is among one of the most validated relationships in information systems research and has been proved in studies which examine AI adoption in education (Chan & Hu, 2023). Therefore:

**H5:** Perceived Ease of Use (PEOU) positively influences Intention to Adopt AI (INTA).

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**Perceived Risks and Concerns**

**Perceived Risk and Concern (PRC)** is a user's subjective eveluations of potential negative outcomes associated with the use of technology, including performance, privacy, and ethical or social risks (Featherman & Pavlou, 2003). For AI adoption, concerns regarding non-transparent algorithms, data misuse, biased outputs, and threats of academic integrity are strong sources of user resistance (Gillani et al., 2022).

Prior research confirms that higher level of Perceived Risk and Concerns significantly erodes trust and weakens the intentions to adopt AI-based technologies (Alalwan et al., 2018). In Vietnam's higher education context, where academic integrity is highly emphasized, PRC is expected to function as a particularly influential barrier to adoption. Accordingly, we hypothesize:

**H6:** Perceived Risks and Concerns (PRC) negatively influences Intention to Adopt AI (INTA).

Integrating the theoretical foundation above, this study proposes the conceptual model shown in **Figure 1**. In the conceptual model, **Digital Literacy (DL)** is treated as a key exogenous variable that influences the dependent variable, **Intention to Adopt AI (INTA),** both directly (H1) and indirectly through **Perceived Ease of Use (PEOU, H2)** and **Self-Efficacy in AI (SEAI, H3). PEOU (H4)** and **SEAI (H5)** are identified as direct positive determinants of INTA. **Perceived Risk and Concern (PRC)** is modeled as a direct negative determinant (H6).

This integrated model will be empirically examine to evaluate its effectiveness in explaining AI adoption intentions within the distinctive context of Vietnamese higher education.

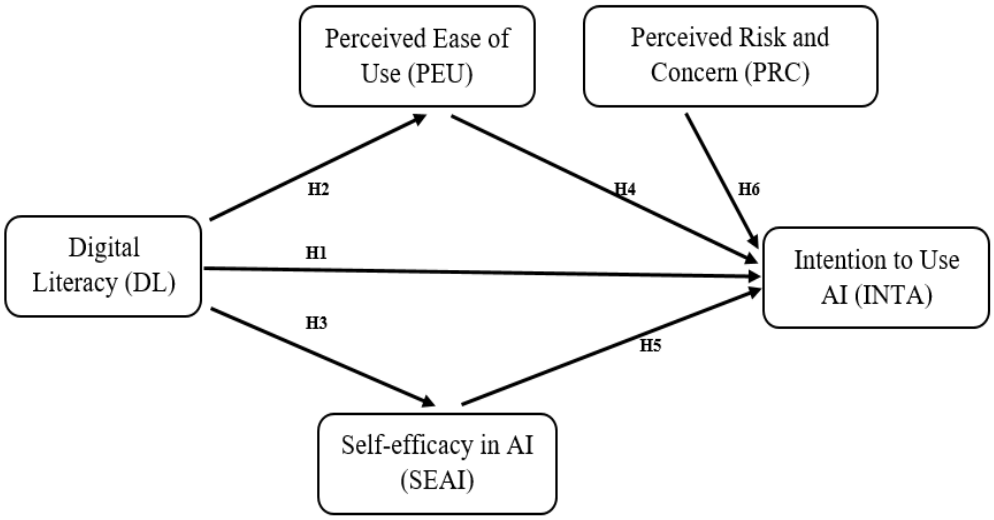


**Fig 1. Research Model**

## Research Methodology

### Research Design

This study uses a quantitative research design to examine the relationships between digital literacy, perceived ease of use, self-efficacy in AI, perceived risk and concern, and intention to use AI. The model is based on the extended Technology Acceptance Model (TAM) framework. A cross-sectional survey method was adopted to collect data from university students who have experience using AI tools in their academic activities.

### Research Framework

The conceptual model illustrates how digital literacy affects perceived ease of use, self-efficacy in AI, and directly influences intention to use AI. Perceived ease of use and self-efficacy act as mediating variables, while perceived risk and concern act as a negative determinant of AI adoption intention.

### Population and Sampling

The population of the study consists of university students in Vietnam, particularly those studying in Ho Chi Minh City. Respondents were selected through convenience sampling to ensure accessibility and feasibility. A total of 305 valid responses were collected and analyzed after excluding incomplete questionnaires.

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**Data Collection Procedure**

Primary data were collected through an online structured questionnaire distributed via email and social media platforms. The questionnaire was divided into two parts:

1. Demographic information, including gender, age, field of study, and prior AI experience.
2. Construct-related questions, measuring digital literacy, perceived ease of use, self-efficacy in AI, perceived risk, and intention to use AI. Responses were recorded using a five-point Likert scale ranging from "strongly disagree" to "strongly agree."

**Data Analysis Method**

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS software. The analysis followed two main stages:

1. Measurement model evaluation, to verify reliability and validity of the constructs through factor loadings, composite reliability, and average variance extracted.
2. Structural model evaluation, to test the hypothesized relationships and determine the strength and direction of each path. Descriptive statistics were also used to summarize respondent profiles and variable distributions.

**Ethical Considerations**

All participants were informed about the purpose of the study and participated voluntarily. Anonymity and confidentiality of the responses were assured. No personal identifying information was collected, and the data were used solely for academic purposes.

This chapter presented the research methodology, including the design, population, data collection procedures, and analytical techniques used. The next chapter provides the results and discussion of the findings based on the structural model.

**Table 3.1**.Respondent Characteristic

The following Table 3.1 summarizes the demographic profile of the respondents to this study. Most respondents in this study were 76.4% female and 24%, male. Meanwhile, in terms of age, 30.2% of the respondents is 18 years old, 40.3% is 19 years old, 24.9% is 20 years old and 4.6% is 21 years old and above, respectively. Then another characteristic is how many years the respondents have used the AI in their study, which shows 52.8% less than 1 year, 37% between 1 and 2 years, 7.2% between 2 and 3 years, 3% over 3 years, respectively. Detailed information on each respondent's demographics is reported in Table 1 below

| | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 70 | 23% |
| | Female | 233 | 76.4% |
| | Not mention | 02 | 0.6 |
| Education | 1st year | 92 | 30.2% |
| | 2nd year | 123 | 40.3% |
| | 3rd year | 76 | 24.9% |
| | 4th year | 14 | 4.6% |
| Years of using Ai | Below 1 year | 161 | 52.8% |
| | Between 1 and 2 years | 113 | 37% |
| | Between 2 and 3 years | 22 | 7.2% |
| | Over 3 years | 9 | 3% |

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**Table 3. 2.** Measurement

| Variable | Variable | Item No. | Questions | Sources |
|---|---|---|---|---|
| **Digital literacy (DL)** | DL1 | 1 | I am confident in formulating keywords to find information on AI systems. | (Ng, 2012) |
| | DL2 | 2 | I have the skills needed to operate AI in learning. | |
| | DL3 | 3 | I can learn to use new technology like AI easily. | |
| **Perceived Ease of Use (PEU)** | PEU1 | 4 | I can use AI anytime and anywhere to understand the problems in my learning. | (Acikgoz & Vega, 2022; Musyaffi et al., 2022) |
| | PEU2 | 5 | I can understand using AI for classroom learning quickly and precisely. | |
| | PEU3 | 6 | The use of AI for learning can be used easily. | |
| | PEU4 | 7 | I can quickly understand and become skilful in class when using AI. | |
| **Self-efficacy in AI (SEAI)** | SEAI1 | 8 | I can complete my task with AI's help if someone is around to explain how to use it. | (Alalwan et al., 2016; Musyaffi et al., 2022) |
| | SEAI2 | 9 | My task can be completed well when using AI, when I can contact someone if there is a problem in the process of using it. | |
| | SEAI3 | 10 | My assignments can be completed using AI when I have much time to do my coursework. | |
| | SEAI4 | 11 | AI can help complete my task when there are adequate facilities to ask for, such as a call centre. | |
| **Perceived Risk and Concern (PRC)** | PRC1 | 12 | The use of AI in the learning process can have opportunities for cheating | (Alalwan et al., 2016; Featherman & Pavlou, 2003) |
| | PRC2 | | Using AI in the learning process can lead to a risk of dependence on AI. | |
| | PRC3 | 13 | When I use AI, there is a potential for my data to be collected and misused. | |
| | PRC4 | 14 | The use of AI will only make the learning process complicated. | |
| **Intention to Use AI (INTA)** | INTA1 | 15 | I will use AI assistance in learning because it can complete tasks more efficiently. | |
| | INTA2 | 16 | When working on assignments, I prioritize using AI to complete tasks. | (Musyaffi et al., 2022; Zhong et al., 2021) |
| | INTA3 | | In general, I use AI assistance in | |
| | | 17 | every learning process. | |
| | INTA4 | | I recommend using AI for | |
| | | 18 | Education to others. | |
| | | 19 | | |


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## RESULTS

The results for construct reliability and validity. All constructs demonstrate strong internal consistency, with Cronbach's alpha values ranging from 0.881 to 0.935, exceeding the acceptable threshold of 0.70. Similarly, composite reliability (ρc) values fall between 0.918 and 0.954, indicating high reliability and stability of the measurement model. The average variance extracted (AVE) values for all constructs are above 0.70, confirming satisfactory convergent validity. These results indicate that the measurement items reliably represent their corresponding latent constructs, supporting the robustness of the measurement model for further structural analysis.

**Table 4.1:** Construct Reliability and Validity Overview

| Construct | Cronbach's Alpha | Composite Reliability (ρa) | Composite Reliability (ρc) | Average Variance Extracted (AVE) |
|---|---|---|---|---|
| Digital Literacy (DL) | 0.905 | 0.907 | 0.940 | 0.840 |
| Intention to Use AI (INTA) | 0.933 | 0.937 | 0.952 | 0.832 |
| Perceived Ease of Use (PEU) | 0.932 | 0.932 | 0.951 | 0.830 |
| Perceived Risk and Concern (PRC) | 0.881 | 0.887 | 0.918 | 0.739 |
| Self-Efficacy in AI (SEAI) | 0.935 | 0.936 | 0.954 | 0.837 |

In table 4.2, the square roots of the Average Variance Extracted (AVE), shown on the diagonal (in bold), are higher than the corresponding correlations between constructs. This indicates that each construct shares more variance with its indicators than with other constructs, confirming adequate discriminant validity. Therefore, all latent variables are empirically distinct and appropriately represent unique theoretical dimensions within the research model.

**Table 4.2:** Discriminant Validity – Fornell-Larcker Criterion

| Construct | DL | INTA | PEU | PRC | SEAI |
|---|---|---|---|---|---|
| DL | **0.916** | | | | |
| INTA | 0.671 | **0.912** | | | |
| PEU | 0.765 | 0.769 | **0.911** | | |
| PRC | 0.546 | 0.584 | 0.638 | **0.859** | |
| SEAI | 0.717 | 0.779 | 0.884 | 0.684 | **0.915** |

Table 4.3 displays the outer loadings of each indicator on its corresponding construct. All loading values exceed 0.70, confirming strong indicator reliability and suggesting that each item contributes significantly to its latent construct. The results confirm that no cross-loadings are present, as each indicator loads highest on its intended construct. Therefore, the measurement model demonstrates excellent convergent validity and reliability, providing a solid foundation for structural model evaluation.

**Table 4.3:** Outer Loadings Matrix

| Indicators | DL | INTA | PEU | PRC | SEAI |
|---|---|---|---|---|---|
| DL1 | 0.907 | | | | |
| DL2 | 0.924 | | | | |
| DL3 | 0.918 | | | | |
| INTA1 | | 0.907 | | | |
| INTA2 | | 0.932 | | | |
| INTA3 | | 0.893 | | | |
| INTA4 | | 0.916 | | | |
| PEU1 | | | 0.888 | | |
| PEU2 | | | 0.921 | | |
| PEU3 | | | 0.913 | | |
| PEU4 | | | 0.923 | | |
| PRC1 | | | | 0.892 | |
| PRC2 | | | | 0.848 | |
| PRC3 | | | | 0.906 | |
| PRC4 | | | | 0.786 | |

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| | |
|---|---|
| SEAI1 | 0.912 |
| SEAI2 | 0.913 |
| SEAI3 | 0.929 |
| SEAI4 | 0.906 |

Table 4.4 presents the specific indirect pathways showing how Digital Literacy (DL) influences Intention to Use AI (INTA) through Self-Efficacy in AI (SEAI) and Perceived Ease of Use (PEU). Both indirect paths are statistically significant: DL → SEAI → INTA ($\beta = 0.281$, $p < 0.001$) and DL → PEU → INTA ($\beta = 0.202$, $p = 0.003$). This indicates that digital literacy improves students' intention to adopt AI by increasing their confidence in using AI tools and by making those tools easier to use. Hence, SEAI and PEU serve as key mediators that strengthen the overall impact of digital literacy on adoption intention.

**Table 4.4:** Specific Indirect Effects – Mean, Standard Deviation, T-values, and P-values

| Path | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics | P Values |
|---|---|---|---|---|---|
| DL → SEAI → INTA | 0.281 | 0.280 | 0.077 | 3.665 | 0.000 |
| DL → PEU → INTA | 0.202 | 0.193 | 0.074 | 2.734 | 0.003 |

The following table reaffirms the mediation results, showing consistent significance across both mediating paths. The indirect effects remain significant for DL → SEAI → INTA ($\beta = 0.297$, $p < 0.001$) and DL → PEU → INTA ($\beta = 0.272$, $p < 0.001$), confirming the robustness of the mediation. These results strengthen the argument that digital literacy influences AI adoption both directly and indirectly through its effects on students' ease of use perception and self-efficacy. The stronger path through SEAI suggests that confidence and competence in AI usage play a more decisive role in shaping behavioral intentions than perceived usability alone.

**Table 4.5:** Confirmatory Indirect Effects – Mean, Standard Deviation, T-values, and P-values

| Path | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics | P Values |
|---|---|---|---|---|---|
| DL → SEAI → INTA | 0.297 | 0.300 | 0.079 | 3.746 | 0.000 |
| DL → PEU → INTA | 0.272 | 0.265 | 0.079 | 3.439 | 0.000 |

Table 4.6 summarizes the total effects of all hypothesized paths in the structural model. The results reveal that Digital Literacy (DL) has a significant positive effect on Intention to Use AI (INTA) ($\beta = 0.636$, $p < 0.001$), Perceived Ease of Use (PEU) ($\beta = 0.764$, $p < 0.001$), and Self-Efficacy in AI (SEAI) ($\beta = 0.717$, $p < 0.001$). These strong coefficients confirm that higher digital literacy directly enhances students' confidence and ease in using AI technologies.

Additionally, PEU ($\beta = 0.265$, $p = 0.003$) and SEAI ($\beta = 0.392$, $p < 0.001$) significantly contribute to AI adoption intention, supporting their mediating influence. However, Perceived Risk and Concern (PRC) has no significant effect ($p = 0.172$), indicating that perceived risks do not meaningfully deter students' willingness to adopt AI tools. Overall, the total effects confirm that digital literacy is the most dominant driver of AI adoption among university students.

**Table 4.6:** Total Effects – Mean, Standard Deviation, T-values, and P-values

| Path | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics | P Values | Decision |
|---|---|---|---|---|---|---|
| DL → INTA | 0.636 | 0.633 | 0.075 | 8.493 | 0.000 | H1 Significant |
| DL → PEU | 0.764 | 0.764 | 0.051 | 14.949 | 0.000 | H2 Significant |
| DL → SEAI | 0.717 | 0.717 | 0.061 | 11.689 | 0.000 | H3 Significant |
| PEU → INTA | 0.265 | 0.254 | 0.097 | 2.735 | 0.003 | H4 Signigicant |
| SEAI → INTA | 0.392 | 0.391 | 0.103 | 3.815 | 0.000 | H5 Significant |

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| | | | | | | |
|---|---|---|---|---|---|---|
| PRC → INTA | 0.064 | 0.068 | 0.067 | 0.946 | 0.172 | H6 Not Significant |

## CONCLUSION

This study sought to examine the influence of digital literacy, perceived ease of use, artificial intelligence self-efficacy, and perceived risk on university students' intentions to adopt artificial intelligence tools in higher education. Guided by the extended Technology Acceptance Model (TAM), results provide strong empirical evidence for most of the hypothesized relationships.

The findings indicate that digital literacy was the best predictor of intention to adopt AI. Students with higher digital competence not only reported having higher self-confidence in using AI but also perceived these systems as easier to use. Self-efficacy in AI (SEAI) and perceived ease of use (PEU) significantly mediate this relationship, confirming that confidence and perceived ease of use are significant factors linking digital skills to behavioral intentions.

Interestingly, perceived concern and risk (PRC) had no deterrent effect on students' adoption intentions. This suggests that while students are aware of their potential privacy or ethical risks, such issues do not place a strong influence on their use of AI tools in learning. This may reflect younger students' growing comfort with digital technologies or a tendency to prioritize learning benefit over potential disadvantages.

Overall, the research findings highlight that digital literacy is a direct and indirect driver of AI using. When students feel able and comfortable using digital tools, they are more likely to experiment and adopt AI technology in their learning. This reflects the pivotal role of digital literacy in creating an active and confident learning environment in the AI age.

### Implication

### Theoretical Implications

The study contributes to the growing body of literature extending the Technology Acceptance Model (TAM) to address AI adoption in high education. By adding digital literacy and self-efficacy with AI as mediating variables, the findings provide new insights into the mechanisms by which cognitive and capability factors affect students' behavioral intentions. The strong mediating affect of PEU and SEAI reinforces previous research, indicating the importance of psychological readiness in technology acceptance **(Venkatesh & Davis, 2000)**

Furthermore, the insignificant influence of perceived risk suggests that TAM-based models may be extendedto account for generational and contextual difference in technological perceptions. For Vietnamese Generation Z students, consideration of risks may be less significant than confidence and perceived usefulness. This offers a deeper understanding of technology acceptance in developing economies with increasingly widespread digital exposure.

### Practical Implications

Practically, the findings emphasize the need to strengthen digital skills in Vietnamese universities. Institutional curricula should be designed to go beyond basic IT education to include AI-related digital skills ( data interpretation, knowledge of algorithms and ethical awareness).

Second, interventions that build students' autonomy ( through workshops, project-based learning, or peer mentoring) can also promote AI adoption. These interventions have been shown to help overcome fears about complex technologies and promote a growth mindset toward AI-assisted learning.

Third, while the risks identified here are statistically insignificant, they should not be ignored. Open data governance policies, transparent ethical codes and communication about responsible AI use remain essential to mantain trust and ensure a long-term use of educational technologies.

To policymakers, the study highlight the requirement for national digital literacy policies, which will contribute to the Ministry of Education's digital transformation agenda. Incorporating AI literacy into the curriculum of higher education could better equip students to meet future labor market demands and narrow the digital skills gap between rural and urban students.

### Limitations and Future Research

Despite being highly contributory, the study has some limitations that should be noted.

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Initially, the study was cross-sectional in design; so causal inferences can not be drawn. Future studies could employ a longitudinal design to track changes in students' perceptions and use of AI over time.

Second, information was collected in Ho Chi Minh City by using a convenience sampling method, which is not necessarily representative of the entire diversity of Vietnamese students across the country. Future research should expand the sampling frame to include universities in other regions, especially in rural areas, to represent a more balanced perception of the digital divide in Vietnam.

Third, the study relied on self-reported evidence which is susceptible to social desirability bias or exaggerated digital expertise. Combining surveys with objective digital proficiency tests or real-world behavioral evidence would provide a better picture of AI readiness.

Finally, this study focused on the student experience. Future studies could include faculty members or administrators to consider pedagogical and institutional factors of incorporating AI. Examining cultural, disciplinary, or ethical variations in adopting AI could provide additional insight regarding context influencing acceptance patterns in higher education.

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