

## **Factors influencing intention to use home healthcare service in Vietnam: A study using the TAM approach**

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**Abstract:** This study investigates the key cognitive, social, and structural determinants influencing Vietnamese consumers' behavioral intention to adopt Home Healthcare Services (HHCS), an emerging healthcare model increasingly supported by telehealth technologies. A quantitative research design was applied using an online survey distributed in major urban centers in Vietnam. Convenience sampling yielded 766 valid responses. The proposed model integrates constructs from TAM/TPB and the COM-B framework, including perceived usefulness, ease of use, reliability, social influence, capability, affordability, attitude, and behavioral intention. Structural Equation Modeling (SEM) was employed to test hypothesized relationships. Results show that perceived usefulness, ease of use, and reliability significantly enhance consumers' attitudes toward HHCS. Financial cost and affordability emerged as the strongest predictors of adoption intention ( $\beta = 0.288$ ), followed by social influence ( $\beta = 0.250$ ), attitude ( $\beta = 0.190$ ), and capability ( $\beta = 0.183$ ). Educational level was also positively associated with intention. The findings confirm that HHCS adoption in Vietnam is driven strongly by practical affordability and collectivist social norms. Service providers and policymakers should therefore prioritize affordable pricing strategies, strengthen service trust, and leverage community influence to promote sustainable HHCS development in emerging markets.

**Keywords:** *Behavioral intention, Emerging markets, Health technology acceptance, Healthcare services (HHCS), Integrated theoretical framework, Technology adoption, Vietnam.*

### **1. Introduction**

Home healthcare services (HHCS) refer to the provision of medical diagnosis, treatment, and follow-up care by professionals at a patient's residence. This model represents an emerging paradigm in healthcare delivery, propelled by converging global trends such as population aging, the rising prevalence of chronic diseases, and rapid advancements in digital health technology. These forces have elevated HHCS as a promising approach to extend care beyond traditional hospital settings and improve healthcare access and efficiency.

However, existing research on HHCS adoption has largely concentrated on developed countries such as the United States, Canada, and the Netherlands [1]. These studies offer valuable insights into clinical efficacy and cost reduction but often overlook the context of developing economies, where adoption determinants can differ markedly. Vietnam serves as a compelling example: unique cultural norms (for example, a traditional preference for hospital-based care) and socio-psychological factors strongly influence consumer attitudes toward HHCS [2]. More broadly, prior evidence from Vietnam and other ASEAN countries suggests that institutional conditions, policy environments, and socio-economic vulnerabilities in emerging economies shape individual and organizational responses to new service models, especially under conditions of systemic stress [3]. Such differences underscore the need to investigate HHCS adoption in settings with distinct cultural and economic conditions.

In addition, much of the literature employs established theoretical frameworks – notably the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM) [4], and the Unified Theory of Acceptance and Use of Technology (UTAUT) [5] – to explain technology adoption. While these models provide useful insights, each on its own addresses only certain facets of the decision process. Applied in isolation, they may not fully capture the multi-dimensional complexity of consumers' decisions to adopt HHCS. In particular, traditional technology acceptance models tend to emphasize individual cognitive beliefs (e.g., perceived usefulness) and assume other conditions remain favorable, which may not hold true in the healthcare context of an emerging market.

In Vietnam, the appeal of HHCS extends beyond global trends to address urgent domestic healthcare challenges. A key issue is severe hospital overcrowding: major central hospitals often receive 6,000–8,000 patient visits per day (according to Hanoinews), including a large share of patients from provincial areas. HHCS presents a viable strategy to alleviate this burden by enabling patients to receive care at home. The need for such services is further heightened by rapid demographic and epidemiological shifts. By 2025, Vietnam is projected to have 16.1 million elderly people, accounting for over 16% of the population (according to Ministry of Health reports). Population aging, coupled with rising rates of chronic conditions such as cardiovascular disease, diabetes, and musculoskeletal disorders, is driving an escalating demand for ongoing medical care. In an overburdened healthcare system, HHCS can help meet this demand by providing convenient and flexible care for patients while reducing the load on hospitals. The government has recognized this potential through supportive policies – for instance, a revised Health Insurance Law effective July 2025 extends insurance coverage to home healthcare for certain groups, which further facilitates the adoption of HHCS.

Given these gaps and needs, the present study sets out to investigate the drivers and barriers influencing the intention to use HHCS in Vietnam, and to provide evidence-based insights for both healthcare policymakers and service providers. To achieve this, we adopt a comprehensive integrated framework that addresses the limitations of prior single-theory approaches. In particular, our model extends traditional technology acceptance constructs (such as perceived usefulness and perceived ease of use) by incorporating critical health-specific factors like perceived health threats and service reliability. Moreover, rather than relying on any single theoretical lens, the model concurrently examines cognitive drivers (e.g., attitude), social influences (e.g., social influence or subjective norms), and key structural enablers (notably user capability and financial cost) within one unified approach. This synthesis bridges the gap between individual technology acceptance perspectives and the practical, structural barriers emphasized in health behavior models. Through this approach, the study aims to develop a holistic understanding of HHCS adoption in an emerging market context. Ultimately, our findings are intended to inform the design of patient-centered services and effective public health strategies, thereby fostering the sustainable development of the home healthcare ecosystem in Vietnam.

## 2. Literature Review

### 2.1. The Theoretical Background of Home Healthcare Service (HHCS)

Home healthcare service (HHCS) is a model of providing medical care at patients' residences. Initially, this concept served as an alternative to inpatient treatment by licensed medical professionals [6, 7]. However, advancements in health information technology have profoundly reshaped this model [8]. Today, HHCS encompasses not only direct in-person visits but also strongly integrates digital tools such as video calls, remote monitoring, and mobile health applications [9]. This combination enables continuous, personalized care and reduces costs while maintaining efficacy [10]. Consequently, modern definitions now characterize HHCS as a hybrid of physical and telehealth services, creating a 'smart medical home' ecosystem [9].

Inheriting these perspectives, home healthcare services (HHCS) are defined as a range of healthcare services provided by multidisciplinary healthcare professionals at the patient's home, such as initial diagnosis, provision of clinical services, acute care, post-acute care, and treatment of chronic diseases.

This model integrates both in-person visits and remote consultations, monitoring, and telehealth examinations.

## 2.2. Relevant Theoretical Frameworks

### 2.2.1. Technology Acceptance (TAM) and Unified (UTAUT) Frameworks

Davis [11] The Technology Acceptance Model (TAM) posits that usage intention is primarily governed by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). In the health context, TAM has been widely applied to explore the acceptance of technologies such as electronic health records and eHealth/mHealth. While meta-analyses consistently affirm these antecedents in health contexts, TAM's parsimony often fails to encompass the multidimensionality of complex healthcare domains, lacking the capacity to account for broader contextual or organizational factors.

To mitigate this limitation, Venkatesh et al. [12] introduced the Unified Theory of Acceptance and Use of Technology (UTAUT), which synthesized eight foundational theories to incorporate key determinants like Social Influence and Facilitating Conditions. In the health domain, UTAUT is regarded as a comprehensive framework capable of reflecting organizational support; nevertheless, the mechanistic application of these models in isolation remains contested. Critiques indicate that such approaches invisibly overlook exogenous factors, including cultural context, idiosyncratic trust in medical services, and critically, the patient's capability and resources. Consequently, while robust in explaining technology acceptance, these models may insufficiently capture the specific psychological and structural barriers endemic to health behavior.

### 2.2.2. The Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB), introduced by Ajzen [13], provides a powerful model for understanding and predicting human behavior through three key constructs. In the healthcare context, TPB has served as a valuable framework, positing that behavioral intention is the central predictor of actual behavior, and this intention is formed by: (1) Attitude toward the behavior, (2) Subjective Norm, and (3) Perceived Behavioral Control.

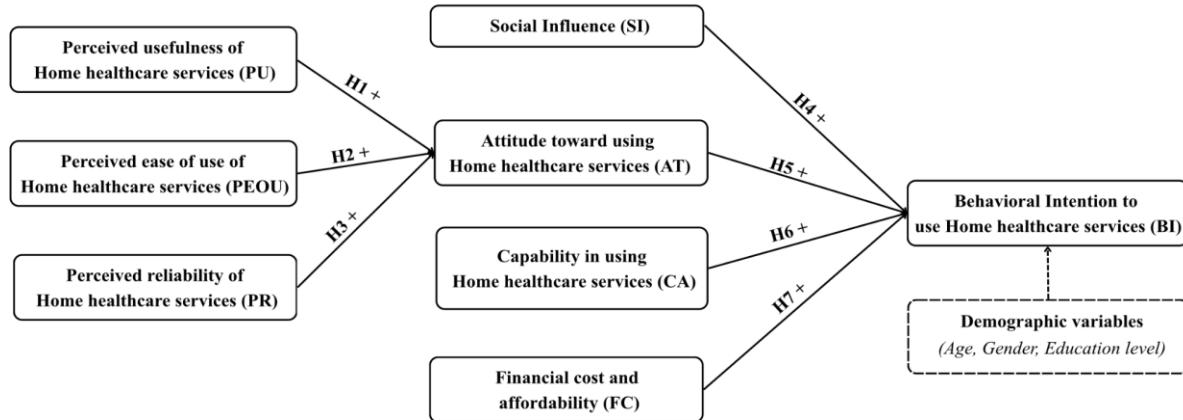
While valuable in healthcare contexts, the model is constrained by the intention-behavior gap [14, 15], implying that intentions do not invariably translate into action. Nevertheless, in emerging markets like Vietnam, where HHC is nascent, measuring intention remains scientifically valid as a proximal predictor of future adoption potential. However, a critical limitation lies in the broadness of the PBC construct, which fails to clearly differentiate between external structural barriers and internal capabilities, necessitating a more nuanced theoretical approach.

### 2.2.3. The Capability-Opportunity-Motivation-Behavior (COM-B) Framework

To address the structural limitations of prior frameworks, Michie et al. [16] offer a comprehensive behavior system, positing that behavior is contingent upon the interaction of Capability, Opportunity, and Motivation. Crucially, this framework isolates internal capability from external opportunity; in health service contexts, recent studies identify financial affordability as a critical dimension of the latter, significantly influencing access even when motivation is present. Although some practitioners deem COM-B complex, it provides a necessary lens to transcend the purely cognitive focus of TAM or TPB, facilitating the examination of practical enablers and barriers, specifically actual skills and affordability, that determine whether an individual can perform the behavior. Consequently, as no single theory fully captures the complexity of HHC adoption, an integrated approach is requisite: TAM/UTAUT elucidate technology acceptance, TPB provides core psychological drivers, and COM-B integrates practical structural and capability barriers, thereby offering a comprehensive understanding of adoption determinants in Vietnam.

### 2.3. Hypothesis Development

The proposed research model integrates TAM, UTAUT, TPB, and COM-B frameworks to comprehensively elucidate the intention to use HHCS services.



**Figure 1.**  
The conceptual model.

Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance his or her job performance [11]. In the health context, perceived usefulness is a primary driver. If users do not believe HHCS is more useful than visiting doctors, they will not form a positive attitude. Research has consistently shown that PU is a strong predictor of attitude, both for physicians [17] and patients [18]. However, prior empirical evidence is largely contextualized within developed markets; the extent to which this factor impacts the Vietnamese context remains to be validated. To examine this potential discrepancy, the following hypothesis is formulated:

*H<sub>1</sub>: Perceived usefulness of HHCS positively influences the attitude toward using HHCS.*

Perceived ease of use is the belief that using the service, including its related technology platforms, will not demand significant effort [11]. HHCS requires users to interact with new processes or technologies (e.g., online booking, video consultations). If this process is perceived as complex, it creates a psychological barrier, dampening positive attitudes even if the service is deemed useful. Numerous studies in the health domain have affirmed that when users perceive health technology as easy to use, their attitudes become more favorable [19, 20]. However, these inquiries are typically situated in contexts with high digital health literacy. Conversely, as the deployment of technology for in-home healthcare is a relatively new phenomenon in Vietnam, the following hypothesis is advanced:

*H<sub>2</sub>: Perceived ease of use of HHCS positively influences the attitude toward using HHCS.*

Perceived reliability is the patient's trust in the physician's professional competence, service consistency, and data safety and security [21]. In the healthcare domain, perceived risk is exceptionally high. HHCS also introduces idiosyncratic concerns about privacy (e.g., allowing strangers into the home) and the quality of remote diagnostics [22]. Therefore, reliability is not merely an additive factor but a prerequisite. Without this fundamental trust in the provider, users cannot form a positive attitude [23]. However, the lack of empirical evidence regarding this determinant's effect in the Vietnamese social setting highlights a critical research gap. Thus, the following hypothesis is suggested:

*H<sub>3</sub>: Perceived reliability of HHCS positively influences the attitude toward using HHCS.*

Social influence, a key construct in both UTAUT and TPB, is the perceived pressure from significant others (e.g., family, friends, physicians) that the individual should use the service [12]. HHCS is a relatively new and uncommon service. In a context of uncertainty regarding a new service,

individuals tend to seek social validation [24]. The opinions and experiences of those they trust will play a critical role in shaping intention. Studies on new health technologies have shown social influence to be a strong predictor of intention [25, 26]. Furthermore, in a culture characterized by high collectivism, such as Vietnam, pressure from reference groups is expected to be amplified. Therefore, the following hypothesis is proposed:

*H<sub>4</sub>: Social influence positively influences the behavioral intention to use HHCS.*

Attitude is the individual's overall positive or negative evaluation of using the service [13]. According to TPB, attitude is the most direct and important predictor of intention. Attitude functions as a central processor, synthesizing beliefs about benefits (H1), effort (H2), and risks (H3) into a general stance. If this overall evaluation is positive, behavioral intention will be formed. This relationship has been shown to be robust in numerous health behavior studies [27, 28]. Therefore, the following hypothesis was proposed:

*H<sub>5</sub>: Attitude toward using the service positively influences the behavioral intention to use HHCS.*

Capability, deriving from the COM-B model, is the individual's psychological or knowledge and physical ability or skills to use the service [16]. This pertains to whether users believe they possess sufficient technological skills and basic health literacy to manage the service at home. If individuals feel incapable (e.g., technologically unskilled, unable to understand instructions), they will hesitate to form an intention, even if their attitude is positive. Studies on m-health have confirmed that self-efficacy is a pivotal factor in determining intention [29, 30]. Although many international studies have confirmed capability as a key factor influencing the adoption of technology-based healthcare services, these studies were predominantly conducted in nations with mature digital health ecosystems. Conversely, in the Vietnamese context, where the application of technology in home healthcare remains relatively novel, the author proposes the following hypothesis:

*H<sub>6</sub>: Capability in using the service positively influences the behavioral intention to use HHCS.*

Financial cost and affordability are factors within the Opportunity component of COM-B. Dodds et al. [31] conceptualize financial cost and affordability as a cognitive trade-off between perceived benefits from the system and the monetary sacrifice for its use. Regardless of positive attitudes, strong social influence, or high personal capability, if the service is perceived as unaffordable, intention will not be formed. It functions as a gatekeeping factor. Empirical evidence consistently shows that high cost is one of the greatest barriers to accessing health services [32] and that affordability is a significant predictor of willingness to use at-home services [33]. Synthesizing the practical observations above within the theoretical constructs of the COM-B model, the following hypothesis is formulated:

*H<sub>7</sub>: Financial cost and affordability positively influence the behavioral intention to use HHCS.*

### 3. Research Methodology

#### 3.1. Data Collection and Analysis

According to Hair et al. [34], the minimum sample size is calculated using the formula  $n=5\times m$ , where  $m$  is the number of observed variables in the model. Since the measurement scale developed by the authors includes 40 observed variables, the required minimum sample size is  $40\times 5=200$  observations. After establishing the minimum sample size, data collection was conducted using a non-probability convenience sampling method, targeting individuals over 18 years old living and working in three major cities: Hanoi, Ho Chi Minh City, and Da Nang.

The survey was administered via a dual-mode approach: online through Google Forms distributed on health and medical forums (targeting the 18-30 age group) and face-to-face at hospitals, polyclinics, and medical centers (targeting the over-30 age group). A total of 802 questionnaires were collected. After a screening process to eliminate invalid responses, 766 valid responses were retained for the study. The data were processed using SPSS 26.0 and AMOS 24 software for analysis.

### 3.2. Research Instrument

The research instruments, including the questionnaire, were designed based on adaptations from previous studies. The questionnaire is divided into two sections. The initial section gathers demographic information from the participants, including their age, gender, and education level. The subsequent section probes into variables or factors relevant to the research model, encompassing a total of eight variables: Perceived usefulness (PU), Perceived ease of use (PEOU), Perceived reliability (PR), Social influence (SI), Attitude toward using (AT), Capability in using (CA), Financial cost and affordability (FC), and Behavioral intention (BI). All items were measured using a 5-point Likert scale, ranging from (1) "Strongly disagree" to (5) "Strongly agree".

## 4. Research Results

### 4.1. The Characteristics of the Participants

Among the 766 survey participants, the study recorded 328 male respondents (42.8%) and 438 female respondents (57.2%). To ensure data validity, the target population was defined as service users aged 18 and above. The sample was stratified into four age groups: under 30 years (137 respondents, 17.9%); 30 to under 45 years (159 respondents, 20.8%); 45 to under 60 years (250 respondents, 32.6%); and 60 years and above (220 respondents, 28.7%). Regarding educational level, the statistics reveal that 58 observations were at the high school level (7.6%). The majority, 505 observations (65.9%), were at the college/university level, while the postgraduate group comprised 203 observations (26.5%).

### 4.2. Measurement Model Validation

Before testing the hypotheses, the measurement model was rigorously assessed for reliability and validity.

#### 4.2.1. Reliability Test (Cronbach's Alpha)

To ensure the internal consistency and reliability of the scales, Cronbach's Alpha (CA) was calculated for all eight constructs. The results show that all scales demonstrated high reliability. The Cronbach's Alpha coefficients ranged from 0.819 to 0.866, all of which comfortably exceed the recommended threshold of 0.60, indicating that all measurement scales are reliable for further analysis.

#### 4.2.2. Exploratory Factor Analysis (EFA)

An EFA was subsequently conducted to assess the underlying factor structure of the measures. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were first performed. As depicted in Table 1, the KMO result is suitable for EFA.

**Table 1.**

Kaiser-Meyer-Olkin (KMO) and Bartlett's Test.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.969
Bartlett's Test of Sphericity	Approx. Chi-Square	17927.914
	df	1225
	Sig.	0.000

The EFA, using principal component analysis, successfully extracted eight distinct factors with eigenvalues greater than 1.0. These eight factors accounted for 56.781% of the total variance, which is above the 50% threshold. Furthermore, as indicated in Table 2, the pattern matrix confirmed that all observational variables loaded appropriately on their intended factors with high loadings, and no significant cross-loadings were observed, ensuring construct validity.

**Table 2.**  
Total Variance Explained (Extraction Sums of Squared Loadings).

Component	Factor Loading	Component	Factor Loading
PU7	0.860	CA3	0.799
PU5	0.813	CA6	0.735
PU4	0.716	CA1	0.717
PU6	0.703	CA2	0.712
PU3	0.693	CA5	0.662
PU2	0.641	CA4	0.640
PU1	0.626	PEOU1	0.764
FC4	0.830	PEOU6	0.747
FC5	0.781	PEOU4	0.740
FC2	0.749	PEOU5	0.719
FC3	0.737	PEOU3	0.678
FC6	0.722	PEOU2	0.676
FC7	0.628	AT3	0.729
FC1	0.591	AT1	0.728
SI3	0.794	AT2	0.714
SI6	0.765	AT4	0.691
SI4	0.739	AT6	0.676
SI5	0.736	AT5	0.583
SI2	0.723	BI2	0.784
SI1	0.698	BI5	0.745
PR4	0.791	BI1	0.701
PR5	0.760	BI4	0.699
PR2	0.751	BI6	0.684
PR3	0.749	BI3	0.651
PR6	0.640	CA3	0.799
PR1	0.640	—	—

#### 4.2.3. Confirmatory Factor Analysis (CFA)

Following the EFA, a CFA was performed to confirm the validity of the measurement model. An initial run (Run 1) yielded acceptable model fit indices; however, convergent validity was not established as the Average Variance Extracted (AVE) for several constructs (PU, FC, PR, CA, PEOU, AT, BI) was below the 0.5 threshold. After removing the problematic items, a second-run CFA (Run 2) was conducted. The revised model demonstrated an excellent fit to the data. As shown in Table 3, all model fit indices were in the acceptable to good range.

**Table 3.**  
CFA Model Fit Indices (2nd).

Index	Value	Recommended Threshold
Chi-square/df	1.395	< 3
GFI	0.935	> 0.90
CFI	0.979	> 0.90
RMSEA	0.023	< 0.08
PCLOSE	1.000	> 0.05

Furthermore, the revised model achieved both convergent and discriminant validity. As detailed in Table 4, the Composite Reliability (CR) for all constructs was above 0.70, and the AVE for all constructs was above 0.50. Discriminant validity was also confirmed, as the square root of the AVE for each construct (bolded diagonal values) was greater than its corresponding inter-construct correlations.

**Table 4.**  
Convergent and Discriminant Validity (2nd).

Construct	CR	AVE	PU	FC	SI	PR	CA	PEOU	AT	BI
PU	0.860	0.507	0.712							
FC	0.870	0.526	0.650	0.725						
SI	0.863	0.512	0.660	0.669	0.716					
PR	0.834	0.502	0.638	0.662	0.657	0.709				
CA	0.838	0.508	0.652	0.654	0.688	0.665	0.713			
PEOU	0.839	0.511	0.646	0.677	0.687	0.647	0.681	0.715		
AT	0.840	0.511	0.686	0.678	0.642	0.667	0.668	0.668	0.715	
BI	0.846	0.523	0.678	0.705	0.688	0.658	0.669	0.680	0.658	0.723

#### 4.3. Hypothesis Testing

To test the research hypotheses, Structural Equation Modeling (SEM) was employed. The structural model also exhibited an excellent fit to the data (Chi-square/df = 1.438; GFI = 0.932; CFI = 0.976; RMSEA = 0.024), allowing the evaluation of the hypothesized paths.

As detailed in Table 5, the results indicate that all seven hypotheses (H1–H7) were statistically significant and supported ( $p < .05$ ).

*Impact on Attitude (AT):* All three antecedents positively and significantly influenced AT. Perceived Usefulness (PU) (Estimate = 0.372,  $p < .001$ ), Perceived Ease of Use (PEOU) (Estimate = 0.299,  $p < .001$ ), and Perceived Reliability (PR) (Estimate = 0.302,  $p < .001$ ) all had a positive impact. Thus, H1, H2, and H3 were accepted.

*Impact on Behavioral Intention (BI):* All four factors hypothesized to directly influence BI were significant. Financial Cost (FC) (Estimate = 0.288,  $p < .001$ ) emerged as the strongest direct predictor. Social Influence (SI) (Estimate = 0.250,  $p < .001$ ), Capability (CA) (Estimate = 0.183,  $p < .001$ ), and the mediating variable Attitude (AT) (Estimate = 0.190,  $p < .001$ ) also showed significant positive impacts. Thus, H4, H5, H6, and H7 were accepted.

**Table 5.**  
Results of Hypotheses Testing (SEM)

Hypothesis	Path	Estimate	S.E.	C.R.	P	Conclusion
H1	AT <--- PU	0.372	0.057	6.572	***	Accepted
H2	AT <--- PEOU	0.299	0.054	5.583	***	Accepted
H3	AT <--- PR	0.302	0.054	5.594	***	Accepted
H4	BI <--- SI	0.250	0.055	4.540	***	Accepted
H5	BI <--- FC	0.288	0.049	5.853	***	Accepted
H6	BI <--- CA	0.183	0.051	3.596	***	Accepted
H7	BI <--- AT	0.190	0.044	4.300	***	Accepted

Note: \*\*\*  $p < 0.001$ .

The explanatory power of the model was substantial. The antecedents (PU, PEOU, PR) explained 62.7% of the variance in Attitude ( $R^2 = 0.627$ ). The complete model collectively explained 63.8% of the variance in Behavioral Intention ( $R^2 = 0.638$ ). Mediation analysis (via bootstrapping,  $N = 2000$ ) confirmed that AT significantly mediates the relationships from PU, PEOU, and PR to BI ( $p < .001$ ), with PU exerting the strongest indirect effect ( $\beta = 0.067$ ). The bootstrap results also confirmed the stability of all path estimates, with Bias/SE-Bias ratios well below.

#### 4.4. Analysis of Demographic Variables

A one-way analysis of variance (ANOVA) was conducted to examine the influence of demographic variables on behavioral intention (BI). The results found no statistically significant differences in BI based on respondents' age or geographic location.

However, a significant difference was found among groups based on education level (Welch's  $F(2, 145.458) = 157.293, p < .001$ ). As illustrated in Table 6, post-hoc comparisons indicated a clear positive

relationship: BI scores were lowest among the High School group ( $M = 2.10$ ) and significantly higher among the University/College group ( $M = 3.66$ ) and the Post-graduate group ( $M = 3.79$ ).

**Table 6.**

Descriptives: Behavioral Intention (M\_BI) by Education Level.

Education Level	N	Mean	Std. Deviation
Highschool	58	2.1000	0.64482
University/College	505	3.6618	0.66260
Post-graduate	203	3.7901	1.12642
Total	766	3.5775	0.91513

## 5. Discussion

The analysis reveals that among the three cognitive factors influencing attitude, Perceived Usefulness (PU) exerts the strongest influence ( $\beta = 0.334$ ), followed by Perceived Ease of Use (PEOU) ( $\beta = 0.287$ ) and Perceived Reliability (PR) ( $\beta = 0.286$ ). The emphasis on PU is consistent with the core propositions of the Technology Acceptance Model (TAM) [11], which posits PU as a primary determinant of attitude. This result also aligns with prior research in health technology contexts, which often finds usefulness to have a stronger impact than ease of use [12]. The specific order of influence in the Vietnamese HHCS context (PU > PEOU > PR) is intuitively significant: users are first concerned with "does this service help me?" (usefulness), then "is it easy to use?" (ease of use), and finally "can I trust it?" (reliability).

Regarding the determinants of behavioral intention, the analysis indicates that Financial Cost and Affordability (FC) ( $\beta = 0.299$ ) and Social Influence (SI) ( $\beta = 0.242$ ) are the most potent predictors, followed by Attitude (AT) ( $\beta = 0.201$ ) and Capability (CA) ( $\beta = 0.190$ ). The emergence of Cost (FC) as the most influential factor is a critical finding. This result diverges from many traditional TAM studies where Attitude often demonstrates the strongest impact. TAM meta-analyses [35] frequently report substantially higher path coefficients from attitude to intention.

This discrepancy can be linked to Vietnam's specific socioeconomic context. HHCS is a new service, potentially perceived as premium, and in a market where out-of-pocket healthcare expenditures are significant, consumers are highly cost-conscious. Similarly, Social Influence ( $\beta = 0.242$ ) demonstrates a stronger impact than Attitude ( $\beta = 0.201$ ). This finding aligns with Vietnam's collectivist cultural context, where family and community ties are strong. It suggests that intention is influenced more by social norms and practical considerations (cost) than by mere attitudinal predispositions. This finding resonates with marketing literature in emerging markets, such as the work by Schepers and Wetzels [36] on consumer behavior.

Other behavioral determinants also significantly impact intention. Attitude, though significant, has a relatively modest impact ( $\beta = 0.201$ ), suggesting that a positive attitude alone is insufficient to overcome practical barriers. Capability (CA) also has a positive influence ( $\beta = 0.190$ ), confirming its theoretical role [37], but its modest coefficient suggests that the greater barriers may be structural (cost) rather than cognitive (skills) in this context.

These findings also contribute important theoretical reflections. First, the modest role of Attitude and the dominance of Cost challenge the classical assumptions of TAM/TPB in the specific context of high-level health services in an emerging market. Second, the significant influence of Cost (from COM-B) and Social Influence (from UTAUT) supports the extension of cognitive models (TAM) by integrating structural and social factors. Third, the dominant role of practical factors (Cost, Social Influence) over individual cognitive factors (Attitude, Capability) refines the model's applicability in the Vietnamese setting, underscoring that practical health decisions are strongly bound by economic barriers and collectivist norms.

## 6. Conclusion and Recommendations

This research provides important insights into the factors that shape consumers' intention to use home healthcare services in Vietnam. The findings confirm that key cognitive determinants from technology acceptance theory, namely Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Perceived Reliability (PR), have significant positive effects on users' attitude toward HHCS, with PU emerging as the most influential driver of a favorable attitude. A positive attitude, in turn, is expected to drive intention.

However, the study also reveals that the ultimate behavioral intention to adopt HHCS is governed more strongly by practical and social considerations than by attitude alone. Financial cost and affordability emerged as the single strongest predictor of intention to use HHCS, followed closely by social influence. These factors surpassed attitude in their impact on consumers' intent to adopt the service. This pattern differs from many classical technology adoption studies in which attitude is the primary determinant of intention. In the context of Vietnam's healthcare market, economic barriers and collectivist social norms appear to outweigh personal attitudinal beliefs when individuals decide whether to use home healthcare. Thus, a noteworthy conclusion is that consumers in this emerging economy prioritize tangible concerns, cost considerations, and social acceptance over purely individual perceptions. These findings enrich the understanding of HHCS adoption in developing contexts and underscore the importance of accounting for structural and cultural factors alongside individual cognitive factors.

From a theoretical standpoint, this study makes several contributions to the literature. First, it introduces an integrated model that combines elements of the Capability-Opportunity-Motivation-Behavior (COM-B) framework with established TAM/TPB constructs. By jointly considering users' capabilities and opportunities (e.g., skill readiness and affordability) alongside their cognitive beliefs and social influences, the model provides a more nuanced explanation of HHCS adoption. This integrated approach answers calls in the health technology literature for cross-disciplinary frameworks that capture both technological and behavioral dimensions of adoption [38]. Second, the research offers empirical evidence on HHCS adoption in a new context, an emerging market healthcare system, highlighting the role of contextualization in adoption theories. The results indicate that certain factors carry different weights in Vietnam compared to the developed markets where models like TAM and UTAUT were originally formulated. In particular, financial considerations and social influence play a more dominant role in this setting, whereas the effect of Attitude on intention is comparatively modest ( $\beta \approx 0.20$  in this study). In contrast, prior studies in developed contexts have often found Attitude to be a much stronger predictor of intention [35]. This discrepancy underscores that technology acceptance models should be adapted to local conditions: practical constraints and cultural norms can moderate the influence of individual perceptions. Finally, this study extends the set of determinants considered in technology acceptance models by empirically validating the importance of factors often underrepresented in those models. Notably, we identify affordability (financial cost) and service reliability as critical drivers of HHCS adoption intent. By incorporating these health-specific and contextual factors, the research refines existing theory to better reflect the realities of healthcare decision-making in developing economies.

Practically, the findings yield several actionable implications for stakeholders, particularly HHCS service providers and policymakers in Vietnam. For service providers, the results highlight the need to align service offerings with the concerns and motivations identified. Providers should emphasize the core value and tangible benefits of HHCS in their communications and service design, given that Perceived Usefulness is a strong driver of positive attitude. This means clearly demonstrating how home healthcare can enhance convenience, improve health outcomes (for example, through early detection or continuous care), and reduce costs compared to traditional hospital care. Providers must also build and maintain trust in service quality, as evidenced by the significant role of Perceived Reliability. Ensuring that medical staff are well-qualified, adhering to high standards of care, and publicizing successful treatment cases or patient testimonials can help establish credibility and

reliability in the eyes of consumers. In addition, companies should leverage social proof and community influence in marketing strategies. The strong impact of Social Influence on intention suggests that word-of-mouth referrals, family or peer endorsements, and community education campaigns could substantially boost adoption. Simplifying the user experience is another practical step: enhancing the ease of use of telehealth platforms or appointment systems can make HHCS more accessible, especially for elderly or less tech-savvy patients. Crucially, service providers need to address affordability. Given that cost is the primary barrier identified, providers might develop flexible pricing schemes or subscription models, offer tiered service packages, and collaborate with insurance programs. By reducing out-of-pocket expenses through such measures, providers can lower the financial hurdle and attract a wider base of consumers who are cost-sensitive.

For policymakers, the study underlines the importance of creating a supportive ecosystem that can nurture HHCS adoption. Government actions should primarily focus on reducing financial barriers and ensuring equitable access. For example, targeted subsidies or expansions in health insurance coverage for home healthcare services could directly alleviate the cost burden on patients, responding to the finding that financial cost is the top concern. Policymakers might also incentivize insurance providers to develop products covering HHCS or encourage public-private partnerships that make home care more affordable. Additionally, there is a need to strengthen the regulatory and infrastructural framework for HHCS. Establishing clear regulations and quality standards for home healthcare will help build public trust in these services and protect patients. Healthcare authorities should work to integrate HHCS into the broader health system, for instance, by facilitating coordination between hospitals, primary care, and home care providers, and by ensuring that patient health records and referral processes can seamlessly support home-based care. Such integration, coupled with robust legal frameworks, will reduce market fragmentation and uncertainty in this nascent sector. In turn, a well-regulated, collaborative environment can encourage more providers to enter the market and more patients to confidently utilize HHCS, thereby accelerating its adoption at the national level.

Despite its contributions, this study has several limitations that should be acknowledged. First, the data were collected using a cross-sectional self-reported survey at a single point in time, which limits our ability to draw causal conclusions. Respondents' stated intentions might not perfectly predict their future behavior, and the snapshot nature of the data cannot capture how perceptions or intentions may change over time. Second, although the research model accounts for a substantial portion of the variance in behavioral intention, it does not capture all possible factors. Some relationships in the model – for example, the link between Attitude and Intention- were only moderate in magnitude, suggesting that additional, unmeasured variables may influence consumers' decision-making. Third, the study assumes linear relationships between determinants and intention and does not examine potential interaction effects. Certain factors may amplify or diminish the influence of others (for instance, the effect of Capability might vary with a user's age or prior experience with healthcare technology), but such moderating influences were beyond the scope of our analysis. Finally, this research focused on behavioral intention to use HHCS rather than actual adoption or long-term use. Intention is a proven antecedent of behavior in many theories, yet the well-known intention–behavior gap means that not all those who intend to adopt a service will ultimately do so or continue to use it. This focus on intention, while appropriate for studying a nascent service context, means the findings do not fully reflect real-world uptake or retention of HHCS.

Building on the above limitations, future research should pursue several directions to deepen and broaden the understanding of HHCS adoption. To address the first limitation, longitudinal studies would be valuable, tracking individuals over time as they move from intention to actual HHCS usage (and perhaps continued use) would shed light on how stable intentions are and how they translate into real behaviors. Such studies could help bridge the intention–behavior gap by identifying which factors predict not just intent but actual adoption and sustained engagement with home healthcare. Next, researchers should consider expanding the set of variables in the adoption model to capture other relevant influences. For example, factors like trust in healthcare providers, perceived risk or privacy

concerns, and specific cultural or family dynamics might play a significant role in this context and could improve the explanatory power of the model if included. Additionally, future work could explore interaction or moderation effects among the determinants of HHCS adoption. Investigating whether, for instance, the impact of capability on adoption intention is moderated by age, health status, or prior experience with technology would provide a more nuanced view of how different subgroups of users make decisions. Identifying such conditional relationships can inform targeted strategies (e.g., tailoring training programs for older adults if their capability influences adoption differently). Lastly, it will be important to measure actual adoption and usage behavior in subsequent studies. As HHCS options become more available, researchers should examine not only who intends to use these services but who actually uses them, how frequently, and with what outcomes. Such research could explore the long-term maintenance of HHCS use and the factors that facilitate or hinder continued engagement. By addressing these future research directions, scholars and practitioners can gain a more comprehensive understanding of home healthcare service adoption and develop more effective interventions to promote this innovative healthcare model in Vietnam and similar emerging market settings.

### Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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