Intentions to Use AI in the Mekong Delta, Vietnam: A Study in Ethics

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Abstract. This study investigates the factors influencing the intentions to use artificial intelligence in the Mekong Delta region, focusing on ethical factors. The research model extends the Technology Acceptance Model by integrating three mediating variables: Responsibility, Subjective Norms, and Ethical Norms, based on the Values - Beliefs - Norms theory. An empirical survey was conducted with 463 participants in the Mekong Delta, and the data were analyzed using SmartPLS 4.0. The results show that the level of perceived usefulness and moral norms have a positive influence on attitudes towards artificial intelligence, while the level of perceived ease of use and subjective norms do not have a significant direct influence. The intentions to use artificial intelligence is strongly influenced by attitudes, moral norms, personal responsibility, and subjective norms. Notably, personal responsibility is the factor that most strongly influences moral norms. The study also contributes to the development of theories on technology acceptance in ethical and cultural contexts, especially in developing countries. The findings provide useful information for organizations, technology companies, and policymakers in designing and deploying AI solutions in a responsible manner. This not only helps to increase user trust and acceptance but also supports the development of ethical frameworks, contributing to promoting the application of AI for public benefit in educational and social settings.

Keywords: Ethical AI, AI Intention, Mekong Delta

1 Introduction

In the context of the world in general and Vietnam in particular taking advantage of AI to promote the United Nations Sustainable Development Goals (SDGs) and technological revolutions reshaping industries, artificial intelligence (AI) has emerged as a disruptive technology with the potential for widespread application in education, healthcare, agriculture, and public administration (Mhlanga, 2021; Nasr et al., 2021; Jan et al., 2023; Katharria et al., 2025). However, the rapid development of AI also brings with it many ethical concerns, such as algorithmic transparency, data privacy, systemic bias, and social responsibility (Baker and Xiang, 2023; Sargiotis, 2024). This is especially important in developing regions such as the Mekong Delta, where access to technology is limited and people are particularly sensitive to social and ethical issues (Danh, 2023).

To explain the intentions to use AI, the TAM model (Davis, 1989) still plays a fundamental role, through two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). However, recent studies show that the TAM needs to be expanded when applied to ethically sensitive technologies such as AI. According to Choung et al. (2021), Jiao and Cao (2024), and M. Mariani et al. (2023), factors such as trust, personal moral norms, and social responsibility are important mediating variables affecting PU and PEOU. Therefore, this study extends TAM by integrating three new variables: Responsibility (R), Subjective Norms (SN), and Ethical Norms (EN), which have never been combined simultaneously in AI research models in Vietnam. Theoretically, the variables R, SN, and EN originate from the Values – Beliefs – Norms (VBN) Theory of Stern et al. (1999), which explains individual behavior based on the chain of values – beliefs – ethical norms. People with a community value orientation and positive beliefs about the social impact of technology will have a strong sense of responsibility and moral obligation, thereby forming the intentions to use technology in a socially beneficial way (Mamun et al., 2022; Zhang et al., 2022)

In Vietnam in general and the Mekong Delta in particular, East Asian culture emphasizes community factors and social prestige, making social norms and ethics especially important factors in AI acceptance (Nguyen et al., 2021; Brijs et al., 2024). People often evaluate technology not only based on personal benefits but also consider whether the technology is fair, transparent, and serves the community's interests. Therefore, measuring factors such as R, SN, and EN in this study helps clarify the mechanism of AI intention formation (IU) from both the technological (TAM) and ethical (VBN) perspectives.

The urgency of this study not only comes from practical needs in developing regions such as the Mekong Delta, but also reflects a large gap in global academic discourse. A series of Calls for Papers from leading conferences and journals such as Empirical AI Ethics (Cambridge Forum), AI Ethics, Governance and Risk (KeAi Publishing),

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ECAI 2025 - Track on Fairness, Ethics, and Trust, or AIES 2025 (AAAI/ACM) all emphasize the urgent need for studies that integrate empirical data, local cultural and ethical contexts into the process of evaluating and implementing AI. These calls demonstrate that the scientific community is seriously lacking in-depth quantitative research on AI ethics in developing countries, where access to technology is fragmented, trust in the system is unstable, and socio-cultural factors play a key role in determining behavior. In this context, this study not only has academic value but also contributes to solving a topical requirement that is of particular interest to the international scientific community.

In summary, the study "Intentions to Use AI in the Mekong Delta, Vietnam: A Study in Ethics" not only contributes to expanding the TAM and VBN models in the specific context of Vietnam but also responds to the international call for localized and socially engaged AI ethics research. Clarifying the roles of R, SN, and EN will provide the necessary empirical evidence to design effective, ethical, and sustainable AI implementation policies in the Mekong Delta.

To address these gaps, this study employed an empirical survey using primary data collected from 463 individuals residing or working in the Mekong Delta region. This approach ensures that the analysis is grounded in local perceptions and realities rather than relying solely on secondary policy reviews.

The study consists of 7 parts: Part 1 - Introduction, presenting the context, importance, research gaps, and research objectives. Part 2 - Overview of theoretical basis, theoretical analysis, and mediating variables. Part 3 - Research methodology, including survey design and data analysis techniques. Part 4 - Research results. Part 5 - Discussion of results and practical implications. Part 6 - Conclusion and theoretical and practical contributions. Finally, part 7 - Limitations and future research directions.

2 Literature

2.1 Theoretical Background

2.1.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was developed by Davis (1989) to explain how users decide to accept and use a new technology. TAM suggests that technology use behavior is influenced by two main factors: perceived usefulness (PU) and perceived ease of use (PEOU). PU reflects the extent to which an individual believes that using the technology will enhance work performance, while PEOU represents the belief that the technology can be used easily without much effort (Davis, 1989; Venkatesh and Davis, 2000). TAM has been widely applied in various contexts, including education, healthcare, e-commerce, and recently in studying the acceptance of smart technologies such as AI (Alalwan, 2020; Dwivedi et al., 2021; Polyportis, 2024). According to Venkatesh and Bala (2008), in addition to PU and PEOU, external factors such as system quality, organizational support, or trust can also indirectly influence the intentions to use technology through the two core factors of TAM.

In the context of studying the intentions to use AI in the Mekong Delta region, TAM continues to demonstrate its value in explaining the behavior of local people with regard to technology acceptance. However, in a social environment influenced by ethics, trust, and transparency, recent studies suggest that the TAM model needs to be extended to include variables related to perceived ethics and social responsibility (Shin, 2021; Chi et al., 2023). This is especially important in the context of AI, a technology that often raises concerns about privacy, transparency, and employment impacts (Cave et al., 2020; Mikalef et al., 2023). In addition, research by Chatterjee et al. (2022) shows that trust in AI plays a mediating role between PEOU, PU, and intentions to use, especially in sensitive areas such as education and healthcare. Meanwhile, studies in developing countries (Bervell and Umar, 2018; Kaur and Haque, 2024) emphasize that local context, technology level, and cultural and ethical values also have significant effects on PU and PEOU. This suggests that AI deployment in the Mekong Delta region needs to consider both technology accessibility and local cultural and ethical values, which are very specific. In this study, TAM is used as a foundational model to assess the intentions to use artificial intelligence (AI) technology. In addition to the two core factors, PU and PEOU, additional factors such as personal responsibility (R), subjective norms (SN), and ethical norms (EN) are also included in the model to more fully explain the factors affecting the acceptance and use of AI in the ethical and social context. Integrating TAM with social and ethical factors enhances the ability to explain AI usage intentions, not only from a technological utility perspective but also in terms of congruence with personal norms and trust in the system.

2.1.2 Value Belief Norm Theory

The Value-Belief-Norm Theory (VBN) was developed by Stern et al. (1999), inheriting from the Norm Activation Model (NAM) of Schwartz (1977). VBN explains individual behavior not only from the perspective of personal interests but also based on the formation of moral standards based on personal values and deep beliefs about social issues. According to Schwartz (1992), values are principles that guide human behavior in life, including three main groups: egoistic values, altruistic values, and biospheric values. These values have a great influence on how individuals perceive responsibility and moral standards, especially in the context of behaviors with high social consequences, such as the use of new technology. In VBN theory, the chain of values → beliefs → moral norms → behavior is central to explaining ethical behavior. Beliefs here include beliefs about the consequences of behavior and personal responsibility (Awareness of Consequences – AC; Ascription of Responsibility – AR), which in turn activate personal norms, the feeling that a person has a moral obligation to act in accordance with his or her values, even in the absence of external pressure (Stern et al., 1999; Nudelman et al., 2021; Obrenovic et al., 2022).

In the context of the study "Intentions to Use AI in the Mekong Delta, Vietnam: A Study in Ethics", VBN theory provides a suitable foundation to explain the intentions to use AI technology from an ethical perspective. When people in the Mekong Delta region perceive that AI is beneficial to society and is consistent with their personal ethical standards, such as transparency, fairness, or supporting sustainable development, they tend to develop a sense of responsibility and ethical norms towards AI application.

In this study, the mediating factors such as Responsibility (R) and Ethical Norm (EN) are used as factors originating from personal value and belief systems, contributing to explaining the intentions to use AI (IU) through positive attitudes towards this technology (Attitude Toward Use (AU). People with altruistic and community-minded values are more likely to feel morally responsible for applying AI in a socially beneficial way. Conversely, if they perceive this technology as potentially morally risky, they may reduce their intentions to use it, regardless of personal benefits.

In short, VBN theory not only helps clarify human moral motivations but is also a suitable analytical tool to study AI application behavior in a specific socio-cultural context, such as the Mekong Delta region, where people are increasingly concerned about sustainability, fairness, and social responsibility in technology.

2.1.3 Artificial Intelligence and AI Ethics

Artificial Intelligence (AI) is playing an increasingly important role in areas such as education, healthcare, finance, and public administration. In the educational context, AI is used to personalize learning experiences, analyze student behavioral data, automate assessments, and support decision-making (Zawacki-Richter et al., 2019). In this context, it is important to distinguish between AI used for administrative purposes, such as managing institutional records or scheduling, and AI applied directly in pedagogy to enhance learning and teaching processes. This distinction has significant ethical implications, especially in educational environments. However, in addition to these potentials, AI also raises many ethical issues related to privacy, transparency, accountability, algorithmic bias, and system trust (Floridi et al., 2018; Cowls et al., 2023). According to Fjeld et al. (2020), the core ethical principles when implementing AI include: respect for human rights, fairness, transparency, responsibility, and safety. Particularly in the education sector, the deployment of AI systems needs to ensure that personal learning data is not misused and that learners are empowered to control their own data. In regions such as the Mekong Delta, where technological literacy is limited, ensuring ethical implementation of AI becomes even more important to build social trust and sustainable technology acceptance (Nguyen et al., 2022).

Recent studies have shown that perceived ethics in technology (Perceived Ethicality) can directly influence the intentions to use AI (Shin, 2021). Users are more likely to accept AI when they believe that the technology is designed and operated in an ethically responsible manner, does not violate privacy, and is transparent in data processing (Cave et al., 2020; Li, 2023).

Another noteworthy aspect is the role of social norms and personal ethics in AI acceptance. In East Asian cultural environments in general and in Vietnam in particular, users often evaluate technology not only based on personal benefits but also consider ethical factors, community influence, and social norms. This means that to promote the intentions to use AI in education in the Mekong Delta, it is necessary to not only raise technical awareness but also clearly communicate about technology ethics, ensuring that the technology is deployed transparently, fairly, and responsibly.

2.2 Hypotheses Development

The Technology Acceptance Model (TAM) proposed by Davis (1989) has become a popular theoretical framework to explain users' technology acceptance behavior. In this model, Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) are two core factors that influence Attitude Toward Use (AU) and finally Intentions to Use (IU).

Many later studies have confirmed these relationships in many fields such as education, e-commerce, healthcare, and information technology.

According to Davis (1989), Perceived Ease of Use (PEOU) is defined as the extent to which users believe that using a technology system will not require much effort. When users feel that the system is easy to use, they tend to develop more positive attitudes toward adopting that technology. A recent study by Korsah (2023) confirmed that PEOU has a significant influence on Attitude Toward Use (AU) in the context of e-learning systems in Ghana. Similarly, Venkatesh and Davis (2000) and Alzahrani (2022) also emphasized the role of PEOU in shaping user attitudes in educational technology and digital media environments. These results reinforce the argument that PEOU is an important factor in promoting positive user attitudes towards new technologies such as artificial intelligence. PEOU not only directly influences attitudes but also indirectly affects intentions to use through Perceived Usefulness (PU). If people in the Mekong Delta perceive AI technology as accessible, they will also easily recognize the practical benefits that AI brings. This is consistent with the results of Davis (1989), which is reinforced by recent studies such as Binyamin et al. (2019) and Zhang et al. (2023), showing that PEOU is an antecedent for users to evaluate PU positively in many technological contexts.

Attitude Toward Use (AU) is an important mediator in the TAM model, which has a strong influence on intentions to use technology (IU). When individuals form a positive attitude towards AI, believing in the effectiveness, reliability, and benefits that AI brings, they will tend to use this technology more in the future. This is confirmed by Davis (1989) and extended in the studies of Venkatesh and Davis (2000) and Shin and Park (2019) in the context of digital transformation and AI.

Therefore, the following hypotheses are proposed:

H1a: Perceived Ease of Use (PEOU) has a positive influence on Attitude Toward Use (AU). H1b: Perceived Ease of Use (PEOU) has a positive influence on Perceived Usefulness (PU). H2: Perceived Usefulness (PU) has a positive influence on Attitude Toward Use (AU).

H5: Attitude Toward Use (AU) has a positive influence on Intentions to Use (IU).

According to Ajzen (1991), SN represents the social pressure that an individual feels from people around him/her (family, friends, teachers, etc.) about whether or not to perform a behavior. In the context of AI use in the Mekong Delta, SN reflects the desire or expectation of the community around an individual about whether or not to use AI technology.

An extension of the TAM model by Teo (2009) confirmed that SN is an important factor shaping teachers' attitudes towards using technology tools, including computers and online learning platforms. Mustofa et al. (2025) also found that SN has a clear impact on students' attitudes towards AI tools in education. In a study on AR technology in tourism, the authors showed that SN has a positive effect on attitudes and intentions to use new technology.

Subjective Norm (SN) has been shown to be an important factor influencing the intentions to use technology, especially in the context of education and new technologies such as artificial intelligence (AI), social networks, or online learning platforms (Zhuanga et al., 2020). In Fuchs' (2022) study on integrating smartphones into teaching, SN was identified as a factor that significantly influenced teachers' intentions to use (IU), especially when they felt expectations and support from colleagues and schools. Similarly, Tran et al. (2023) also showed that SN from students, parents, and colleagues had a direct impact on the intentions to use Zalo as a tool for teaching and communication in the Vietnamese educational environment. In addition to the effects on attitudes and usage behavior, many recent studies have also shown that SN can play a role in forming and reinforcing ethical norms (EN) when individuals perceive ethical expectations from the academic or social community. According to Kajiwara and Kawabata (2023), adherence to ethical norms when using AI tools comes not only from personal awareness but also from the influence of people around them, who can guide and reinforce ethical values in the process of learning and using technology.

Therefore, the study proposes the following hypotheses:

H3a: Subjective Norm (SN) has a positive influence on Attitude Toward Use (AU). H3b: Subjective Norm (SN) has a positive influence on Intentions to Use (IU).

H3c: Subjective Norm (SN) has a positive influence on Ethical Norm (EN).

According to Norm Activation Theory (NAM), personal responsibility is a moral activator that plays a central role in promoting ethical behavior (Schwartz, 1977). In the context of technology, especially artificial intelligence (AI), personal responsibility is expressed in the sense that users feel morally obligated to use technology appropriately and consider social consequences (Asante et al., 2024; Dong and Bocian, 2024). Muzumdar et al. (2025), through the MEAAM (Model for Ethical Adoption of AI in Medicine) model, showed that feeling morally responsible when using AI not only enhances positive Attitude Toward Use but also enhances actual usage intentions. In addition, in research related to corporate social responsibility (CSR), Arachchi et al. (2023) also found that the sense of responsibility positively affects both attitudes and usage behavior (such as consumption decisions). People who feel highly responsible for the community or the environment will tend to accept, support, and use ethical products or technologies. In particular, responsibility does not stop at usage behavior but is also related to the formation of personal ethical norms (Ethical Norm – EN). When individuals are clearly aware of the ethical consequences of their behavior, such as improper use of AI, they will develop a set of internal standards to evaluate right/wrong behavior, thereby contributing to the formation of personal ethical norms (Kajiwara and Kawabata, 2024).

Based on the theoretical and empirical foundations discussed above, this study proposes the following hypotheses:

H4a: Responsibility (R) has a positive influence on Attitude Toward Use (AU). H4b: Responsibility (R) has a positive influence on Intentions to Use (IU).

H4c: Responsibility (R) has a positive influence on Ethical Norm (EN).

In the context of artificial intelligence (AI) technology, ethical norms (EN) reflect users' intrinsic beliefs about the appropriate, fair, and socially responsible use of technology. These norms serve as a moral compass, guiding how individuals approach and make decisions regarding the use of technology. A recent study by Al Migdadi et al. (2024) in Jordan found that ethical perceptions of AI were significantly positively associated with attitudes toward the use of AI as well as with intentions to use it. This study highlights the role of ethical norms in shaping positive views of technology in academic and professional settings, especially among medical students who are trained in environments that emphasize humanity and responsibility.

Similarly, the study by Kwak et al. (2022) on Korean nursing students also showed that professional ethics and awareness of AI significantly contributed to the formation of positive Attitude Toward Use, especially when students understood principles such as transparency, fairness, and responsibility. In addition, Taghibaygi and Alibaygi (2024) study in Iran on the use of digital technology in agriculture also showed that ethical norms not only promote a sense of personal responsibility but also enhance the intentions to use technology, by activating emotional responses such as pride or guilt when not acting in accordance with the norms. Based on the above research results, this study proposes two hypotheses:

H6a: Ethical Norm (EN) has a positive influence on Attitude Toward Use (AU). H6b: Ethical Norm (EN) has a positive influence on Intentions to Use (IU).

3 Methods

3.1 Data Collection

Before conducting the official survey, the study conducted a pilot survey with 20 participants to check the level of understanding, as well as the accuracy of the questionnaire. The comments from the pilot survey group were recorded and adjusted by the study to complete the final questionnaire. There were some scales inherited from foreign studies, so the study used the back-and-forth translation method (A.M.B et al., 1994), converting from English to Vietnamese and vice versa, then comparing to re-evaluate whether both translated versions were suitable for the context and the survey subjects. After completing the questionnaire, data were collected through an online survey using Google Forms, and the study employed a non- probability convenience sampling technique to reach a broad range of respondents.

To determine eligibility, the survey included screening questions asking respondents whether they lived or worked in the Mekong Delta region and were familiar with AI technology. Those who answered "no" to either of these questions were excluded from the survey. Before starting the survey, respondents were provided with a brief introduction to the study and a simple explanation of the applicability of AI and the ethics of its use. This introduction was intended to help respondents understand the key concepts that would be covered in the following questions. The survey took approximately 3 to 5 minutes to complete, and respondents were assured of the confidentiality of their responses.

After data cleaning, 463 valid questionnaires remained for analysis. The final sample size was 463, exceeding the recommended minimum threshold of 370, calculated using the 10 times rule according to the instructions of Hair et al. (2014) to determine the minimum sample in PLS-SEM. To minimize non-response bias, all participants were informed about the research objectives and committed to the confidentiality of personal information.

Table 1 shows the demographic characteristics of the 522 survey participants with a relatively diverse distribution across gender, age, occupation, and income. Females accounted for a slightly higher proportion at 54%, while the age group from 18 to 24 years old accounted for the largest proportion (37.5%), followed by the 25-34 age group (27%). In terms of occupation, students accounted for the majority at 40.6%, followed by lecturers/teachers (25.7%) and freelancers (18%). Income was primarily concentrated in the range under 5 million VND (33%) and between 20 to under 30 million VND (20.9%). Overall, the survey sample reflected the target group of young people with diverse occupations and income levels, which is suitable for research related to the behavior and views of the current young generation.

Table 1. Demographic characteristics.

Variable	Responses	Total number	Percentage %
Gender	**Total**	**522**	**100**
	Male	240	46
	Female	282	54
Age	**Total**	**522**	**100**
	Under 18 years old	4	0.8
	From 18 to 24 years old	196	37.5
	From 25 to 34 years old	141	27.0
	From 35 to 44 years old	86	16.5
	From 45 to 54 years old	76	14.6
	Over 55 years old	19	3.6
Occupation	**Total**	**522**	**100**
	Lecturer/Teacher	134	25.7
	Office worker	59	11.3
	Freelancer	94	18.0
	Student	212	40.6
	Entrepreneur	19	3.6
	Other	4	0.8
Income	**Total**	**522**	**100**
	Under 5 million VND	172	33.0
	From 5 to under 7 million VND	76	14.6
	From 7 to under 10 million VND	42	8.0
	From 10 to under 15 million VND	17	3.3
	From 15 to under 20 million VND	85	16.3

From 20 to under 30 million VND	109	20.9
Over 30 million VND	21	4.0

(Source: Collected by authors)

A five-point Likert scale was used, with response options ranging from "strongly disagree" (1) to "strongly agree" (5). This format was chosen because of its simplicity and user-friendliness, requiring less time and cognitive effort from participants than scales with more response options. Additionally, the five-point scale is well-suited to mobile device interfaces, reducing respondent fatigue while still providing sufficient granularity to capture their views accurately. To enhance the validity and reliability of the constructs, this study adapted measurement items from a combination of existing and newly developed scales. Specifically, the Perceived Ease of Use, Perceived Usefulness, Attitude Toward Use, and Intentions to Use scales were adapted from the study of Davis (1989), Responsibility and Ethical Norm items were adapted from Taghibaygi and Alibaygi (2024), and Subjective Norm from Ajzen (1991).

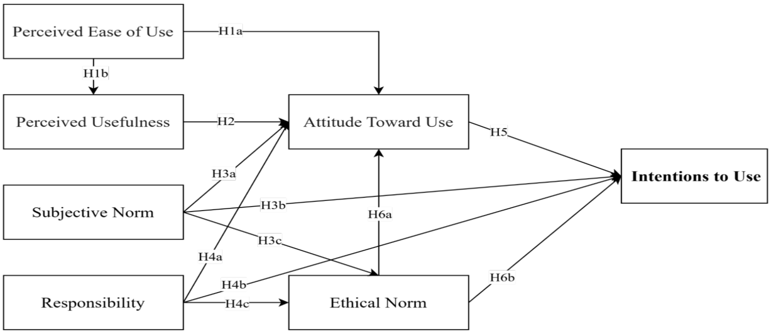

Fig. 1. Research model.

(Source: Authors' construction)

3.2 Data Analysis

To test the theoretical model and proposed hypotheses (see Figure 1), this study used the partial least squares structural equation modeling (PLS-SEM) approach with the support of SmartPLS 4 software (Ringle et al., 2022). The PLS-SEM method is particularly suitable for studies that both aim to explain the relationships between factors and focus on the predictive ability of the model (Lim et al., 2023). Unlike traditional covariance-based methods, PLS-SEM does not require data to follow a strict normal distribution, thus making it well-suited for analyzing for analyzing complex models with many components, measurement indicators, and linkages between factors (Hair et al., 2017). This method also proves to be effective in handling models with mediators, moderators, as well as higher-level abstract concepts, which may consist of multiple reflective or formative indicators. (Becker et al., 2023; Cheah et al., 2023). In addition, PLS-SEM can analyze multiple independent variables simultaneously and is suitable for models built on a synthetic basis. With these advantages, Thus, SmartPLS 4 was employed for model estimation and hypothesis testing in this study.

4 Result

4.1 Common Method Bias (CMB)

Common Method Bias (CMB) is a phenomenon that explains the variation in research data due to a common measurement method, which is also an issue that needs to be noted in studies that collect data at a single point in time (MacKenzie and Podsakoff, 2012). To limit the potential influence of CMB, the study employed both procedural remedies to control for CMB and statistical techniques to detect it. The method to control for CMB was implemented in the data collection design stage (before the survey), while the statistical method of identifying the CMB phenomenon was applied after data collection (after the survey).

The method of controlling the CMB phenomenon focuses on minimizing or eliminating the CMB through careful questionnaire design. Many previous studies have shown effective ways to control CMB during the questionnaire design process (Baumgartner and Weijters, 2012; MacKenzie and Podsakoff, 2012; Podsakoff et al., 2012). Specifically, respondents were informed that there will be no right or wrong answers, and the study also commits to keeping the information of the survey respondents confidential. The survey is also designed to be concise, avoiding duplication so that respondents do not get tired or answer carelessly. In addition, the questionnaire also includes questions that are expressed in both positive and negative ways to limit bias in the answers. At the same time, the research team also used the "psychological separation" technique so that participants would not perceive direct links between independent and dependent variables, thereby avoiding their answering according to the research purpose speculation (Podsakoff et al., 2012). Regarding statistical control to detect the CMB phenomenon, the research team used the Harman single-factor test to assess the influence of CMB (MacKenzie and Podsakoff, 2012).

Results showed that the first factor accounted for only 35.398% of the variance, lower than the 50% threshold, so the study concluded that CMB did not exist (Cooper et al., 2020). In addition, the variance inflation factor (VIF) test according to the total correlation test method (Kock and Lynn, 2012) was also performed. The VIF indices ranged from 1.329 to 2.563, below the cut- off of 3.33, indicating that common method bias did not significantly affect the results of the study.

4.2 Measurement model

As shown in Table 2, most of the outer loading values are above 0.7, which indicates that the indicators are strongly related to their corresponding constructs. One exception is item IU2, which has a loading of 0.663. However, this value is still acceptable because, as Hair and Alamer (2022) suggest, items with loadings between 0.4 and 0.7 can be kept if the overall reliability of the construct is good.

Looking at reliability, the Cronbach's Alpha values for all constructs range from 0.787 to 0.865. These values are higher than the recommended minimum of 0.7, showing that the items within each construct are consistent with one another (Hair and Alamer, 2022). Similarly, the Composite Reliability (CR) values are all above 0.86, which meets the standards suggested by Bagozzi and Yi (1988). This confirms that the constructs are measured reliably. The Average Variance Extracted (AVE) values are all above 0.5, ranging from 0.571 to 0.718. According to Fornell and Larcker (1981), this means that each construct explains more than half of the variance in its indicators, which supports good convergent validity. Overall, the results show that the measurement model is reliable and valid so that it can be used in the next steps of the analysis.

Table 2. The reliability and convergent validity

Constructs/variables	**OL**	**CA**	**CR**	**AVE**
AU: Attitude Toward Use		0.865	0.908	0.712
AU1	0.876			
AU2	0.843			
AU3	0.816			
AU4	0.838			
EN: Ethical Norm		0.812	0.869	0.571

EN1	0.789			
EN2	0.783			
EN3	0.768			
EN4	0.721			
EN5	0.713			
IU: Intentions to Use		0.812	0.870	0.574
IU1	0.823			
IU2	0.663			
IU3	0.775			
IU4	0.779			
IU5	0.739			
PEOU: Perceived Ease of Use		0.825	0.884	0.656
PEOU1	0.839			
PEOU2	0.850			
PEOU3	0.777			
PEOU4	0.772			
PU: Perceived Usefulness		0.804	0.872	0.630
PU1	0.846			
PU2	0.797			
PU3	0.774			
PU4	0.756			
R: Responsibility		0.787	0.862	0.610
R1	0.791			
R2	0.778			
R3	0.753			
R4	0.802			
SN: Subjective Norm		0.804	0.884	0.718
SN1	0.877			
SN2	0.869			
SN3	0.794			

Note: OL: Outer loadings; CA: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted; AU: Attitude Toward Use; EN: Ethical Norm; IU: Intentions to Use; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; R: Responsibility; SN: Subjective Norm.

(Source: Collected by authors)

To ensure that the latent variables in the model are distinct, the study conducted a discriminant validity test using two methods, including Fornell-Larcker and Heterotrait-Monotrait ratio (HTMT). The results of the discriminant validity assessment according to the Fornell-Larcker criterion (Table 3) showed that the square root of the AVE value for each latent variable was greater than the correlation coefficient between those variables and the remaining latent variables. This proves that the concepts in the measurement model are distinct, ensuring that each variable accurately measures the theoretical concept they represent. Therefore, the measurement model met the discriminant validity requirement as proposed by Fornell and Larcker (1981).

Table 3. Fornell-Larcker criterion

	AU	**EN**	**IU**	**PEOU**	**PU**	**R**	**SN**
AU	0.844						
EN	0.416	0.756					
IU	0.507	0.526	0.758				
PEOU	0.337	0.540	0.512	0.810			
PU	0.570	0.485	0.539	0.458	0.794		
R	0.408	0.595	0.547	0.522	0.521	0.781	
SN	0.253	0.453	0.447	0.635	0.396	0.518	0.847

Note: AU: Attitude Toward Use; EN: Ethical Norm; IU: Intentions to Use; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; R: Responsibility; SN: Subjective Norm

HTMT is an index to assess discriminant validity, proposed by Henseler et al. (2015). According to the proposal of Henseler et al. (2015), the discriminant validity between two latent variables is guaranteed when the HTMT index is less than 0.9. The analysis results in the table below show that all HTMT coefficients are less than 0.9. Therefore, it can be affirmed that the concepts in the research model achieve discriminant validity, ensuring that the concepts are clearly distinguished in terms of measurement.

Table 4. Heterotrait-monotrait ratio (HTMT)

Source: Collected by authors

	AU	**EN**	**IU**	**PEOU**	**PU**	**R**	**SN**
AU							
EN	0.482						
IU	0.599	0.644					
PEOU	0.391	0.658	0.624				

PU	0.681	0.591	0.664	0.558		
R	0.492	0.745	0.684	0.647	0.650	
SN	0.298	0.557	0.549	0.770	0.485	0.649

Note: AU: Attitude Toward Use; EN: Ethical Norm; IU: Intentions to Use; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; R: Responsibility; SN: Subjective Norm.

(Source: Collected by authors)

4.3 Structural model

After conducting a bootstrapping procedure with 5,000 resamples using SmartPLS 4 software, the results of the structural model assessment presented in Table 5 indicate that the R^2 values range from 0.210 to 0.449. Specifically, the variable Intentions to Use (IU) has the highest R^2 value of 0.449, suggesting that the model explains 44.9% of the variance in the intentions to use AI technology. Other variables, such as Attitude Toward Use (AU) and Ethical Norm (EN), also demonstrate moderate levels of explanatory power, with R^2 values of 0.357 and 0.353, respectively. Meanwhile, Perceived Usefulness (PU) has the lowest R^2 value (0.210), indicating that it is relatively less influenced by the independent variables in the model. Overall, the model demonstrates moderate to substantial explanatory power, reflecting a reasonable and reliable structural framework within the context of this study.

Table 5. R Square

Variables	**R-square**	**R-square Adjusted**
AU	0.357	0.350
EN	0.353	0.352
IU	0.449	0.444
PU	0.210	0.208

Note: AU: Attitude Toward Use; EN: Ethical Norm; IU: Intentions to Use; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; R: Responsibility; SN: Subjective Norm.

(Source: Collected by authors)

The hypotheses were accepted when the p-value was less than 0.05 (Rasoolimanesh et al., 2016). The results of the hypothesis testing in Table 6 show that the relationships between the variables in the model have different levels of significance, reflecting the role of each factor in this study. The test results show that most of the hypotheses were accepted with a statistical significance level of $p < 0.05$, reflecting the significant relationship between the factors in the research model.

The results of hypothesis testing presented in Table 6 show the difference in the level of influence between the variables in the model, reflecting the distinct role of each factor in forming the intentions to use artificial intelligence (AI) in the Mekong Delta region from an ethical perspective. Most of the hypotheses were accepted with high statistical confidence ($p < 0.05$), indicating that most of the proposed relationships are significant. Specifically, Perceived Usefulness (PU) has a positive and strong influence on Attitude Toward Use (AU) ($\beta = 0.457$), Perceived Ease of Use (PEOU) has a significant impact on PU ($\beta = 0.458$), but does not directly affect AU ($p > 0.05$), indicating that learners value usefulness more than convenience in forming positive attitudes toward AI. In addition, Subjective Norm (SN) significantly affects Intentions to Use (IU) ($\beta = 0.169$) and Ethical Norm (EN) ($\beta = 0.198$), indicating that social factors play an important role in shaping behavior and ethical standards, although they do not directly affect attitudes. In particular, Responsibility (R) has a very strong influence on EN ($\beta = 0.492$) and IU ($\beta = 0.224$), confirming the central role of personal responsibility in guiding ethical AI behavior. However, similar to SN and PEOU, R also does not directly affect attitudes ($p > 0.05$). Finally, both AU ($\beta = 0.292$) and EN ($\beta = 0.195$) have significant effects on IU, with EN also hurting AU ($\beta = 0.145$), indicating that ethical factors not only contribute to promoting behavior but also influence attitudes. From this, it can be affirmed that perceived usefulness, personal responsibility, and ethical norms are key factors promoting the intentions to use AI, while convenience or social influence only play a secondary or indirect role.

Table 6. Path Coefficient, Original sample (O) - β, P values – P

Hypothesis	β	P	Decision
PEOU → AU = **H1a**	0.043	0.454	Rejected
PEOU → PU = **H1b**	0.458	0.000	Accepted
PU → AU = **H2**	0.457	0.000	Accepted
SN → AU = **H3a**	-0.072	0.209	Rejected
SN → IU = **H3b**	0.169	0.001	Accepted

SN → EN = **H3c**	0.198	0.000	Accepted
R → AU = **H4a**	0.098	0.083	Rejected
R → IU = **H4b**	0.224	0.000	Accepted
R → EN = **H4c**	0.492	0.000	Accepted
AU → IU = **H5**	0.292	0.000	Accepted
EN → AU = **H6a**	0.145	0.021	Accepted
EN → IU = **H6b**	0.195	0.000	Accepted

Note: AU: Attitude Toward Use; EN: Ethical Norm; IU: Intentions to Use; PEOU: Perceived Ease of Use; PU: Perceived Usefulness; R: Responsibility; SN: Subjective Norm

(Source: Collected by authors)

5 Dicussion

The objective of this study is to analyze the factors influencing the intentions to use artificial intelligence (AI) in the Mekong Delta region, with a special emphasis on the role of ethical factors. The study extends the Technology Acceptance Model (TAM) by integrating variables related to personal responsibility, social norms, and ethical standards. Thereby, the study aims to provide a practical and theoretical basis for the application of AI in an ethical, sustainable, and culturally appropriate manner.

First, the results of the study show that the hypothesis H1a (PEOU → Attitude Toward Use) is rejected due to lack of statistical significance ($\beta = 0.043$, $p > 0.05$), while H1b (PEOU → PU) is accepted with a very high significance ($\beta = 0.458$, $p < 0.05$). This implies that although respondents in the Mekong Delta perceive AI as easy to use, this factor is not enough to form a positive attitude if they do not find AI really useful. This result is consistent with some recent studies, such as Kajiwara and Kawabata (2024) and Geddam et al. (2024), in which PEOU does not directly affect attitude but has an indirect effect through PU. The notable difference in this study is that the implementation in a rural context, where familiarity with technology is limited, highlights the mediating role of PU as an attitudinal trigger. Therefore, this study makes a novel contribution by being one of the first to test the extended TAM model with ethical factors in this diverse community context, thereby suggesting policy directions to promote AI applications that are appropriate to local culture and perceptions.

Second, the results of testing hypothesis H2 show that perceived usefulness (PU) has a positive and statistically significant effect on attitudes towards using AI ($\beta = 0.457$, $p < 0.05$). This suggests that people in the Mekong Delta will have a more positive attitude towards AI if they perceive AI to bring practical value in their work or life. This result is completely consistent with many recent studies, such as Gado et al. (2021), Li

(2023), and Mustofa et al. (2025), in which PU was identified as the strongest predictor of attitudes in the TAM model. However, the new contribution of this study lies in testing this relationship in the context of rural Vietnam, where the level of access and awareness of AI is still relatively low. The identification of PU as a key determinant of attitudes suggests that the practical effectiveness of the technology is a prerequisite for promoting AI adoption in this region. Therefore, the study adds a localized perspective to the TAM model and is one of the first studies to examine this relationship in the context of incorporating ethical factors in the Mekong Delta region.

Third, the results of testing the three hypotheses related to Subjective Norm (SN) showed significant differences between the relationships. Specifically, hypothesis H3a (SN → Attitude Toward Use) was rejected (β = -0.072, $p > 0.05$), indicating that social norms do not directly affect attitudes toward using AI. In contrast, hypothesis H3b (SN → Intentions to Use) was accepted (β = 0.169, $p < 0.05$), and hypothesis H3c (SN → Ethical Norm) was also accepted (β = 0.198, $p < 0.05$), indicating that social influence plays a significant role in promoting intentions to use AI as well as forming ethical norms when approaching technology. This result is consistent with some recent studies, such as Taghibaygi and Alibaygi (2024), who found that SN has a significant influence on both IU and EN in an educational setting in Iran, especially when learners are influenced by peers, friends, and instructors. Li (2023) also noted that SN is a strong predictor of IU in the context of educational technology acceptance in China, while no significant influence was found on attitude, similar to the H3a result of the current study. Mustofa et al. (2025) study in Indonesia emphasized the role of social environment in promoting ethical technology behavior, but did not directly test the relationship with attitude to use. These findings support the conclusion that Subjective Norm does not directly influence attitude - AU, but has a significant influence on intentions to use - IU and ethical norms - EN (Roy et al., 2025). This suggests that in the research context, social influence can promote AI use behavior directly, or indirectly through shaping personal ethical standards, rather than through purely perceived attitudes. The outstanding contribution of this study is the simultaneous examination of three directions of SN impact (i.e., on Attitude, Intention, and Ethical Norms) in an integrated model in the specific context of the Mekong Delta - where social factors such as community, tradition, and collectivity have a strong influence on behavior Mai et al. (2023).

Fourth, the results also show that Responsibility positively affects Ethical Norms (β = 0.492, $p < 0.05$) and also directly affects IU (β = 0.224, $p < 0.05$). However, R is not statistically significant for AU ($p > 0.05$), emphasizing the central role of responsibility in forming ethical norms related to technology. This finding is consistent with the research of Tzeng et al. (2022), Choung et al. (2023), and Taherdoost et al. (2025), emphasizing responsibility as a fundamental factor for ethical AI development. In the medical field, Muzumdar et al. (2025) also noted that ethical factors, including responsibility, are the premise for promoting AI application behavior, reinforcing hypothesis H4b. In addition, the research of Smith et al. (2025) found that responsible behaviors often do not clearly influence usage attitudes, but are key factors in making actual action decisions, showing compatibility with rejecting H4a but accepting H4b and H4c in the current study.

Furthermore, the results of the study showed that positive attitudes toward AI use significantly influenced the intentions to use AI (H5, β = 0.292, $p < 0.05$). This suggests that individuals who have positive perceptions of AI, such as usefulness, practicality, or relevance to learning and work needs, will be more likely to plan to apply AI in practice. This finding is completely consistent with recent studies applying the TAM and TPB models in the context of education and technology. For example, studies by Suparman et al. (2023) and Ma et al. (2024) both confirmed that attitudes are a direct and strong predictor of the intentions to use AI in learning environments. Similarly, Alahmari et al. (2023), Bui et al. (2025) also noted a significant influence of attitudes on IU in their study of AI applications in distance education. In the context of developing countries, Dahri et al. (2024) also emphasized that positive attitudes can partly compensate for technological skills limitations, thereby enhancing AI acceptance. This result reaffirms the AU → IU relationship in a specific context such as the Mekong Delta - where ethical factors, responsibilities, and social norms are intertwined in the technology acceptance process - helping to reinforce the universal value of this relationship, while suggesting that individual attitudes remain a key "bridge" between technological awareness and practical action, even when users are also influenced by the surrounding community and social environment.

Finally, the results of the study show that Ethical Norms (EN) have a positive and statistically significant influence on both AI adoption attitudes ($\beta = 0.145$, $p < 0.05$) and AI adoption

intentions ($\beta = 0.195$, $p < 0.05$). This finding is consistent with the study of Enriquez et al. (2024), which showed that the infusion of ethical principles such as transparency and fairness enhances trust and positive attitudes in educational settings. Similarly, the analysis of Kousa and Niemi (2022) also confirmed that awareness of AI ethics promotes attitudes and willingness to adopt technology in higher education. The latest empirical study by Wang et al. (2025) also developed the AI Ethical Reflection Scale, which showed a strong correlation between ethical reflection competence and trust in AI.

These practical implications also directly align with Vietnam's key national strategies on science, technology, and digital transformation. Resolution 57-NQ/TW (2024) of the Politburo emphasizes breakthroughs in science, technology, innovation, and digital transformation as decisive factors for national development in the new era, underscoring the importance of ethical, human-centered technological deployment. Resolution 52-NQ/TW (2019) further stresses proactive participation in the Fourth Industrial Revolution by integrating advanced technologies such as AI into socio-economic development, while promoting social responsibility and minimizing inequalities. Additionally, Decision 127/QĐ-TTg (2021) on the National Strategy for AI Development sets out specific objectives to foster AI applications across sectors, including education and governance, with a clear focus on ensuring fairness, transparency, and trust. By providing localized empirical evidence from the Mekong Delta, this study offers insights that can inform these policies, highlighting how perceived usefulness, ethical norms, and personal responsibility serve as essential levers to drive AI adoption in a way that is not only technologically effective but also ethically robust and culturally appropriate. This emphasizes the need for integrating AI ethics into teacher training, public communication, and curriculum design to prepare communities for responsible and sustainable AI deployment, thus supporting Vietnam's broader aspirations of becoming a prosperous and technologically advanced nation.

6 Conclusion

6.1 Theoretical Implications

This study contributes significantly to the expansion and consolidation of the theoretical framework of the Technology Acceptance Model (TAM), especially in the context of developing economies such as the Mekong Delta region.

The results reaffirm the central role of Perceived Usefulness (PU) as a key factor directly influencing Attitude Toward Use (AU). Although Perceived Ease of Use (PEOU) does not directly influence attitudes, it has a significant impact on PU, which indirectly shapes positive attitudes toward AI use. This finding adds empirical evidence to the mediation hypothesis of PU - a relationship that has been proposed but not fully tested in studies in rural areas where users may have limited access to technology.

The study extends the TAM model by integrating Ethical Norms (EN) and Responsibility (R) - two ethical factors that are increasingly of concern in the context of AI development. The results show that EN has a positive and statistically significant influence on both AU and IU, demonstrating that ethical values such as transparency, fairness, and privacy protection play an important role in shaping attitudes and intentions to use AI.

In particular, the study is the first to examine the relationship between Responsibility (R) and variables in the extended TAM model. R has a significant influence on EN and IU, but does not directly affect AU. This finding suggests that the factor of personal responsibility acts as a foundation to promote the formation of ethical norms, thereby indirectly influencing attitudes and behavioral intentions. This is a new point of theoretical significance, contributing to the integration of ethical and responsibility factors into a traditional technological theoretical framework such as TAM.

The study also re-explored traditional relationships in TAM by placing them in the specific cultural and social context of the Mekong Delta. The results show that Subjective Norm (SN) has a strong influence on IU and EN, but not directly on AU. This reflects the dominant role of collectivist culture and social influence in rural areas, where technology use decisions are often more communal than individual. This finding highlights the need to adapt modern technology models when applied to non-Western cultures. This study both strengthens the basic relationships of the TAM model and contributes to the theory by proposing and testing new variables derived from ethics and culture. In particular, the integration of EN and R not only extends the TAM but also helps to better theorize the process of technology acceptance in the AI era, where ethical factors are increasingly essential. This opens up new directions for future research on the relationship between technology, ethics, and social context in developing countries.

6.2 Practical Implications

The study provides many important practical implications to guide the effective deployment and application of artificial intelligence (AI) technology in the Mekong Delta region, in accordance with the socio-cultural characteristics and actual conditions of the locality.

First, the perception of the usefulness of AI is a fundamental factor that shapes positive attitudes and promotes the intentions to use. This shows that management agencies, technology enterprises, and educational institutions need to promote communication activities, skills training, and sharing practical applications of AI in life and work. Specifying benefits such as saving time, improving learning and working efficiency, and supporting decision making will help users clearly perceive the value of technology, thereby promoting active acceptance.

Second, the factors of personal responsibility (R) and ethical norms (EN) have significant effects on both attitudes and intentions to use AI, reflecting the importance of integrating technological ethics into training programs, communications, and policies. Courses or guidance materials should emphasize the rights and obligations of AI users, responsible behavior, as well as ethical risks that may arise during the application of AI. This not only helps build a safe and transparent technological environment but also enhances trust and social consensus.

Third, the indirect effects of social norms (SN) through EN and IU demonstrate the role of community, collective culture, and local traditions in promoting technological behavior. Leveraging social resources such as teachers, students, mass organizations, and local leaders will create a ripple effect in the community. AI promotion campaigns, if linked to collective values, role models from influential people, and social consensus, will create strong motivation to change technological behavior in a positive and sustainable way.

Finally, given the rural characteristics and limitations in infrastructure and technology access, AI development policies in the Mekong Delta need to prioritize technical support, improve digital infrastructure, and implement training programs appropriate to the level, needs, and living conditions of the people. This practical solution will help narrow the digital divide, ensure equitable access to technology, and increase practical effectiveness in implementing AI locally.

In short, the study provides a practical foundation for policymakers, educational institutions, technology enterprises, and local communities to design AI development strategies that are sustainable, responsible, and appropriate to the socio-cultural characteristics of the Mekong Delta region in the national digital transformation process.

7 Limitations and Future Research

Although the study has achieved important results in expanding the technology acceptance model (TAM) and elucidating the factors influencing the intentions to use artificial intelligence (AI) in the Mekong Delta, there are still some limitations in methodology and personal factors that may affect the generalizability and reliability of the results.

First, in terms of methodology, the study sample was mainly collected from certain areas in the region, so it cannot fully represent the entire population of the Mekong Delta. This may create bias in the data and affect the generalizability of the results. Although the sample size of 463 is relatively suitable for performing some statistical analyses, it may not be large enough to test all the complex relationships in the model. In addition, the study is limited by the lack of previous academic works on AI acceptance behavior in this region, making it difficult to compare and contrast the results with other contexts. The use of online survey methods also somewhat limits the ability to reach out to populations that are not familiar with technology or do not have Internet access, thereby reducing the diversity of the survey sample.

Second, on the researcher's side, limited access to some data groups, short research time, and the possibility of being influenced by cultural biases or personal factors can lead to biases in instrument design, subject approach, and data analysis.

Given the above limitations, future research directions should consider expanding the scope of the survey to many other provinces in the region and conducting more diverse sampling in terms of age, occupation, and education level to increase representativeness. In addition to quantitative methods, combining with qualitative methods such as in-depth interviews or case studies will help to further explore the socio-cultural dynamics that influence technological behavior. In particular, future studies should further analyze the role of indigenous cultural factors, community practices, and rural characteristics in shaping technological attitudes and behaviors. In addition, expanding the scope of research to other digital technologies such as blockchain, Internet of Things (IoT), educational technology (EdTech), or digital transformation platforms in the fields of agriculture and healthcare is also a valuable direction. Comparing acceptance behavior between different types of technology will help build a more comprehensive picture of the process of technology adoption and application in the Mekong Delta region, thereby contributing to the development of sustainable technology development policies that are suitable for local conditions.

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