AI Acceptance among Vietnamese University Students: Key Influencers and Perspectives

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***Abstract*—This study investigates Vietnamese university students' perceptions and acceptance of Artificial Intelligence (AI) in higher education, identifying key factors influencing their adoption. A multifaceted survey of 757 students across diverse academic disciplines in Southern Vietnam focused on seven variables: perceived usefulness, understanding, familiarity, accessibility, concerns, barriers, and the overall AI acceptance. Data were analyzed using Pearson correlation and explainable AI techniques, including Decision Tree Regressor and SHAP values with XGBoost Regressor. Findings revealed that 75% of respondents recognized AI's potential benefits, but only 31% reported high familiarity with AI tools, and 40% indicated strong comprehension; 48% found AI tools easily accessible. Concerns about data security, AI errors, technical difficulties, and lack of training were significant barriers. Notably, the most important factor affecting AI acceptance was perceived usefulness. The study highlights the need to close the gap between theoretical knowledge and real-world AI application in Vietnamese higher education. It provides recommendations for students, institutions, policymakers, and AI developers to effectively leverage AI, aligning Vietnam's AI education with global trends and enabling AI to play a transformative role in higher education.**

***Keywords*—student acceptance, higher education, Vietnamese universities, explainable AI techniques, technology adoption**

I. Introduction

A. Background

Artificial Intelligence (AI) offers previously unheard-of levels of efficiency and customization in every sector. Recent research [1, 2] shows that many workplaces not only use AI tools but place a high priority on new hires' AI competency. In the education sector, AI is revolutionizing learning through personalized student experiences, adaptive learning technologies, and automated administrative tasks.

However, despite global enthusiasm, the integration of AI into Vietnamese higher education is still in the nascent stages. Language barriers, limited access to advanced technological infrastructure, and a general lack of AI literacy significantly shape student attitudes and acceptance levels [3]. Research points out that while the potential benefits of AI are recognized universally, the practical application and acceptance of such technologies in Vietnamese universities have been markedly slower compared to global standards. This gap highlights the critical need for targeted research that considers the Vietnamese socio-economic and cultural specifics [4].

This study, therefore, examines Vietnamese university students' perceptions of AI in higher education, exploring how these perceptions influence their acceptance and use of AI tools. By addressing the gap between global advancements in AI and localized student attitudes in Vietnam, the research aims to provide actionable recommendations for students, educators, institutions, policymakers, and AI developers. This, in turn, can foster a more inclusive and effective educational environment tailored to the Vietnamese context.

B. Research Objectives

This study examines the acceptance of AI among Vietnamese university students, focusing on six key variables: Perceived Usefulness, Understanding, Familiarity, Accessibility, Concerns, and Barriers. Perceived Usefulness is central to acceptance, as students are more likely to adopt AI if they believe it will enhance their performance. Understanding plays a key role, as greater comprehension of AI tends to increase students' willingness to embrace it. Familiarity with AI can reduce uncertainty, positively influencing acceptance. Accessibility is equally important, as easy access to AI tools boosts the likelihood of adoption. While addressing Concerns, such as privacy or security fears to foster acceptance, identifying and overcoming Barriers, like cost or technical limitations, is critical for broadening adoption.

Previous research has explored some of these factors individually or in smaller combinations [5–9]. However, this study combines all six to provide a more comprehensive analysis. These six 'conditioned variables' aim to strike a balance between comprehensiveness and manageability, enabling a multifaceted analysis without overwhelming the scope of the study. By analyzing these key variables, the study seeks to identify the factors affecting students' willingness to embrace AI in their learning process.

Understanding these factors is key to optimizing AI-driven tools to support students' diverse learning styles and needs, potentially influencing their academic performance. The research aims to achieve three primary objectives: (i) examine the concept of 'conditioned acceptance', identifying adaptations to make AI tools culturally relevant in Vietnam, (ii) highlight differences between global AI trends and the Vietnamese educational context, with the ultimate goal of developing an inclusive framework for integrating AI into Vietnamese higher education practices, incorporating cultural adaptability, scalability, and sustainability, and (iii) offer empirically-grounded recommendations to students, educators, institutions, policymakers, and AI developers to enhance the acceptance and effectiveness of AI tools in Vietnamese higher education.

II. Literature Review

This literature review examines existing research through the lens of the Technology Acceptance Model (TAM), focusing on factors influencing university students' adoption of AI. The original TAM posits that technology adoption is driven mainly by Perceived Usefulness and Perceived Ease of Use [10]. Although effective in many contexts, this traditional model may benefit from including other factors that reflect user expectations, institutional and technological aspects. We extend this framework with additional user-centric factors: Understanding, Familiarity, and Accessibility, that operationalize ease-of-use in the context of AI, as well as two specific contextual factors, Concerns and Barriers, addressing potential inhibitors in the Vietnamese higher education setting.

A. Variables Affecting AI Attitudes and Hypotheses

1) Perceived usefulness

Perceived Usefulness (PU) refers to the degree to which a person believes that using a technology will enhance their performance" [11]. In the context of AI in education, a substantial body of research confirms PU as a critical driver of adoption. Students are far more likely to embrace AI tools when they perceive tangible learning benefits or performance improvements [11]. For example, AI's ability to personalize learning experiences and provide tailored support has been shown to boost student engagement and motivation [12]. Likewise, integrating AI can lead to smarter content delivery and greater efficiency in educational processes [13]. AI tutors and analytics can offer immediate feedback and adaptive guidance, helping students address their weaknesses more quickly than in traditional settings [12, 13]. Such improvements, from higher engagement to better performance, illustrate why perceived usefulness is central in determining AI acceptance. In line with TAM and our research objectives, we expect this variable to positively influence students' intention to use AI. That is, when learners see AI as useful for their studies, they are more inclined to adopt it (*Hypothesis 1*).

2) Understanding

Understanding refers to a student's knowledge of and clarity about how AI works and how it can be used. This factor is regarded as an aspect of perceived ease-of-use. If a technology is better understood, it feels more "free of effort" to use. Prior studies indicate that limited understanding or awareness of AI can hinder acceptance. For example, individuals with only a rudimentary understanding of AI are significantly less likely to support AI applications than those well-versed in the technology [14]. In an educational setting, many students acknowledge gaps in their AI knowledge. A global survey reported that 58% of students feel they do not have sufficient AI-related knowledge or skills [15]. Such a knowledge deficit can lead to uncertainty or misuse, reducing students' confidence in using AI tools. Conversely, improving students' conceptual understanding of AI, e.g., through AI literacy training, can demystify the technology and reduce anxiety. This aligns with TAM's emphasis on ease of use: when students comprehend how to use an AI application, the effort and intimidation factor decrease, making adoption more likely [16]. Therefore, we anticipate that greater understanding will facilitate higher AI acceptance (addressing our objective of enhancing user readiness), leading us to propose that students with a stronger understanding of AI will be more willing to use it (*Hypothesis 2*).

3) Familiarity

Familiarity denotes the extent of one's practical experience with AI tools or similar technologies. Even if a student conceptually understands AI, hands-on familiarity can further ease the adoption process by building user confidence. This factor is closely related to "computer experience" often discussed in extended TAM studies. Alyoussef et al. (2025) found that students with greater familiarity with AI were more likely to adopt it for collaborative learning purposes in higher education [17]. Similarly, Mustofa et al. (2025) observed that familiarity can diminish the perceived difficulty of using AI tools, reducing reliance on perceived ease of use as a determinant [18]. In other words, familiarity breeds acceptance, exposure alleviates the initial learning curve and fear of the unknown. In the student context, familiarity might come from using AI-based learning apps, chatbots, or even advanced features in everyday software. Such experience can strengthen students' self-efficacy in dealing with AI-driven systems, which in turn enhances perceived ease of use. Building on TAM and our proposed framework, we thus expect that students who are more familiar with AI tools will have fewer usage hurdles and greater intention to adopt AI in their learning (*Hypothesis 3*). This hypothesis aligns with our objective of identifying prior experience as a facilitator of AI acceptance.

4) Concerns

Unlike the above factors which generally encourage use, concerns introduce hesitation by highlighting potential negative consequences of AI in education. Students are concerned about the need to protect personal data as AI systems often require large amounts of student information, raising serious security issues [19]. Likewise, privacy is "an important concern in applying agent-based personalized learning" [15, 20] and therefore, must be resolved before such technologies are widely adopted. Another growing concern in higher education is academic integrity. The advent of generative AI (like AI writing assistants) has led to fears that students might misuse these tools for plagiarism or shortcut learning, potentially causing erosion of academic honesty and fairness in assessment [21, 22]. Thus, this study included "Concerns" as a variable hypothesized to negatively affect AI use. We assume that higher levels of concern will correlate with a lower likelihood of AI acceptance (*Hypothesis 4*).

5) Accessibility

Accessibility refers to the availability of resources and opportunities that enable students to use AI – for instance, having the necessary hardware, software, internet connectivity, and institutional support. Having access to AI is an important factor affecting student acceptance, according to recent research [23, 24]. For example, generative AI attracts students as it viewed as easy to use and comprehend [23]. Students of diverse abilities must also have access to AI in ways that will appeal to their variety of needs [13, 24]. In the context of Vietnamese higher education, we hypothesize that greater accessibility and institutional support will positively impact students' AI acceptance. Based on this premise, this study posits *Hypothesis 5: Student acceptance of AI is positively correlated with access to AI tools.* Student learning experiences will be enhanced by access to easy-to-use tools.

6) Barriers

Finally, our model considers a broader factor of barriers that might impede AI adoption among students. These barriers include limited budgets, infrastructure, limited expertise, teacher reluctance, and concerns about data privacy [12, 25–28]. Barriers can cause frustration among students and unwillingness to use AI, affecting learning [26]. In Vietnam, such issues will be even more prominent because of various factors related to education, culture, the economy, institutions, and infrastructure. Considering this critical variable, we posit *Hypothesis 6: Student acceptance of AI is negatively affected by barriers to its use.* By explicitly acknowledging "Barriers" in our extended TAM model, we account for these roadblocks that can be addressed through improved infrastructure, enhanced training programs, and maintained ethical use standards [26, 29].

7) Acceptance

Student acceptance of AI in education is shaped by a complex interplay of enablers and inhibitors. Factors such as perceived usefulness, understanding, familiarity, and accessibility generally facilitate greater acceptance, as they enhance confidence, reduce perceived complexity, and align with learners' educational goals [30, 31]. For instance, students who find AI tools beneficial and have had prior exposure to them are more likely to feel comfortable and adopt such technologies with less hesitation [32]. In contrast, concerns can undermine trust and limit students' willingness to engage with AI, even when benefits are evident [33]. Furthermore, institutional barriers such as a lack of resources, poor integration into curricula, or inadequate training can prevent students from accessing and effectively using AI tools [23, 26]. These constraints not only reduce practical opportunities for engagement but also signal a lack of institutional readiness, further eroding confidence.

Taken together, the aforementioned variables suggest that student acceptance of AI is not driven by any single factor, or just a couple of factors, but rather by a multifactorial dynamic involving both individual perceptions and external constraints. Therefore, we posit Hypothesis 7: *Student acceptance of AI in education can be predicted by a combination of factors, including perceived usefulness, understanding, familiarity, concerns, accessibility, and barriers.* This framework offers a comprehensive lens for exploring AI adoption in Vietnamese higher education. By examining how these enablers and inhibitors interact, the study aims to inform targeted interventions that support AI integration in Vietnamese higher education contexts.

B. Research Gap in the Vietnamese Context

Although students' connections to AI in education have been examined in previous research, analyses have focused on looking at the variables separately rather than viewing variables as a panoramic picture. Dang (2020)'s work, for example, examined perceived ease of use (PEU) and perceived usefulness (PU) [6], but this restricted understanding of how the factors together influence student acceptance of AI [9]. Some research looked at a variety of variables as a whole, but only a limited number of variables were used. Cruz-Benito et al. (2019) focused on five variables: perceived usefulness (PU), perceived ease of use (PEU), attitude towards use (AU), behavioral intention of use (BI), and actual use (U) [5]. Kelly et al. (2023) examined AI use in industry sectors by analyzing factors such as trust, attitude, anticipated effort, anticipated level of performance, and perceived usefulness [7].

Though the use of AI in K-12 education is still in its beginning stage, support is needed to include AI in educational curricula [34]. Much of the research has focused on Western countries or developed countries in Asia, resulting in a lack of understanding about such factors as culture, economy, and infrastructure in Vietnam [35, 36]. Maheshwari (2023) notes the potential for AI in Vietnam, but says that more research is needed to examine the limitations as well as possibilities in the Vietnamese context [8]. In addition, there is a lack of data in the literature on how variables looked at together influence AI acceptance in education. Traditional statistical methods use linear correlations, and as a result, the measurement of the level of AI acceptance lacks subtlety. Therefore, there is a pressing need for a comprehensive methodology that can examine all aspects of the issue to provide holistic understanding.

Given this need, our study employed a methodology that combines conventional analytical techniques with explainable AI tools. This integrated approach allows us to better examine the interactions among the six additional proposed variables and gain a deeper insight into AI acceptance in Vietnam education.

C. Conceptual Framework

To understand the factors that affect acceptance and use of new technology, a structured theoretical framework is helpful to study student attitudes about AI. As mentioned above, a very common framework for explaining technology adoption was created by Davis in 1989, called The Technology Acceptance Model (TAM). Under the TAM, two factors, perceived usefulness (PU) and perceived ease of use (PEU). While PU reflects how individuals view the technology's effect on their performance and how learning outcomes are affected by AI, PEU means the perceived effort needed to use a technology. These two have been to be "antecedent factors affecting acceptance learning with technology" [11]. However, this traditional model may not fully capture the complexity of advanced technology adoption, particularly in educational contexts.

Building upon the original TAM, which emphasizes PU and PEU, our study extended the framework by incorporating additional empirical factors-each quantitatively assessed-to comprehensively examine their influence on AI adoption. We further proposed a robust analytical method to identify and rank these impact factors using both traditional statistics and Explainable AI techniques. Specifically, we combined a traditional statistical method, Pearson correlation analysis and using Explainable-AI techniques, which provides feature importance under a Decision Tree Regressor and SHAP Values with the XGBoost Regressor. The XGBoost expresses complexity by creating highly accurate models while the SHAP describes the contributions of each factor, leading to the model's predictions, offering further understanding of the decision-making of Vietnamese students.

Our methodology reveals patterns and relationships that might not show up in more traditional methods. Explainable AI techniques can help to reveal the interactions between multiple variables and student attitudes. The methodology we use lends itself to exposing subtler distinctions compared to more traditional methods. Our analysis can also point to further areas that need to be studied in the educational technology field, and can also highlight areas of need in Vietnam. The use of AI-Explainables, therefore, provides deeper analyses. Despite this, the accuracy of the findings is dependent on the quality and accessibility of data. In addition, the XGBoost requires both expertise and resources. Thus, SHAP should be transparent and interpretable, and this can be met by taking challenges seriously and creating trust in the eventual analyses of the research.

To conclude, we have gone beyond the original TAM in order to reach a fuller understanding of acceptance of AI in education. By using Explainable-AI, nuanced and deeper insights about the factors that affect the attitudes and decision-making of students can be discovered. As previously noted, the limitations of previous research can be overcome by using a more holistic perspective. This type of perspective can also provide further impetus to the field of research that examines students' acceptance of AI in education.

III. Methodology

This study's methodology is described in the sections below, which address: research instruments, data collection procedures, analytical framework, data analysis techniques, and reasons for the ensemble method.

A. Research Instruments

1) Description of data collection survey

A survey employing several methods was used to arrive at a more comprehensive understanding of Vietnamese university students' attitudes towards AI. The survey was given to students in institutions throughout Southern Vietnam. Demographic data from the questions included age, gender, and academic background. Questions on a Likert scale, ranging from 1 for "*Strongly Disagree*" to 5 for "*Strongly Agree*", focused on the factors related to AI's usefulness and its ease of use. Multiple-choice questions dealt with familiarity with AI tools, barriers encountered when using the technology, and how students learned how to use it. In particular, the survey was translated and modified to be culturally relevant for Vietnamese. The response rate from our multi-pronged approach was especially high, with 757 students from 19 universities in Southern Vietnam, with varying majors and years of study. Those surveyed offered helpful insights about AI adoption based on their everyday real lives. Our survey employed best practices used in educational research, such as the Likert scale for assessing student attitudes and multiple-choice questions for addressing specific barriers.

2) Overview of the questions and their relevance

Keeping in mind our research objective of understanding Vietnamese students' attitudes towards AI in education, we carefully composed the survey by mapping each question to key variables. These variables, chosen after an exhaustive review of the literature on AI in educational settings, were: Perceived Usefulness, Understanding, Familiarity, Accessibility, Concerns, Barriers, and Acceptance. These factors are crucial in assessing student perception of and interaction with AI tools in educational contexts.

This research investigates Vietnamese higher education students' attitudes towards AI, focusing on a framework that includes *Perceived Usefulness*—the belief that AI can enhance learning—as a central variable. *Understanding* and its functions strengthens this conviction, a key predictor of adoption. While *Familiarity* fosters comfort with AI in learning, *Accessibility*, ensuring easy access to AI tools and support, further facilitates integration. However, *Concerns* such as security, ethics, and technical challenges can hinder adoption. Students' *Acceptance*, capturing the cumulative impact of these factors, measures their willingness to use AI. It reveals the complex dynamics influencing students' decisions to adopt AI tools. This interconnected analysis highlights the multifaceted nature of AI acceptance, emphasizing the need for a holistic approach to understanding and enhancing student perceptions and utilization of AI in education.

By structuring the survey to thoroughly cover these six key variables, the research ensured a comprehensive understanding of student attitudes towards AI. This approach not only aligned with the research objectives of exploring AI's impact on learning outcomes but also identified global and local trends, providing a foundation for strategic recommendations to enhance AI integration in Vietnamese education.

B. Data Collection and Processing

1) Sampling method

Conducting a comprehensive survey on a large population like university students presents logistical challenges and even impracticality due to resource constraints, time limitations, and accessibility issues [37]. To address limitations and ensure feasibility, we adopted a purposive sampling method informed by Yıldırım and Şimşek (2013) [38]. This approach allowed us to collect data from a representative subset and diverse groups of participants, enriching the study with a wider range of perspectives.

In order to achieve a representative sample reflecting the diversity of the Vietnamese student population in Southern Vietnam participating in the study, we utilized stratified random sampling. Given that the Southeast hosts many of the 101 universities in Southern Vietnam (Vietnam Ministry of Education and Training, 2023), the survey was conducted at universities located in Ho Chi Minh City and neighboring areas. This approach ensures a comprehensive representation of student experiences across prominent academic institutions. Consequently, the study was finalized with data from 19 universities. This method divided the population into subgroups based on characteristics like universities and their geographical areas, then randomly asked participants from each stratum (age, gender, fields of study, and years of study) to volunteer to participate in the survey. This approach ensures that the sample more accurately reflects the broader population being studied. By university, we surveyed 757 students from 19 universities, stratifying by university ensures that differences in institutional resources, teaching quality, and curriculum are accounted for. This makes the results more generalizable across different educational contexts. Stratifying by major ensures that students from various fields of study are represented. Different majors may have distinct academic experiences, levels of difficulty, and teaching methods, which could influence study outcomes. Stratifying by year of study ensures that participants at different stages of their education (e.g., freshmen vs. seniors) are included. This captures differences in experience, knowledge accumulation, and academic maturity. This stratified random sampling approach ensures representativeness, reduces bias, and improves data precision [26, 39]. The sample size and allocation considered confidence level, margin of error, and estimated population variability, ensuring equal selection probability and comprehensive representation of attitudes towards AI in education. To ensure that this survey instrument is both reliable and valid, leading to more trustworthy and accurate findings, we conducted Pearson correlation, feature importance analysis by Decision Tree algorithm, and XGBoost (Extreme Gradient Boosting).

2) Data collection process

This study employed a rigorous data collection process to ensure reliable and valid insights into Vietnamese students' attitudes towards AI in education. The questionnaire incorporated multiple-choice, Likert scale, and open-ended questions for both quantitative and qualitative data. The target population reached universities in Southern Vietnam. The online survey, administered over three months from February 2024 to May 2024, aimed for high response rates and captured potential shifts in attitudes. Online distribution through university channels and social media maximized reach and cost-effectiveness for the geographically dispersed population. Additionally, paper surveys in classrooms ensured inclusivity for students with limited online access.

The study prioritized ethical considerations, requiring informed consent, anonymized responses, and secure data storage with restricted access to the research team. Data integrity was ensured through meticulous cleaning, and statistical analysis, including descriptive statistics, correlation analysis, decision trees, and XGBoost, was used to explore variable relationships and make predictions. The study employed SHAP values and Python libraries for machine learning models to gain a comprehensive understanding of factors influencing student attitudes towards AI in Vietnamese higher education.

3) Data processing

To ensure the quality and reliability of data analysis in this study, we processed the survey dataset in three important steps, including data conversion, missing data addressing, and data normalization for consistency.

First, regarding data conversion, our survey included seven multi-choice questions (Questions 21–27). To facilitate analysis, these responses were converted into numerical data. This involved assigning a unique number to each possible response option. For example, if a student selected two choices, the correspondent value would be assigned 2. This approach simplifies analysis and allows for statistical comparison.

To address missing data, this study then used the *MissingNo library*[1] in the first phase to identify missing values. To maintain data integrity, columns, and rows with missing data more than 30% were removed. In the subsequent phase, we used the Multivariate Imputation by Chained Equations (MICE) by Van Buuren and Groothuis-Oudshoorn (2011) for the remaining missing values [40]. MICE is a statistical method that employs multiple imputation techniques to estimate missing data points. It creates multiple imputed datasets, and combines them to make the final dataset with a statistically plausible value for the missing values[2].

Finally, for the data normalization, in our study, Questions 21–27 were multiple-choice items with different response ranges. We normalized the scores for these questions in order to achieve consistency and enable relevant comparisons. Normalizing data involved scaling the scores from their original range to a standard range of 1 to 5.

C. Analytical Methods

1) Pearson correlation analysis

Initially, Pearson correlation is utilized to assess the degree of linear dependence between each independent variable and the target variable, acceptance of AI. While Pearson correlation effectively identifies the strength and direction of linear relationships, it does not provide detailed insights into the nature of these relationships or their relative importance.

2) Feature importance via decision tree algorithm

To address the limitations of Pearson correlation, the study applies Feature Importance (also known as information gain) using the Decision Tree algorithm. This method identifies the most significant predictors of AI acceptance by evaluating the contribution of each feature in splitting the data. Feature Importance is particularly useful for presenting a hierarchical view of how student acceptance of AI is influenced by various factors [41]. This approach provides a clearer understanding of which variables have the most substantial impact on the target variable.

3) XGBoost model with SHAP for interpretation

Building on the insights gained from the Decision Tree, the study further employs the XGBoost (Extreme Gradient Boosting) model to capture complex, non-linear interactions between variables. XGBoost is known for its high accuracy and efficiency in handling large datasets with multiple features. After training the XGBoost model on the dataset comprising the six independent variables and the target variable, SHAP (SHapley Additive exPlanations) is used to interpret the model's predictions. SHAP values explain the contribution of each feature to the final prediction, offering a transparent and interpretable understanding of how each variable influences AI acceptance [42].

[1] https://github.com/ResidentMario/missingno

[2] https://scikit-learn.org/stable/modules/impute.html

D. Data Analysis

1) Variable-based analysis

The key variables in the study are examined in the sections below to assess their effects on student attitudes about AI in education.

a) Perceived usefulness

The variable of perceived usefulness reflects student beliefs about how AI tools will improve their learning and academic output. Personalized learning, time-saving benefits, and improved understanding of complex ideas are some of the factors related to usefulness. Over 75% of students agreed (4 or 5 rating on 5-point Likert scale) that AI tools have educational benefits, the survey found. Seventy percent said that AI tools helped to further their progress academically (mean rating: 4.1). And 65% felt that AI tools their future careers (mean rating: 4.2), and 68% agreed that AI tools save time (mean rating: 4.0). It appears that students can see and value the benefits of AI in education. This perceived usefulness is a critical factor affecting adoption of technology in educational settings [12, 13].

b) Understanding

An understanding of AI is important for students' grasp of AI concepts, functions, and implications, and how AI can be used. Our survey showed that 60% of students rated understanding of AI concepts at 4 or 5 (mean rating: 3.8). And, 58% said they understood how AI tools work (mean rating: 3.7), and 55% said they understood the effects of AI tools (mean rating: 3.6). The survey shows a moderate level of understanding, which is needed for engaging with AI technologies. Research shows that a good grasp of AI positively influences acceptance and use of AI in education [43].

c) Familiarity

The variable of familiarity reflects students' previous experience with AI tools. This includes their comfort level and frequency of use. Regular use of AI apps (Alexa, Siri, and ChatGPT) occurred with about 70% of students. Courses (45%), university modules (30%), and peers (15%) were the main resources for learning. Students who are very familiar with AI tools feel more comfortable and, thus, are more willing to accept AI use in education [44].

d) Concerns

Privacy, data security and reliability were concerns of 55% of respondents (mean rating: 3.9). Concern about AI errors was 50% (mean rating: 3.8), and 45% had worries about overdependence on AI (mean rating: 3.7). And 40% showed concern about the reduced role of traditional teachers (mean rating: 3.6). Willingness to accept AI improves if concerns about privacy and reliability are allayed [45].

e) Accessibility

Accessibility refers to the ease with which students can find, use, and receive support for AI tools. Our study displayed that around 60% of students rated accessibility of AI tools at 4 or 5. Also, 55% felt they had sufficient resources and support to use AI tools effectively (mean rating: 3.8). The analysis showed that easy access to AI tools and adequate support systems are crucial for fostering positive attitudes towards AI. Ensuring accessibility can significantly enhance students' willingness to adopt AI technology [13].

f) Barriers

Barriers include challenges such as technical difficulties, lack of training, and insufficient resources that hinder the effective use of AI tools. The result indicated around 50% of students reported encountering significant difficulties when using AI tools (mean rating: 3.8), with lack of training (30%), inadequate technical support (25%), and insufficient resources (20%) being the most common barriers. Identifying and addressing these barriers is critical to improving AI adoption. Providing adequate training and technical support can help overcome these challenges and facilitate the integration of AI in education [46].

g) Acceptance

Acceptance refers to the overall willingness of students to use AI tools in their learning processes. The survey indicated a high level of acceptance, with 86% of students agreeing or strongly agreeing to use AI for learning and daily tasks (mean rating: 4.1) that reflected high acceptance levels are influenced by the perceived usefulness, understanding, familiarity, accessibility, and the ability to address concerns and barriers. Enhancing these factors can lead to broader adoption and integration of AI in education (Ma & Siau, 2018).

By analysing these variables, we gain a comprehensive understanding of the factors influencing student attitudes towards AI in education. This variable-based analysis provides insights into areas that need attention to enhance AI acceptance and integration in Vietnamese higher education.

2) Impact factor

To identify the impact factor of key variables (features) on students' AI acceptance (target), we averaged answers to questions for each defined variable, as each variable comprises multiple questions. We then employed three common data science and machine learning approaches. First, *Correlation Measurement* was used to gauge linear correlation between features and target, ranging from *-1* to *1*. Values near *0* indicate no linear correlation, while those near *1* or *-1* suggest strong positive or negative correlations, respectively. Then, derived from a *Decision Tree algorithm*, Feature Importance Score indicates how much a feature contributes to the prediction of the model. It returns a list of important scores, with higher values implying greater importance. Finally, an approach from cooperative game theory, *Shapley values*, was utilized to represent the average of marginal contributions to all possible coalitions. In machine learning, it explains how a model predicts results.

We combined these three approaches to determine the final impact factor of key variables on students' AI acceptance in education, as seen in Fig. 1 for an overview of our approach. This comprehensive approach leveraged both traditional and advanced statistical techniques of Correlation Analysis, Decision Tree Analysis, XGBoost, and SHAP to offer a nuanced understanding of the complex interplay between various factors. The gained results will inform targeted interventions to foster a more receptive environment for AI, shaping student acceptance of AI in Vietnamese education.

E. Rationale for Method Selection

Traditional statistical techniques like Pearson correlation provide foundational insights but fall short in capturing the intricate interactions between multiple variables. By integrating advanced machine learning methods such as Decision Trees and XGBoost, together with interpretative tools like SHAP, which explains the individual contributions of each factor to the model's predictions [42], this study ensures a robust and comprehensive analysis. This ensemble approach not only identifies the significant predictors of AI acceptance but also elucidates the underlying mechanisms driving student decision-making processes.

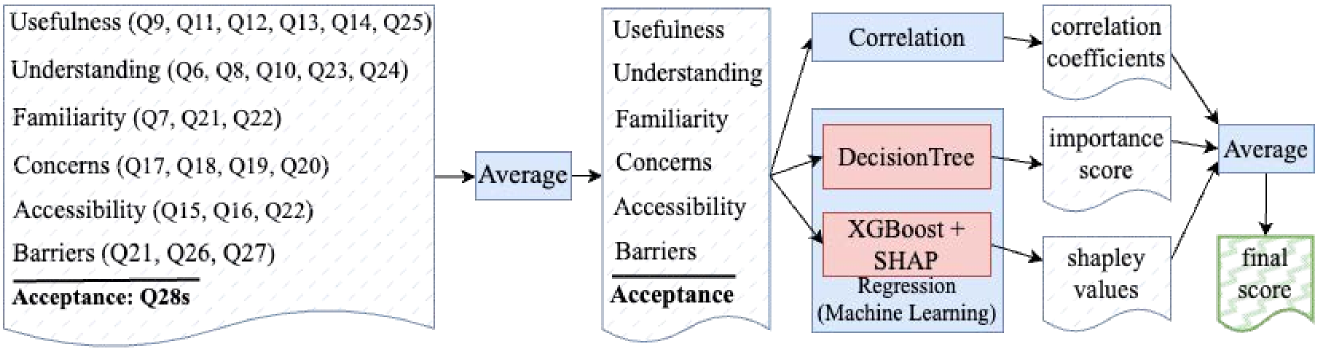

Fig. 1. The overall approach of impact factor calculation.

IV. Results

This section presents our findings on factors influencing AI acceptance in education in Southern Vietnam from students' perspectives. We begin with a summary of participant demographics, followed by a detailed analysis of the key variables. The results are presented with statistical numbers and visualizations, discussing them in the context of relevant literature. Feature importance is explored to identify the most influential factors in student acceptance. Synthesizing the findings across all variables allows us to offer an integrated view of overall attitudes.

A. Data Description

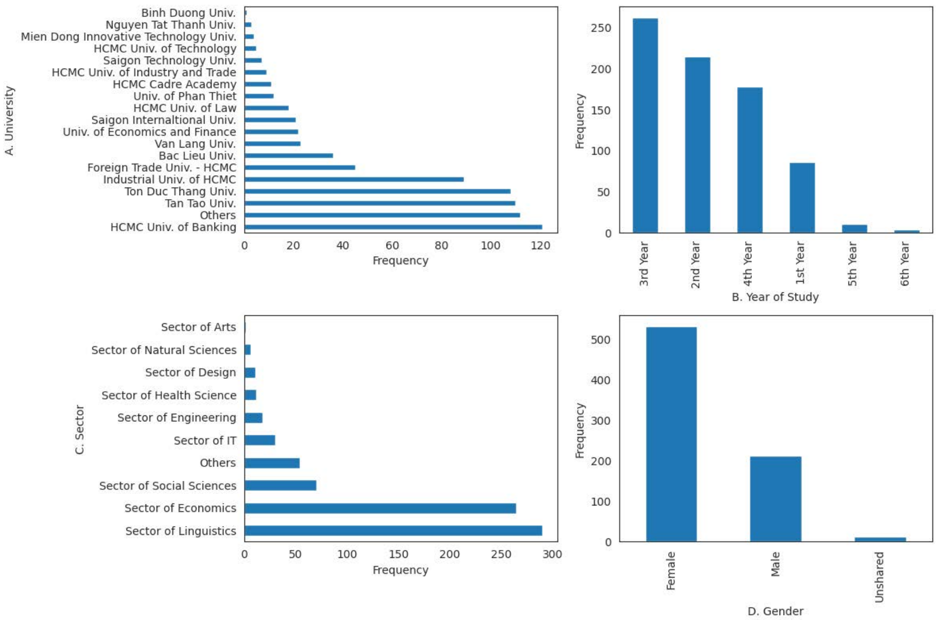

Fig. 2. Distribution of universities and demographic strata.

1) University distribution

We surveyed nineteenth key universities in Southern Vietnam and received responses from 757 participants. The participation of multidisciplinary students from various universities provides an excellent opportunity to explore attitudes towards AI in education across different institutions. Fig. 2 shows the largest number of respondents from Ho Chi Minh City (HCMC) University of Banking, with 121 students (16%), 110 students (15%) from Tan Tao University, 108 students (15%) from Ton Duc Thang University, 12% of the participants from Industrial University of HCMC with 89 students, and 45 students (6%) from Foreign Trade University of HCMC, and other respondents from other universities in Southern Vietnam also showed a considerable figure.

2) Student major distribution

The survey covers several categories of student majors, including (i) STEM (Science, Technology, Engineering, and Math), (ii) social sciences and humanities (social sciences, languages, arts, design, business and economics), (iii) health sciences, and (iv) other majors. Among them, the student majors of social sciences (literature, history, and geography), economics (business administration, international business, finance, accounting, and marketing), and languages (English, Chinese, Japanese, Korean, and Vietnamese) accounted for 9%, 35%, and 38%, respectively. Therefore, non-STEM majors account for 82.4% of our survey respondents, forming the dominant group (Fig. 2).

3) Years of study distribution

As can be seen from Fig. 2, the distribution of students by year can be summarized as: 3rd year (35%), 2nd year (28%), 4th year (24%), and 1st year (11%). A minority of 5th and 6th year students are from medicine programs. This distribution aligns with our survey's main respondents being non-STEM majors from social sciences, economics, and language programs, where Bachelor's degree programs typically last four years. The results indicate that students (2nd year and above) show more interest in AI adoption in education.

4) Gender distribution

Female respondents (72%) in the survey outnumber male counterparts (28%) by a ratio of 2.6 to 1 (Fig. 2). The predominant fields of study for students are social sciences, humanities, and economics. This gender distribution is in line with the gender ratios typically found in these majors at Vietnamese universities, where female students tend to dominate in social sciences, humanities, and economics training programs.

B. Results of Key Variables

This study examined the key variables: *Usefulness* (Q9, Q11, Q12, Q13, Q14, and Q25), *Understanding* (Q6, Q8, Q10, Q23, and Q24), *Familiarity* (Q7, Q21, and Q22), *Accessibility* (Q15, Q16, and Q22), *Concerns* (Q17, Q18, Q19, and Q20), and *Barriers* (Q26, Q27, and Q21), corresponding to the target variable - *Acceptance* (Q28s). For questions in the statement form, respondents rated them on a five-point Likert scale, where 1 represents "*Strongly Disagree*," 2 for "*Disagree*," 3 for "*Neutral,*" 4 for "*Agree*," and 5 for "*Strongly Agree*".

1) Usefulness

Regarding AI's Usefulness (**Q9, Q11, Q12, Q13, Q14,** and **Q25**) in Vietnamese higher education, 75% of students responded positively as shown in Fig. 3 below. Specifically, 70% of respondents rated 4 and 5 for the statement "*AI tools help me make progress in my learning*" with a mean rating of 4.1. 65% of students agreed or strongly agreed that "*AI tools will have a positive impact on my future career*" with a mean rating of 4.2. The collected data also showed that 68% of respondents believed that AI tools help them save time (mean rating of 4.0), and 60% felt that AI tools facilitate grasping complex concepts more easily (mean rating of 3.9). Our findings fit with research on the perceived usefulness of AI in education [12, 13, 47]. These studies indicate that students who recognize benefits like personalized learning, career preparation, and simplified concepts are more likely to adopt AI tools. This highlights the importance of emphasizing AI's practical benefits to promote its use in education.

2) Understanding

The distribution of Understanding **(Q6, Q8, Q10, Q23,** and **Q24)** shows less than half of respondents (40%) expressed strong understanding toward AI, suggests that students are still in the process of discovering and familiarizing themselves with the tools. Specifically, 62% understand the term 'Artificial Intelligence - AI (mean rating:3.8), while 4% fewer (58%) understand how AI tools work (mean rating: 3.7). A further 3% lower (55%) understand the consequences of using AI tools. When asked to describe how an AI tool works, 60% of respondents provided accurate descriptions (Fig. 3, Section Understanding). The findings align with existing literature emphasizing the importance of AI understanding for its acceptance in education [48], supporting their conclusions in that AI literacy positively influences students' acceptance of AI tools and is crucial for fostering AI adoption in education.

3) Accessibility

Accessibility (**Q15, Q16,** and **Q22**) is similar to Understanding, reflecting the new adapting technology. Specifically, the survey indicates 60% can easily find and use AI tools, with a mean rating of 4.0, while 55% have sufficient resources and support for effective AI tool use, with a mean rating of 3.8, and 65% regularly use AI tools (Fig. 3, Section Accessibility). These results are consistent with previous studies [13, 23, 24] highlighting that ease of access significantly influences students' willingness to adopt AI technologies. This study supports their conclusions, demonstrating that accessible AI tools with sufficient resources lead to higher acceptance and usage. Ensuring AI accessibility and support is crucial for fostering positive attitudes towards AI in education.

4) Familiarity

The survey results show that only 31% of students are familiar with AI tools (**Q7, Q21**, and **Q22**). This relatively low level of familiarity reflects the ongoing adaptation to AI tools in educational settings. Key findings reveal 70% use AI applications for study and life. Respondents reported their learning of AI through online courses, university courses, and peers/friends with 45%, 30%, and 15%, respectively. Also, 65% of respondents regularly use AI tools in studies and daily life (Fig. 3, Section Familiarity). These findings align with literature on familiarity's role in technology acceptance [44, 49], demonstrating that regular AI interaction and diverse knowledge sources positively influence AI acceptance, and increasing AI literacy and familiarity through frequent usage and education is crucial for fostering AI adoption in education.

5) Concerns

The survey results revealed significant concerns **(Q17, Q18, Q19,** and **Q20)** among students regarding AI tools in education, with 74% expressing worries on a Likert scale of 4 and 5. Primary concerns included security and personal information safety (55%, mean 3.9), AI errors impacting learning (50%, mean 3.8), overdependence on AI (45%, mean 3.7), and the diminishing role of traditional teachers (40%, mean 3.6) (Fig. 3, Section Concerns). These findings align with previous research by Labadze et al. (2023) on privacy concerns [45], Sit *et al*. on the impact of AI errors on learning, and Holmes *et al*. [50] on AI dependency and changing teacher roles. While students recognize AI's benefits, addressing these concerns is crucial for improving acceptance. This can be achieved through enhanced security measures, transparent error-handling protocols, and ensuring AI complements rather than replaces traditional teaching methods, ultimately fostering greater student acceptance of AI in education.

6) Barriers

While 90% of respondents expressed minimal disagreement with a statement suggesting little or no barriers, further analysis showed around 50% of participants marked only one or two options when presented with multiple potential barriers (Fig. 3, Section Barriers). This finding suggests that while certain barriers exist, surprisingly, their impact is neither pervasive nor severely limiting for most students. The concentration of concerns around a few specific barriers indicates they are not widespread hindrances to AI acceptance in educational contexts. This response pattern suggests a relatively high level of adoption of AI, since perceived benefits appear to outweigh barriers. Educators, institutions, and AI developers, therefore, consider the issue and focus on addressing specific barriers through targeted interventions to further the acceptance and effectiveness of AI in learning settings.

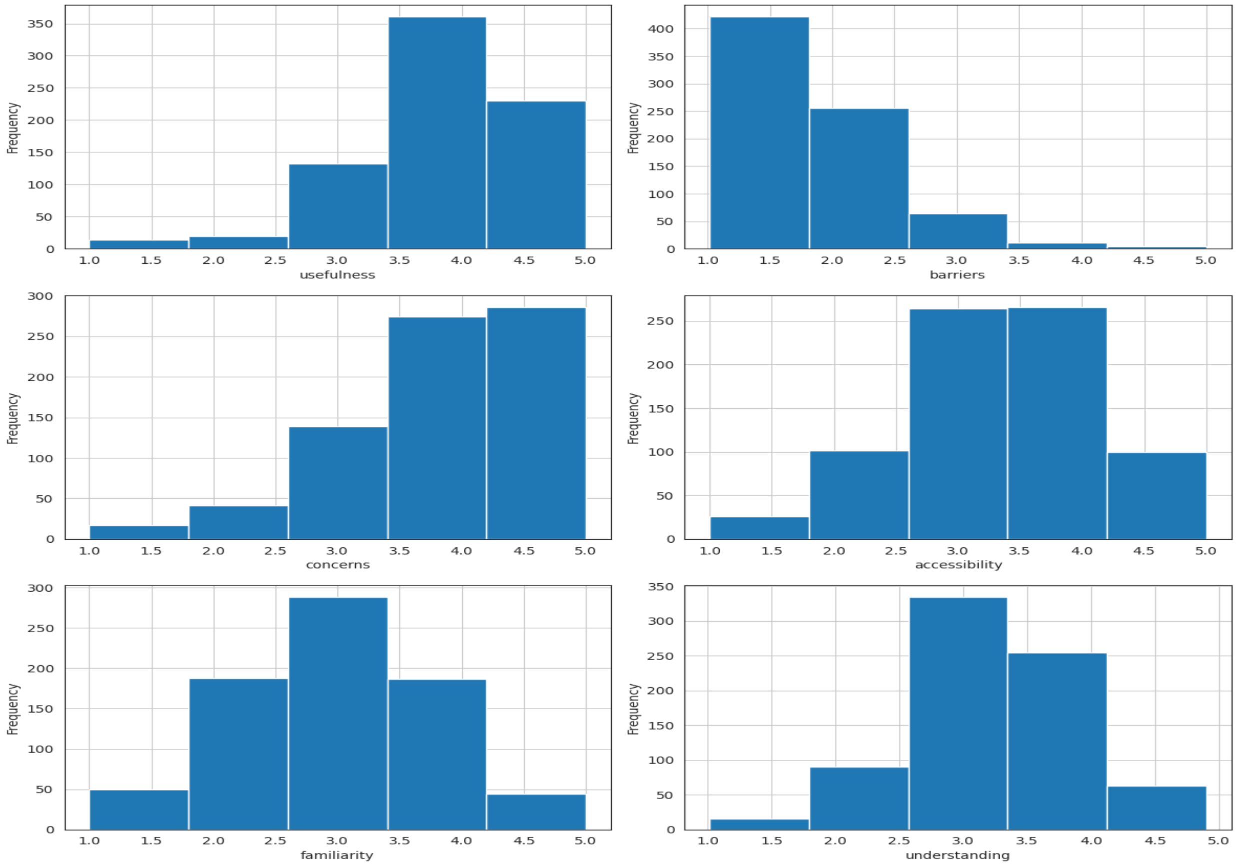

Fig. 3. Distribution of the six key variables.

7) Acceptance

The survey revealed a high level of acceptance for AI in education, with 86% of students agreeing or strongly to use AI for learning and other tasks (Q28s). This is consistent with existing literature, such as studies by Ma et al. (2018) and Alzahrani (2023), which emphasize the importance of perceived ease of use, usefulness, trust, and benefits in determining students' acceptance of AI [30, 51]. While the overall acceptance is high, it's contingent on several factors. To enhance AI adoption, institutions should focus on improving the usability and perceived benefits of AI tools and providing adequate training and support. These efforts are critical for effective integration of AI in educational settings, ensuring students can fully leverage technologies in their academic pursuits and other activities.

Students identified several key conditions for AI acceptance in Vietnamese higher education. The top considerations were privacy insurance (40%), cost-effectiveness (38%), language interface (35%), perceived value (30%), and ease of access (25%). Also, information availability and institutional endorsement received the highest, indicating their importance (Fig. 4.). These specific factors provide valuable insights for stakeholders seeking to promote AI use among students. By addressing the factors, institutions could significantly enhance AI adoption in educational settings.

C. Impact Factor

The Pearson correlation analysis revealed significant relationships between the independent variables and student acceptance of AI. Perceived usefulness ($r = 0.58$, $p < 0.01$), understanding ($r = 0.41$, $p < 0.01$), familiarity ($r = 0.36$, $p < 0.01$), and accessibility ($r = 0.42$, $p < 0.01$) were all positively correlated with acceptance. While concerns about AI were expected to negatively correlate with acceptance, the results suggest a surprising positive correlation ($r = 0.30$, $p < 0.01$), possibly indicating that students are willing to accept AI despite their concerns. Barriers to using AI, however, had a minimal impact on acceptance ($r = 0.089$, $p < 0.05$). Additionally, strong correlations were found between perceived usefulness, accessibility, and understanding ($r = 0.64$, $p < 0.01$; $r = 0.63$, $p < 0.01$), suggesting interrelationships among these variables (Fig. 5).

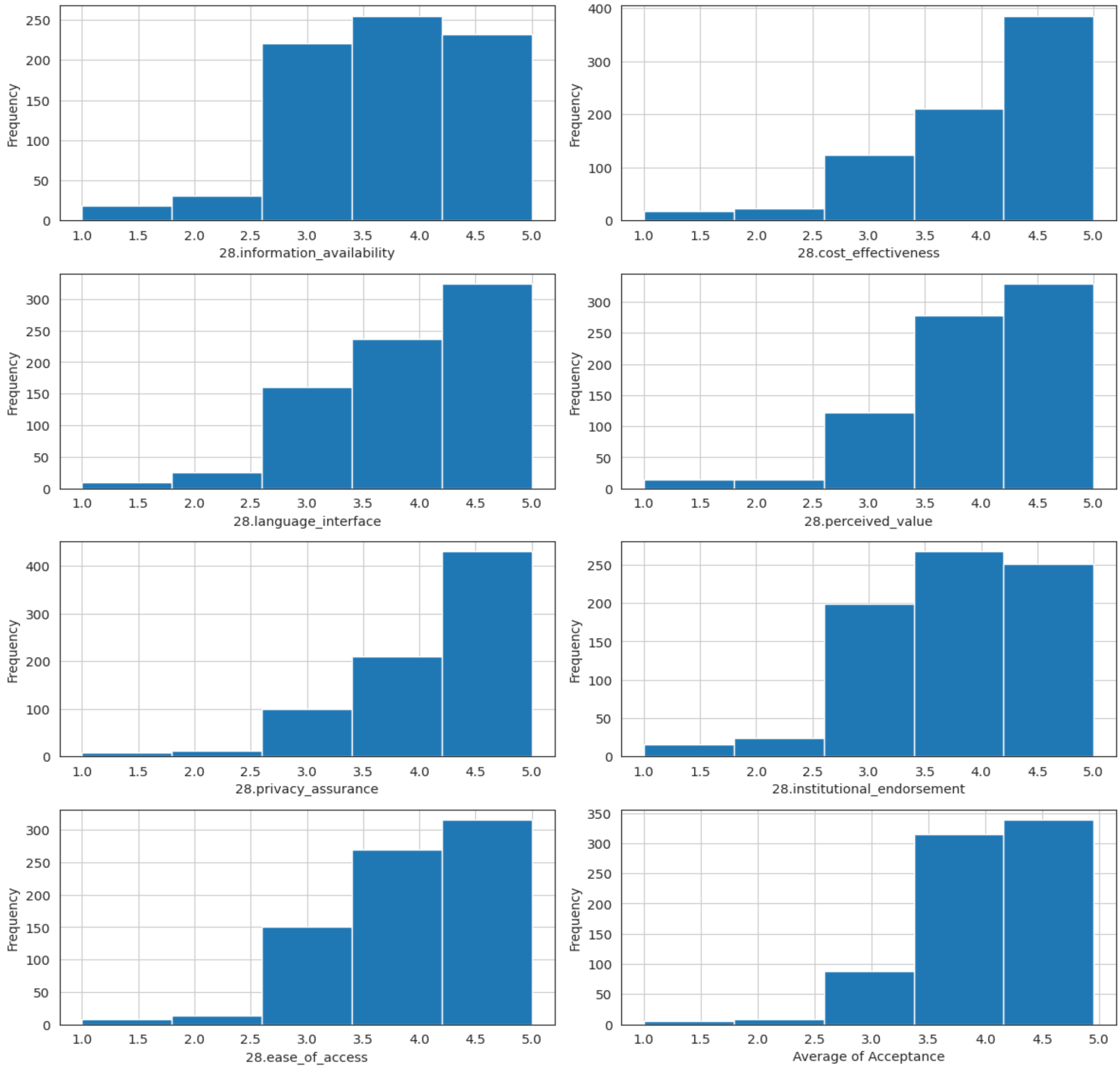

Fig. 4. Specific conditions for AI adoption.

Fig. 5. Pearson correlation.

The results of the Decision Tree Regressor model, which provides insights based on distribution and statistics show that the overall R^2 (coefficient of Determination) score of the model is 0.997. This remarkably high R^2 value indicates that the model explains 99.7% of the variability in the data, suggesting a very strong fit between the predictor variables and the outcome variable. The Decision Tree Regressor results further illuminate the factors influencing student acceptance of AI. The perceived usefulness of AI emerged as the most critical factor, with an importance score of 0.446 (Fig. 6). Understanding and familiarity also played significant roles, corresponding to the importance score of 0.157 and 0.135. In contrast, concerns, accessibility, and barriers showed lesser impact, with importance scores ranging from 0.076 to 0.108.

To validate these findings, we employed an XGBoost Regressor model with SHAP (SHapley Additive exPlanations) values, an approach grounded in game theory. This model yielded results consistent with the Decision Tree Regressor, demonstrating a similarly high explanatory power with an R^2 score of 0.976. This consistency across different analytical approaches reinforced the validity of the identified impact factors.

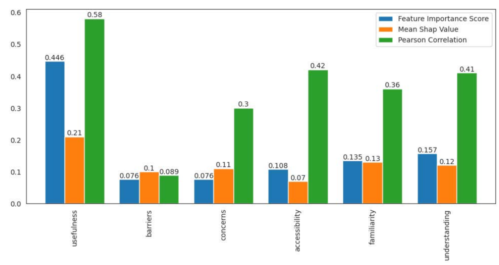

Fig. 6. Importance score from decision tree, SHAP values XGBoost regressor, and Pearson correlation.

The SHAP analysis, applied to an XGBoost Regressor model, revealed that perceived usefulness (SHAP value: 0.21) was the most influential factor affecting students' AI acceptance. Familiarity and concerns (Shapley values: 0.13 and 0.11) also played significant roles, while understanding, barriers, and accessibility (Shapley values: 0.07–0.12) had lesser impacts (Table 1). It is worth noting that SHAP values and feature scores sum to 1, whereas the sum of correlations exceeds 1. Therefore, it is essential to normalize the correlation sum to 1 before calculating the average with SHAP and feature scores to ensure a fair calculation of the average value.

Table 1. Average score and rank factors affecting students' AI acceptance

Method Variables	Pearson correlation	Pearson correlation (Normalized)	Importance score	Shapley value	Average score	Rank factor
Usefulness	0.58	0.269	0.446	0.21	0.308	1
Understanding	0.41	0.19	0.157	0.12	0.156	2
Familiarity	0.36	0.167	0.135	0.13	0.144	3
Accessibility	0.42	0.195	0.108	0.07	0.124	4
Concern	0.3	0.139	0.076	0.11	0.108	5
Barrier	0.089	0.041	0.076	0.1	0.072	6

As presented in Table 1, Perceived Usefulness and Accessibility - closely aligned with PU and PEU in the original TAM - collectively collected for approximately 50% of the total impact on AI adoption. The remaining 50% was attributed to additional factors introduced in our study, including Understanding, Familiarity, Concerns, and Barriers, each supported by quantitative scores. These findings offer a significant contribution to the existing literature by identifying and validating a broader set of determinants involving students' adoption of AI in higher education.

The results of the hypothesis testing supported the positive influence of perceived usefulness, understanding of AI, familiarity with AI technologies, accessibility, and a combination of these factors on students' AI acceptance. While concerns were initially hypothesized to have a negative impact, the data and data analysis revealed an opposite direction, suggesting a more complex correlation. Similar to the concerns, barriers were found to have a weak negative impact on the student acceptance of AI. Overall, the findings highlight the importance of various factors in promoting student acceptance of AI in educational settings.

V. Discussion

A. General Discussion

Acceptance is a composite variable that is influenced by perceived usefulness, understanding, familiarity, accessibility, concerns, and barriers [51]. The present study discovers and analyses these key factors affecting student acceptance by leveraging Pearson correlation and advanced statistical methods, including XGBoost and Random Forest.

All three methods in our study confirm that the usefulness is the most critical factor affecting the student acceptance of AI (Table 1). According to Pearson correlation, Decision Tree regressor and XGBoost Regressor, understanding and familiarity are the second and third most important factors in student acceptance. The results also highlight that accessibility plays an important role toward the student adoption of AI, while concerns and barriers impact less significantly.

Abdaljaleel *et al*. [46] explored how Arab university students (over 2,200 surveyed from Iraq, Kuwait, Egypt, Lebanon, and Jordan) perceive and use AI tools for learning, such as ChatGPT. The research found that while over half had heard of ChatGPT and more than half had used it previously, their attitudes and actual usage varied. Factors like ease of use, perceived usefulness, a positive outlook on technology, and social influence all played a significant role in student adoption. These findings from Abdaljaleel *et al.*) [46] strongly resonate with the factors influencing student acceptance of AI in our study. Additionally, their research emphasizes the need for adaptable AI integration policies within universities. This recommendation corresponds to our focus on understanding the key factors driving AI acceptance in educational settings, highlighting the importance of context-specific approaches to implementing AI in higher education.

In the context of Vietnamese education, this study identifies usefulness as the most critical factor affecting student acceptance of AI. In other words, students who perceive AI as useful are more likely to accept it. This finding matches Chen *et al.*'s [13] research in that perceived usefulness significantly influences the adoption of technology in educational settings. Several studies [12, 13, 44] demonstrate that when students and educators recognize the benefits of AI, they are more likely to embrace and integrate these technologies into their learning and teaching processes.

Students' acceptance of AI in education is closely linked to their perception of its usefulness. When students find AI tools helpful in improving their learning experiences, they are more likely to engage with these technologies actively. This engagement, in turn, fosters better learning outcomes and higher retention rates [12, 13]. The successful adoption of AI in education, however, depends on institutional support. Institutions that invest in AI technologies and provide adequate training for educators and students are more likely to see positive outcomes [12]. This institutional commitment can significantly enhance the perceived usefulness of AI for all stakeholders [12].

Familiarity was the third top factor influencing Vietnamese students in our survey. Chan & Hu (2023) note that students who regularly use AI are more cognizant of its benefits and have a more open attitude toward its adoption [49]. Alzahrani (2023) also found that previous experience with AI tools affected attitudes toward perceived usefulness and user-friendliness [30]. Familiarity builds trust, and makes AI seem more approachable [52].

Nevertheless, variations in student familiarity with AI exist across contexts [30, 53, 54]. For example, students in STEM programs, or other areas in technology, usually show a higher degree of familiarity because of AI use for their academic work or other activities [53, 54]. Non-STEM fields, however, show less AI adoption or willingness by students [30]. To promote the use of AI in multiple disciplines, strategic interventions to enhance understanding and reduce concerns can be of assistance.

Similar to Suh and Ahn (2022), our current study found that understanding AI plays a significant role in Vietnamese student adoption [44]. Students who grasp AI's functionalities are more likely to use them effectively. Accessibility, as emphasized by Zawacki-Richter *et al*. [12] and studies on infrastructure and resources, is also vital for effective AI integration.

Our findings indicate that concerns (moderately impactful with Pearson correlation $r = 0.3$, importance score = 0.09, and Shapley value = 0.11) influence Vietnamese student acceptance of AI. Addressing these concerns, as suggested by Labadze et al. (2023), is essential for fostering a positive attitude [45]. While having a lesser impact ($r = 0.089$, importance score = 0.089, and Shapley value = 0.09), barriers still merit attention [46]. Understanding these barriers helps design interventions that improve AI adoption.

B. Variable-Based Analysis

1) Perceived usefulness

Referred to as the degree to which students believe AI tools can enhance their learning experience and academic performance [13]. Referred to as the degree to which students believe AI tools can enhance their learning experience and academic performance [13]. The results showed high, relatively consistent agreement rates: 70% agreed that AI tools help make progress in learning ($M = 4.1$), 65% believed AI tools will positively impact their future careers ($M = 4.2$), 68% felt AI tools help save time ($M = 4.0$), and 60% agreed that AI tools assist in grasping complex concepts more easily ($M = 3.9$). Our findings strongly support our **Hypothesis 1** Perceived Usefulness positively correlates with student acceptance of AI and also align with existing literature on AI's Perceived Usefulness as a key determinant of technology acceptance in education [12, 13, 47].

2) Understanding

Understanding how AI operates and functions, as well as its benefits, can improve acceptance [43]. Our data showed that more than 60% described AI functions well and understood AI ($M = 3.8$). The respondents also had a fairly high understanding of how AI works ($M = 3.7$) and its consequences ($M = 3.6$). The findings confirm our **Hypothesis 2**, and support the studies by Timms (2016) and Siemens & Baker (2012) highlighting the importance of AI literacy for use in education [48]. In other words, AI literacy increases the adoption rate and improves AI understanding, forming a supportive environment.

3) Familiarity

Regarding Familiarity referred to as students' experience using AI applications in daily life and academics, our analysis revealed high familiarity ($M = 4.2$), with a combined 70% using AI applications frequently, demonstrating learning primarily through online resources (45%), university courses (30%), and peers (15%). The findings support **Hypothesis 3** that familiarity positively correlates with student acceptance, and aligns with the findings by Chan and Hu (2023) and Suh and Ahn (2022) in that regular interaction with AI tools increases comfort levels, reducing anxiety and fostering a positive attitude toward AI integration into learning [44, 49].

4) Concerns

Our survey revealed significant concerns among students: 55% worried about security and privacy ($M = 3.9$), 50% about AI errors impacting learning ($M = 3.8$), 45% about AI dependency ($M = 3.7$), and 40% about diminishing teacher roles ($M = 3.6$). Unexpectedly, the correlation between concerns and acceptance was positive ($r = 0.30$, $p < 0.01$), contrary to the initial hypothesis. The importance score for concerns was lower in the Decision Tree Regressor (0.076) but had a SHAP value of 0.11. These findings do not support **Hypothesis 4**, which posited a negative correlation between concerns and acceptance. This suggests a level of critical engagement where concerns do not hinder acceptance but rather coexist with recognition of AI's benefits. Educational institutions should address these concerns, and further research is needed to explore the nuanced relationship between concerns and acceptance.

5) Accessibility

Regarding Accessibility including the availability of AI resources, institutional support, and the overall user-friendliness of AI tools [55], our data showed the high AI accessibility among students: 60% easily find and use AI tools, rating 4 or 5 for the statement "*I can easily find and use AI tools*", 55% report sufficient resources and support (M= 3.8), and 65% regularly use AI tools. This supports our **Hypothesis 5** of a positive correlation between accessibility and student acceptance of AI, and corroborates the literature (e.g., Chen *et al*. 2020) in that easy access and adequate support increase AI integration in learning [13].

6) Barriers

Barriers to using AI tools in education manifest through various challenges that students encounter, impacting their adoption of these technologies. Our study identified the most common barriers as lack of training, inadequate technical support, and insufficient resources, affecting 30%, 25%, and 20% of students, respectively. The correlation between barriers and acceptance was weak ($r = 0.089$, $p < 0.05$). The importance score from the Decision Tree Regressor was 0.076, and the SHAP value was 0.10. These findings partially support **Hypothesis 6**, suggesting that while barriers exist, their impact on acceptance is minimal. This can suggest that students may perceive barriers but still be willing to adopt AI tools, possibly due to the perceived benefits outweighing the obstacles. Therefore, addressing barriers is important, as advised in the literature (e.g., Scherer & Tondeur, 2019; Aggarwal *et al.* 2023) to reduce barriers and facilitate smoother integration of AI [29, 56].

7) Acceptance

The acceptance variable equates with student willingness to use AI tools in their studies. This variable assesses receptiveness towards AI, which can be influenced by perceptions of usefulness, ease of use, and trust [32]. Our survey results indicated high level of acceptance, with 60% rating a willingness to use AI tools. This supports our Hypothesis 7, positing that six factors (perceived usefulness, understanding, familiarity, concerns, accessibility and barriers) would together predict student acceptance of AI in educational settings. These combined six factors have an effect on variables in the Technology Acceptance Model and its proposed extensions, with Perceived Usefulness and Accessibility - closely aligned with PU and PEU in the original TAM - collectively accounting for approximately 50% of the total impact on AI adoption, and the remaining 50% attributed to additional factors introduced in our study, including Understanding, Familiarity, Concerns, and Barriers. Thus, we suggest that educational institutions employ our holistic approach which takes into consideration a multiplicity of factors that influence acceptance of AI.

C. Condition-Based Analysis

Given the high level of AI tool acceptance we found among students, our deeper analysis explored specific factors influencing student willingness to use AI tools. These conditions include perceived ease of use, perceived usefulness, access to training and support, and trust in technology [32]. Perceived ease of use emerged as a significant factor (M = 4.3), with 70% of respondents indicating a higher likelihood of using AI if it is user-friendly, which aligns with the importance of accessibility in the Decision Tree analysis (importance score: 0.101). Similarly, perceived usefulness played a crucial role (M = 4.2), with 65% expressing their willingness to use AI tools if they perceived significant benefits in their academic performance and learning efficiency, supported by the high perceived usefulness score (0.461) from the Decision Tree model. Approximately 60% of respondents emphasized the need for institutional backing (M = 4.0), underlining the importance of support in AI adoption. Institutional endorsement (M = 4.0) also featured moderately in the analysis. Finally, while trust in AI's reliability and accuracy (M = 3.9) was important to 55% of students, concerns around security and AI errors had a lower importance score (SHAP: 0.11), indicating that while these concerns exist, they do not heavily influence students' willingness to use AI.

These results align with existing literature on factors influencing AI acceptance in education, especially in relation to the Technology Acceptance Model (Davis, 1989), where ease of use and perceived usefulness are emphasized [10]. The positive correlation between concerns and acceptance suggests that students critically engage with AI but remain willing to adopt it as long as perceived usefulness is high. Therefore, educational institutions should focus on providing AI tools that clearly demonstrate academic benefits while addressing usability concerns to ensure higher acceptance rates.

VI. Recommendations

Regarding Vietnamese students' acceptance of AI in educational settings, we propose a broad set of recommendations to increase acceptance through initiatives that feature key concerns and that exploit the potential of AI technologies (see Fig. 7). Recommendations, based on the relationships among these factors that affect student acceptance, should be geared to specific groups of students and their respective needs and study fields. Those in a position of authority such as educational institutions and policymakers should ensure that efforts to promote AI are cross-disciplinary. And AI developers should give priority to tools that will help students face challenges and reach goals.

Students can play an active role by using AI tools that enhance learning, help with time management, and assist with the understanding of complex concepts (Q12, Q13, Q14, Q25). The factor of perceived usefulness has the strongest impact on AI acceptance (Q14), our study found. Students taking part in AI educational programs can reduce the knowledge gaps that were seen in responses to Q6 and Q8.

AI's disadvantages and potentialities have been revealed in our analysis. Students should inform authorities about any concerns they have and give feedback about obstacles in using AI tools by taking part in surveys, student forums, and talks with teachers about how AI affects how they learn (Q18–Q19). Experimenting with AI tools can also increase students' confidence and comfort.

Adaptive strategies, such as training that employs AI along with demonstrations, can encourage student acceptance. These strategies should prioritize students' interests stated in Q23 and Q24, incorporate AI tools in curricula (Q25), and offer technical support. To address the high level of importance of Perceived Usefulness (score 0.462), educational institutions should emphasize the practical benefits of AI tools in training courses. To address concerns about the negative effects on traditional teaching methods or an over-reliance on technology (Q19, Q20), institutions should show how AI can be used as a complementary tool in education by holding workshops, creating ethical standards, ensuring transparent handling of data, and periodically evaluating AI integration. Faculty development programs are also critical in encouraging AI acceptance. Collaboration in educational settings, combining traditional educational values and AI tools, can offer a foundation for use of AI in students' future personal and professional lives, which can promote responsible AI usage.

Policymakers have a crucial stewardship role in ensuring the ethical, responsible use of AI in education. Advocacy for and support for educational content simplifying complex AI concepts is essential. And acknowledging understanding's effect on AI acceptance (evidenced by a Pearson correlation of 0.41) is important. Also essential is the funding of projects for AI infrastructure that includes accessible instructional materials and creating AI policies calling for AI inclusion in standard curricula at all educational levels. Authorities should also protect student data privacy, develop clear guidelines for ethical AI use, and create a framework that balances support for innovation with defence of student rights and safety. These standards can create trust in AI technologies and promote responsible student use, thus encouraging AI adoption and long-term success in education.

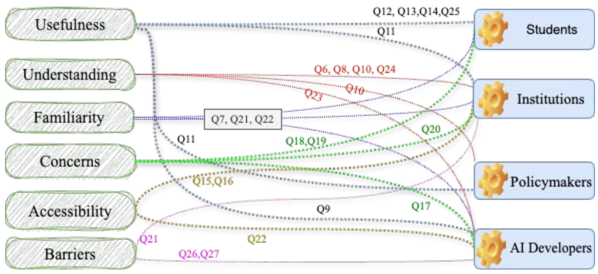

Fig. 7. Overview of the relationship between factors and related stakeholders.

Development of user-friendly tools that aid in academic progress should be a priority of developers of AI tools. Based on our survey's responses to Q25, accessibility, prompt feedback, and adaptive learning methods that tailor activities to individual students should be emphasized to improve attitudes toward AI. AI tools that affect students' personal and academic lives should have user-friendly interfaces and understandable functions. Smartphones, tablets and computers can all be more easily used if compatibility is created to exist across all platforms. Attention to student preferences should also be taken into consideration to achieve academic goals.

Our study focused on the six variables of perceived usefulness, understanding, familiarity, accessibility, concerns, and barriers. If these variables are attended to, and involved parties such as students, institutions, policymakers and AI developers become involved, then the likelihood of acceptance and use of AI will increase. In addition, AI tools should serve the varying needs of diverse groups in multiple fields. Collaboration among all involved parties, along with actions taken based on empirical evidence, can help to further acceptance of AI in education.

VII. Conclusion

This study examined the attitudes toward AI held by Vietnamese university students. Our study showed that Perceived Usefulness and Accessibility - closely aligned with PU and PEU in the original TAM – are still the impact factors and they collectively accounted for approximately 50% of the total impact on AI adoption. However, the remaining 50% was attributed to additional factors introduced in our study to make an extended TAM version. Notably, Perceived Usefulness was the strongest factor, followed by Understanding, Familiarity, and others. The results suggest that when students perceive AI's value in their learning and educational experiences, they are more prone to accept its use.

The present study had two limitations regarding the sample size and the research sites conducted only in Southern Vietnam. Further research should study regional variations and different educational levels, while qualitative methods should be used to reach deeper insights. Future research could prove to be fruitful in several areas, such as learning outcomes over long periods, AI interventions, and AI literacy programs. Ethical aspects of AI usage are also important to consider. By surveying students and analyzing the data, our research findings allow us to be in a better position to connect the gap that exists between the theoretical advantages and the actual, practical application of AI in Vietnam. Our study is hoped to create a foundation for further research about AI's use in education in Vietnam as well as in other countries.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Nhon Dang led the project, contributing to the conceptualization, design of the study, and critical revision of the manuscript. Tien-Dung Cao performed data analysis and interpretation. Trung Vu Hieu Nguyen led the proposal development, conducted the main writing, coordinated the research project and he is the corresponding author. Thanh-Long Nguyen was responsible for data collection and initial data processing. Thanh-Dien Nguyen performed the interpretation and validation of the data analysis. Mai-Lam Nguyen provided administrative, technical, and materials support. All authors had approved the final version.

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