WHAT DRIVE YOUNG VIETNAMESE CONSUMERS TO ADOPT MEDICAL AI?

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Abstract: ***This study investigates the factors influencing young consumers' intention to adopt AI-based Medical Decision Support Systems (AIMDSS) in Vietnam, an emerging economy, using an extended Theory of Planned Behavior (TPB) framework. This research incorporates initial trust into the TPB model as a key antecedent of attitude to better capture the dynamics of adopting novel technologies. A survey of 216 Vietnamese consumers aged 18–30 reveals that attitude, perceived behavioral control, and subjective norm significantly predict intention, with attitude being the strongest predictor. Initial trust exerts a substantial influence on attitude, underscoring its importance in shaping early-stage evaluations of AI in healthcare. The study contributes to theory by extending the TPB framework with initial trust as a critical antecedent of attitude, enhancing its ability to explain behavioral intention in high-uncertainty contexts involving novel technologies such as medical AI. It also offers practical insights for developers and policymakers on fostering trust, usability, and social endorsement to encourage AIMDSS adoption in an emerging market.***

• Keywords: *artificial intelligence, initial trust, Theory of Planned Behavior, young consumers, healthcare.*

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1. Introduction

Artificial intelligence (AI) is rapidly transforming healthcare delivery, offering tools that enhance diagnostic accuracy, personalize treatment, and improve patient outcomes. Among these innovations, AI-based Medical Decision Support Systems (AIMDSS) are gaining attention for their ability to assist both professionals and end-users in making informed health decisions. Despite their technological promise, consumer adoption of such medical AI systems remains limited, particularly in transitional economies where digital readiness and trust in health technology are still developing.

Understanding the behavioral factors that drive adoption is therefore critical. The Theory of Planned Behavior (TPB; Ajzen, 1991) provides a well-established framework for explaining intentional behavior through attitudes, subjective norms, and perceived behavioral control. However, TPB does not explicitly account for the role of trust, a key determinant in the adoption of unfamiliar, high-risk technologies like medical AI. Given the novel, complex, and often opaque nature of AI-based systems, users, particularly in transitional economies like Vietnam, must rely heavily on trust in the technology and its providers to form initial evaluations.

This study addresses a gap in the literature by extending TPB with the construct of initial trust and applying it to examine young consumers' intention to use AIMDSS in Vietnam, a representative transitional economy with a rapidly digitizing healthcare landscape. While prior research has focused on healthcare professionals or technology acceptance in developed contexts, limited work has explored how young consumers in emerging markets form adoption intentions toward AI-driven health tools. This research contributes to both theory and practice by offering an integrated model of behavioral intention and identifying the psychological and social mechanisms that influence early adoption of medical AI.

2. Theoretical framework and hypotheses development

Huang and Rust (2018) defined Artificial Intelligence (AI) as the capability of machines to carry out functions that typically require human intelligence, including learning, reasoning, and problem-solving. In the context of services, AI is viewed as a tool that can either support or replace human roles in decision-making and customer interactions. The growing presence of artificial intelligence (AI) in healthcare has spurred research into understanding user acceptance of AI technologies, particularly AI-based Medical Decision Support Systems (AIMDSS). Prior studies have employed a range of theoretical frameworks to examine AI adoption of consumers in

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different context, including healthcare. Major theories have been applied to study this topic, including the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Health Belief Model (HBM) (Jain et al., 2024; Khanijahani et al., 2022). These models have consistently identified perceived usefulness, ease of use, and perceived risk as key drivers or barriers to adoption. However, these approaches often emphasize rational and functional factors, with limited attention to social-psychological dimensions such as trust and normative influences (Khanijahani et al., 2022).

Among those theories, the Theory of Planned Behavior (TPB; Ajzen, 1991) provides a comprehensive framework that captures cognitive, normative, and control-related determinants of behavioral intention. TPB posits that intention is shaped by three constructs: attitude (the individual's evaluation of the behavior), subjective norm (perceived social pressure), and perceived behavioral control (PBC; the perceived ease or difficulty of performing the behavior). This framework has been successfully applied in different context, including healthcare (Hassan et al., 2016; Ye et al., 2019), where it has demonstrated strong explanatory power. Yet, its application in the context of medical AI adoption, particularly among young consumers in transitional economies remains limited.

However, the healthcare context involves high uncertainty and opacity, which can hinder user confidence and engagement. In such settings, users often lack the experiential basis to form attitudes through direct interaction, making initial trust a critical antecedent in shaping early evaluations and behavioral intentions. This underscores the need to incorporate initial trust into the TPB framework to more effectively capture the determinants of user adoption in high-uncertainty healthcare environments. Initial trust, refered as the willingness to rely on a technology without prior experience (McKnight et al., 2002), has been shown to play a pivotal role in early adoption contexts. It influences attitude formation by reducing perceived risk and enabling favorable evaluations (McKnight et al., 2002). In this study, we extend TPB by incorporating initial trust as a cognitive antecedent to attitude.

Despite the growing interest in AI adoption, empirical research on consumers' adoption of medical AI remains limited, particularly in transitional economies. Most prior studies have focused on clinical users or populations in high-income countries, leaving a gap in understanding how digitally literate but healthcare inexperienced consumers, such as young adults in Vietnam, evaluate and engage with AIMDSS. Moreover, while trust has been incorporated into TPB extensions in technology use (Wu and Chen, 2005), its role as an antecedent of attitude remains underexplored in the context of medical AI adoption, particularly among young consumers in transitional economies. Given potentially high levels of perceived uncertainty and limited user experience with AIMDSS, owing to its nascent stage of adoption, initial trust is likely to play a foundational role in shaping early evaluative judgments.

Hypothesis Development

Grounded in the extended TPB framework, four hypotheses are proposed to examine the intention to adopt AIMDSS among young consumers in Vietnam. Attitude is defined as the individual's positive or negative evaluation of performing a behavior (Ajzen, 1991). In the context of medical AI, attitude reflects whether the user perceived the usage of AIMDSS positively, for instance, in terms of its potential to improve decision-making, enhance convenience, or support better health outcomes. A favorable attitude typically leads to a stronger intention to adopt technology. Empirical research has consistently shown that attitude is a key determinant of technology use, including in healthcare (Zhao et al., 2018). For example, Hussein et al. (2017) found that consumer attitude significantly and positively influences the intention to use mHealth services, highlighting attitude as a key predictor of adoption behavior.. Following that, we propose:

H1: Attitude toward using AIMDSS positively influences the intention to adopt it

Perceived behavioral control refers to the perceived ease or difficulty of performing a behavior, influenced by access to resources, time, and knowledge (Ajzen, 1991). In healthcare setting, this can be interpreted as the perception of how easy the AIMDSS is to access, and integrate into medical examination practice. When users believe that adoption is within their control, their intention to adopt increases. This relationship has been supported across multiple health IT studies (Ye et al., 2019; Zhao et al., 2018), thus we propose:

H2: Perceived behavioral control positively influences the intention to adopt AIMDSS.

Subjective norm is defined as the perceived social pressure to engage or not engage in a behavior (Ajzen, 1991). In collectivist cultures like Vietnam, social influence from family, friends, and healthcare professionals can strongly affect adoption decisions. When individuals perceive that others support or expect them to use AIMDSS, their intention to adopt is likely to increase. Prior research has shown that subjective norms significantly predict digital health adoption, particularly in contexts where professional or peer recommendations are influential (Ye et al., 2019; Zhao et al., 2018). Therefore, the third hypothesis is as followed:

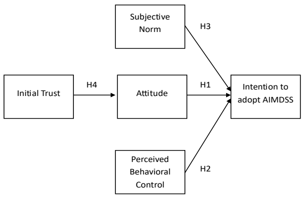
H3: Subjective norm positively influences the intention to adopt AIMDSS.

Initial trust is defined as the belief in the reliability, competence, and integrity of a system prior to any direct experience (McKnight et al., 2002). For novel technologies like AIMDSS, users must often decide whether to trust the system based on indirect cues such as brand reputation, endorsements, or perceived credibility. Trust reduces uncertainty and facilitates the formation of positive attitudes (Gefen et al., 2003). Study of Wu and Chen (2005) on technology adoption in e-commerce have shown that trust positively influences consumer attitudes, extending this logic to healthcare, we hypothesize that:

H4: Initial trust in AIMDSS positively influences attitude toward using it.

Based on the TPB model, we proposed the research work incorporating intention to use AIMDSS, attitude, perceived behavioral control, subjective norm and initial trust (see Figure 1).

Figure 1. Proposed Research Framework



3. Methodology

This study aimed to examine the factors influencing young consumers' intention to adopt the AI-based Medical Decision Support System (AIMDSS), focusing on individuals aged 18 to 30. A quantitative approach was chosen to empirically test the proposed model. Measurement items were adapted from established literature. Constructs related to attitude, perceived behavioral control, subjective norm, and intention were drawn from Ajzen's (1991), while items assessing initial trust were adapted and modified from Oliveira et al. (2014). All variables were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The final questionnaire comprised items representing the five core constructs, followed by demographic questions covering gender, age, occupation, and monthly income.

To ensure clarity and consistency in understanding, a brief description of the AIMDSS was provided at the beginning of the questionnaire. The original English items were translated into Vietnamese using a back-translation process to maintain semantic equivalence. A pilot test was conducted with a small group of young consumers, and necessary modifications were made based on their feedback to ensure clarity and appropriateness of the content.

Data collection and analysis

Participants were recruited through offline channels, targeting young individuals either studying at universities or employed in early-stage careers. A total of 216 valid responses were collected and included in the final analysis. The demographic characteristics of the sample are summarized in Table 1.

Table 1. Sample characteristics

Variable	Type	Frequency	Percentage
Gender	Male	106	49.10%
	Female	110	50.90%
Age	18 - 20	111	51.39%
	21 - 25	82	37.96%
	26 - 30	23	10.65%
Monthly income (VND)	< 5 million	109	50.46%
	5 -10 million	50	23.15%
	10-15 million	27	12.50%
	15-20 million	14	6.48%
	20-25 million	6	2.78%
	> 25 million	10	4.63%
Occupation	Student	143	66.20%
	Management	6	2.80%
	Marketing/ Sales	12	5.60%
	Administrative jobs	41	19%
	Other	14	6.50%

The proposed research framework was evaluated using PLS-SEM. Given the early stage of medical AI adoption and the lack of established distributional assumptions for the target population, PLS-SEM was deemed an appropriate analytical approach (Hair et al., 2019). The analysis followed a two-step procedure by assessing the measurement model using the PLS algorithm, and followed by evaluating the structural model through a bootstrapping procedure (Hair et al., 2019).

4. Results and discussion

4.1. Measurement model assessment

Measurement model assessment started with examining outer loadings, composite reliability (CR), and Average Variance Extracted (AVE). All outer loadings exceeded the recommended threshold of 0.70, indicating that the measurement items have strong indicator reliability and adequately reflect their respective constructs. This result confirms the convergent validity of the measurement model, as suggested by Hair et al. (2019).

Table 2. Outer loadings of measurement items

	ATT	INT	PBC	SN	IT
ATT1	0.885				
ATT2	0.842				
ATT3	0.886				
INT1		0.903			

	ATT	INT	PBC	SN	IT
INT2		0.928			
INT3		0.853			
INT4		0.893			
PBC1			0.794		
PBC2			0.821		
PBC3			0.771		
SN1				0.858	
SN2				0.865	
SN3				0.819	
SN4				0.882	
IT2					0.891
IT3					0.873
IT4					0.92

Table 3. Reliability of Measurement

	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Attitude	0.842	0.904	0.759
Intention	0.916	0.941	0.8
Perceived Behavioral Control	0.71	0.838	0.633
Subjective Norm	0.878	0.917	0.733
Initial Trust	0.876	0.924	0.801

All constructs demonstrated acceptable internal consistency, with Cronbach's alpha and composite reliability values exceeding the recommended threshold of 0.70, indicating good reliability (Hair et al., 2019). One item (IT1) was excluded from the initial trust construct due to its Cronbach's alpha falling below the acceptable threshold. Furthermore, the average variance extracted (AVE) values for all constructs were above the 0.50 threshold, confirming satisfactory convergent validity of the measurement model.

Table 4. Discriminant Validity

	Attitude	Intention	Perceived Behavioral Control	Subjective Norm
Attitude				
Intention	0.816			
Perceived Behavioral Control	0.623	0.657		
Subjective Norm	0.782	0.644	0.469	
Initial Trust	0.766	0.555	0.47	0.697

Discriminant Validity - HTMT < 0.9 (for conceptually similar construct)

The discriminant validity of the constructs was assessed using the Heterotrait-Monotrait ratio (HTMT). All HTMT values ranged from 0.469 to 0.816, which are below the conservative threshold of 0.85 suggested by (Hair et al., 2019). These results provide evidence of adequate discriminant validity, indicating that each construct in the model is empirically distinct from the others (table 4).

Multicollinearity was assessed using the Variance Inflation Factor (VIF). All VIF values were below the conservative threshold of 3.3, as recommended by Hair et al. (2019) and Kock (2015), indicating that multicollinearity is not a concern in the structural model. Furthermore, based on Kock's (2015) full collinearity assessment approach, VIF values below 3.3 also suggest that common method bias is unlikely to be a significant issue. These findings support the stability and reliability of the path coefficient estimates.

Structural model assessment

Table 5. Structural model assessment

Endogenous latent constructs	R^2	Q^2	Effect size
Attitude	0.437	0.432	Moderate
Intention	0.564	0.406	Moderate

The explanatory power of the structural model was evaluated using the coefficients of determination (R^2) and predictive relevance (Q^2). The R^2 values for Attitude (0.437) and Intention (0.564) indicate moderate explanatory power, as values between 0.33 and 0.67 are considered moderate (Hair et al., 2019). Similarly, the Q^2 values of 0.432 for Attitude and 0.406 for Intention also demonstrate moderate predictive relevance, confirming that the model has satisfactory predictive accuracy. The effect sizes further support these findings, indicating that the predictors contribute meaningfully to the explained variance of the endogenous constructs.

Hypothesis Testing

Table 6. Hypothesis Test

Direct effect	Path coefficients	f^2	P values	Hypothesis	Result
Attitude -> Intention	0.501	0.281	0	H1	Supported
Perceived Behavioral Control -> Intention	0.231	0.785	0	H2	Supported
Subjective Norm -> Intention	0.154	0.095	0.03	H3	Supported
Initial Trust -> Attitude	0.663	0.03	0	H4	Supported

To examine the proposed hypotheses, a bootstrapping procedure with 5,000 resamples was employed, using a two-tailed test at a 0.05 significance level. The detailed results of the hypothesis tests are presented in Table 6

The results of the structural model analysis support all proposed hypotheses. Attitude had a significant and strong positive effect on Intention ($\beta = 0.501$, $p < 0.001$, $f^2 = 0.281$), confirming H1. Perceived Behavioral Control also significantly influenced Intention ($\beta = 0.231$, $p < 0.001$), with a large effect size ($f^2 = 0.785$), supporting H2. Subjective Norm exhibited a weaker but still significant effect on Intention ($\beta = 0.154$, $p = 0.03$, $f^2 = 0.095$), supporting H3. Additionally, Initial Trust had a strong and significant impact on Attitude ($\beta = 0.663$, $p < 0.001$, $f^2 = 0.03$), supporting H4. These findings indicate that all hypothesized relationships are statistically significant and contribute meaningfully to the model.

This study examined young consumers' intention to adopt AI-based Medical Decision Support Systems (AIMDSS) using the Theory of Planned Behavior (TPB), extended with initial trust. All four hypothesized relationships were supported. Attitude emerged as a strong predictor of intention, confirming prior findings that favorable evaluations drive behavioral intentions in technology adoption (Ajzen, 1991). Perceived behavioral control (PBC) also showed a significant influence with a large effect size, suggesting that when young users feel capable and perceive low usage barriers, their intention to adopt would be higher, a finding consistent with Ye et al. (2019).

Subjective norm had a smaller but significant effect, indicating that while close social referents such as friends, family, and significant others do influence young consumers' intention to adopt AIMDSS, their impact is less pronounced compared to individual factors like personal attitude and perceived behavioral control. Additionally, our model found that initial trust significantly influenced attitude, supporting its role as a key antecedent in high-uncertainty contexts like AI adoption (Gefen et al., 2003; McKnight et al., 2002) since it is considered to reduce perceived risk and enhanced confidence in the system's reliability, fostering more favorable attitudes, consistent with findings in fintech and online service adoption (Kim et al., 2008; Pavlou and Fygenson, 2006).

Theoretically, this study extends the Theory of Planned Behavior (TPB) by incorporating initial trust as an antecedent to attitude. While prior research has examined the direct effect of initial trust on attitude in domain such as e-commerce (e.g., Wu and Chen, 2005), this relationship remains underexplored in the healthcare context, particularly in relation to AI-driven systems. Existing studies on trust in medical AI have primarily focused on its direct influence on intention to use (Tran et al., 2021), or its moderating role in the relationship between perceived usefulness and intention (Ye et al., 2019). By positioning initial trust as a precursor to attitude, this study provides new theoretical insight into how trust shapes early-stage evaluations of AI in healthcare, thereby strengthening the TPB's ability to explain user adoption of healthcare technologies in uncertain and unfamiliar settings.

Practically, this study suggests that developers and marketers should prioritize strategies that foster initial trust, such as enhancing system transparency, leveraging endorsements from credible experts, and incorporating interface elements that signal reliability and professionalism. To strengthen subjective norms, social marketing efforts may focus on showcasing peer adoption and trusted authority recommendations to reinforce social approval. Additionally, improving usability and ensuring digital accessibility can enhance users' perceived behavioral control, thereby increasing their intention to adopt AIMDSS.

This study is subject to some limitations, including its reliance on a single-country context and a sample composed primarily of young consumers, which may limit the generalizability of the findings to other age groups and cultural settings. Thus, future research should seek to validate the extended TPB model for AI adoption in healthcare setting across broader demographic segments and in different cultural or economic contexts to assess its generalizability. Additionally, longitudinal studies tracking actual adoption behavior, as well as deeper exploration of multi-dimensional trust constructs, would offer valuable insights into the sustained use of medical AI systems over time.

Conclusion: This study investigated the factors influencing young consumers' intention to adopt AI-based Medical Decision Support Systems (AIMDSS) in a transitional economy, using an extended Theory of Planned Behavior (TPB) framework. The results affirmed the significance of attitude, perceived behavioral control, and subjective norm in predicting intention, while also establishing initial trust as a critical antecedent of attitude. By integrating initial trust into TPB, the study offers a theoretical advancement in understanding how trust facilitates favorable evaluations of emerging technologies in high-uncertainty contexts like medical AI. Practically, the findings highlight the importance of designing trustworthy, accessible, and socially supported systems to enhance user acceptance. These insights are particularly valuable for health tech developers, marketers, and policy-makers seeking to drive consumer adoption of AI in transitional markets such as Vietnam. Future research should extend this model across populations and contexts, and explore how trust is formed, evolves, and interacts with behavioral drivers over time.

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