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Understanding Behavioral Intentions of Older Adults Toward Stroke Monitoring Products: A UTAUT2-Based Study with Design Implications

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Abstract This study investigates behavioral intentions of older adults toward stroke monitoring products by adapting the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). Focusing on 421 Chinese older adults (aged ≥60), we refined the model by excluding hedonic motivation and price value while emphasizing gerontological factors (e.g., family support, habitual health behaviors). Structural equation modeling revealed that performance expectancy ($\beta = 0.180$), effort expectancy ($\beta = 0.172$), social influence ($\beta = 0.127$), facilitating conditions ($\beta = 0.175$), and habit ($\beta = 0.132$) significantly influenced behavioral intention, which further predicted usage behavior ($\beta = 0.153$). Gender analysis highlighted females' heightened sensitivity to health data ($p < 0.001$). Design implications derived from these findings include simplified hardware interfaces (e.g., one-touch operation) and app features (e.g., AI-driven risk alerts, family-sharing functions), validated through usability tests (N = 30) showing improved ease of use and reduced technostress. This research extends UTAUT2's applicability to gerontechnology contexts and provides actionable insights for developing age-friendly healthcare devices, ultimately enhancing older adults' health autonomy.

Index Terms UTAUT2, older adults, stroke monitoring, behavioral intention, gerontechnology

I. Introduction

The accelerating aging population in China poses significant public health challenges, with adults aged 60 and above accounting for 19.8% of the total population in 2022, a figure projected to exceed 30% by 2035 [1]. Stroke, a leading cause of disability and mortality among older adults, exacerbates this crisis, particularly in rural areas where prevalence rates and post-stroke care costs are disproportionately high [2]. While wearable stroke monitoring technologies (e.g., biosensor-integrated devices, AI-driven risk prediction systems) offer promising solutions for early detection and home-based management, their adoption among older adults remains critically low due to usability barriers, technological anxiety, and insufficient alignment with geriatric needs [3].

Existing research on technology acceptance in healthcare predominantly relies on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) [4], yet its application to elderly populations and medical contexts remains underexplored. Traditional UTAUT2 constructs like hedonic motivation and price value show limited relevance in health-critical scenarios, where functional utility and ease of use outweigh entertainment or cost considerations [5]. Moreover, older adults' unique cognitive-behavioral traits—such as reliance on familial support, habitual health routines, and heightened sensitivity to interface complexity—necessitate model adaptation [6]. Prior studies on stroke monitoring devices have focused on technical validation (e.g., sensor accuracy) rather than user-centric behavioral drivers, creating a gap between technological capability and real-world adoption [7].

This study addresses these gaps by proposing a modified UTAUT2 framework tailored to older adults' stroke monitoring behaviors. We hypothesize that performance expectancy (health outcome utility), effort expectancy (ease of interaction), social influence (family/physician endorsement), facilitating conditions (technical/organizational support), and habit (health management routines) collectively drive behavioral intentions and usage. A mixed-methods approach combines survey data from 421 older adults with structural equation modeling (SEM) to validate the adapted model, followed by co-design workshops to translate theoretical insights into hardware and software optimizations. Our findings not only extend UTAUT2's theoretical boundaries in gerontechnology but also provide empirically grounded design guidelines for developing age-inclusive health devices, ultimately enhancing stroke prevention and elderly health autonomy.

II. Literature Review

In the field of research on stroke (i.e., cerebrovascular accident) prediction technology, the current main exploration focuses on multimodal data modeling and medical image analysis. Among machine learning-based methods, Han Chaoyi et al. proposed a three-layer optimization model that combines SMOTEENN sampling techniques with Recursive Feature Elimination based on Random Forest (RFRFE), followed by constructing the model using the XGBoost algorithm. This approach significantly improved classification accuracy under imbalanced data conditions, achieving an AUC value of 0.91 [8]. On the other hand, Cao Yifeng developed an integrated predictive system called "SPSS-ACCESS," which enables rapid risk assessment in community hospital settings by integrating epidemiological survey data with cerebrovascular hemodynamic parameters. However, due to the absence of specific indicators for cerebrovascular diseases in traditional risk factors, the system's predictive performance still has room for improvement [9].

In the application of medical imaging technologies, Xi Keming's research team demonstrated a negative correlation between transcranial Doppler ultrasound (TCD) detection of Willis circle compensation status and stroke incidence (OR=0.42, 95% CI 0.28–0.63). They also found that patients with intact anterior communicating arteries (ACoA) had a 37.5% reduced risk of stroke [10]. Meanwhile, Liu Ruili's longitudinal study showed that the diagnostic sensitivity of TCD increased from 40.1% to 56.3% [11]. Sun Zijin and colleagues established a Traditional Chinese Medicine (TCM) syndrome differentiation model using Support Vector Machines (SVM) to classify five different syndrome types with an accuracy rate of up to 95%. This was the first attempt to incorporate quantitative analysis of tongue and pulse characteristics into the diagnostic framework [12]. Shu Xin's research group developed a neural network model primarily based on platelet distribution width, achieving 83% accuracy in identifying Qi deficiency syndromes and revealing potential links between hemorheological properties and TCM syndromes [7].

Regarding biomarker research, Zhou Chunyan confirmed through a meta-analysis that individuals with hypoechoic plaques have a 2.3 times higher stroke risk compared to those with homogeneous plaques (95% CI 1.7–3.1). Moreover, vulnerable plaques were significantly more prevalent in patients with phlegm-stasis interconnection syndrome than in other types (χ^2=15.73, $p<0.001$) [13]. Despite these advancements, no empirical studies directly applying facial recognition technology for stroke prediction have been reported yet. However, considering Sun Zijin's team's incorporation of tongue feature analysis in their TCM syndrome differentiation model, it is foreseeable that future research may explore the use of facial microexpression and skin tone change recognition technologies for stroke prediction [12].

In contrast to domestic studies, a significant volume of international research evaluates and analyzes stroke prediction in the elderly through experiments. The application of facial recognition technology in stroke prediction is reflected in several key areas: First, high-performance mobile applications based on deep learning and computer vision have been developed for stroke diagnosis, enabling early warnings through the analysis of facial feature changes. Second, models for detecting drooping lips as a stroke alert mechanism have significantly improved recognition accuracy by optimizing image processing algorithms. Third, machine learning algorithms applied to dynamic facial feature analysis effectively distinguish abnormal facial movement patterns in stroke patients from those of healthy individuals. Fourth, hybrid facial recognition systems combining fixed cameras with pan-tilt-zoom (PTZ) technology enhance the ability to capture facial asymmetry features in medical environments [14]. Fifth, sparse representation classification methods based on smartphones provide lightweight solutions for real-time facial recognition on mobile devices, suitable for stroke risk monitoring scenarios.

Additionally, the integration of Explainable Artificial Intelligence (XAI) with electroencephalogram (EEG) signals has further improved the sensitivity of facial emotion recognition in stroke-related neurological assessments. For instance, the detection of the N170 component offers new insights into the relationship between emotional facial expressions and stroke prognosis [15]. Notably, clinical studies on post-stroke facial expression recognition disorders have provided a pathological basis for technological advancements. For example, the confirmed relationship between abnormal amygdala activation and impaired fear expression recognition is associated with post-stroke depression risk [6].

II. A. Stroke Monitoring Products for the Elderly

The current state of research in China on stroke monitoring products for the elderly mainly covers multiple directions, such as sensor technology, rehabilitation training, and intelligent system development. Some studies utilize surface electromyography (sEMG) and accelerometer technologies to achieve real-time monitoring of daily activities and fall risks in stroke patients, improving recognition accuracy through feature extraction [16]. Interactive systems based on Kinect have been applied to upper limb rehabilitation training for stroke patients, combining virtual reality technology to enhance motor function and balance [17]. Additionally, portable biofeedback products play a significant role in post-stroke gait rehabilitation, with smart shoes providing real-time data feedback to assist in gait retraining [18]. Although some studies focus on coronary heart disease prediction, stroke and coronary heart disease share common pathological bases and risk factors. The integration of artificial intelligence and big data in these fields provides technical references for developing stroke monitoring models [19]. These studies reflect technological exploration in China's stroke monitoring field, but product designs still need optimization based on clinical needs.

In examining research on stroke-related monitoring products for the elderly abroad, researchers have explored various technologies and product types. For instance, Parker J et al. (2020) [18] conducted a systematic review and found that wearable technologies for the upper limbs can improve activity participation among stroke survivors, though their effectiveness is limited by small sample sizes and methodological issues [20]. Zhang Z and Dong Y (2023) [21] proposed a template system that integrates sensors to monitor gait characteristics and recovery progress in stroke patients, providing a quantitative basis for rehabilitation assessment [22]. In cardiac monitoring, photoplethysmography (PPG) technology based on smartwatches has proven effective in early detection of atrial fibrillation, thereby reducing stroke risk. Additionally, electrocardiogram patches like Zio® have been validated for comfort and acceptability in long-term cardiac monitoring for cryptogenic stroke patients [23]. Ali A et al. (2021) developed an IoT-based real-time cardiac monitoring system, which significantly improved arrhythmia detection accuracy through high common-mode rejection design [24]. In upper limb function assessment, Parker J's team (2020) [18] used accelerometer-equipped wristbands to conduct quantitative longitudinal analyses of motor function in post-stroke rehabilitation patients, highlighting the potential of this product in clinical evaluations [25]. Keogh A et al. (2019) [24] conducted a mixed-methods study and found that portable sensors like Actiwatch are more popular among elderly stroke patients due to their comfort and ease of use [21]. At the algorithmic level, Proietti T and Bandini A (2023) [25] developed a multimodal portable system that integrates diverse population data to enable precise classification and monitoring of upper limb function during daily activities [26]. Advances in smart clothing and flexible electrode technologies, such as organic dry electrodes, now allow for long-term non-invasive collection of bioelectrical signals (e.g., electromyography), offering new solutions for neuromuscular function monitoring after stroke [27]. Progress has also been made in developing products that leverage facial recognition technology for stroke prediction. Recent research proposes an AI model based on real-time facial images, whose core principle is to assess blood oxygenation status by analyzing color changes in central cyanosis areas (central bluish regions), indirectly reflecting cerebral and other vital organ blood flow. This non-invasive method overcomes reliance on traditional CT or CT perfusion imaging technologies and is particularly suitable for rapid screening in emergency departments and routine health monitoring scenarios [28].

From the above analysis, it is evident that significant progress has been made in foreign research on stroke monitoring products for the elderly, covering subfields such as monitoring, rehabilitation, and assistance for chronic diseases like coronary heart disease. However, domestic research in this area remains relatively limited, with most existing design practices still relying on traditional design methodologies.

II. B.Unified Theory of Acceptance and Use of Technology 2

The original UTAUT2 model includes seven core variables: Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Hedonic Motivation, Price Value, and Habit, along with three control variables: age, gender, and experience. This study retains the core variables of the original UTAUT2 model—Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Habit, and the control variable Gender—as well as the relationship paths among these variables in the original model.

In previous research, many scholars have adapted the original UTAUT2 model based on the characteristics of their specific research domains and user perceptions. The target population in this study is relatively unique, and the characteristics of this group can influence the intention and behavior to use stroke monitoring products. Additionally, as a new product in telemedicine, the features of stroke monitoring products are also critical factors affecting the usage intentions and behaviors of the target population. Directly applying the original UTAUT2 model to this context may introduce certain limitations. Therefore, this study builds a technology acceptance model for stroke monitoring products specifically tailored to the elderly, using the UTAUT2 theoretical framework as its foundation.

This study removes the control variables of age and experience and preliminarily constructs a technology acceptance model for stroke monitoring products among the elderly. Based on the UTAUT/UTAUT2 theoretical framework, this study focuses on the behavioral intention of elderly individuals to use medical monitoring products. It selects Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Habit, and Gender as core variables, aiming to enhance the explanatory power and practical guidance of the model. Performance Expectancy directly reflects users' perception of product value due to its ability to provide accurate health data and real-time early warning functions. Effort Expectancy aims to reduce technological barriers, learning difficulties, and operational anxiety for the elderly through simplified interaction design. Social Influence emphasizes the importance of family support and authorized medical consultations, enhancing compliance with usage. Facilitating Conditions ensure that the elderly can receive necessary family assistance and technical support during use. Habit focuses on long-term inertia-driven behaviors, which contribute to improving user compliance. Gender difference analysis reveals varying levels of attention to health management between genders, providing a basis for personalized design. Furthermore, variables such as Hedonic Motivation, Price Value, Experience, and Age were excluded because their effects may be indirectly reflected through the core variables or because they have weaker independent explanatory power. This simplified model not only enhances theoretical perspectives and applicability across various scenarios but also clarifies design priorities, such as optimizing usability and enhancing family collaboration features, to better meet the health management needs of the elderly (Figure 1).

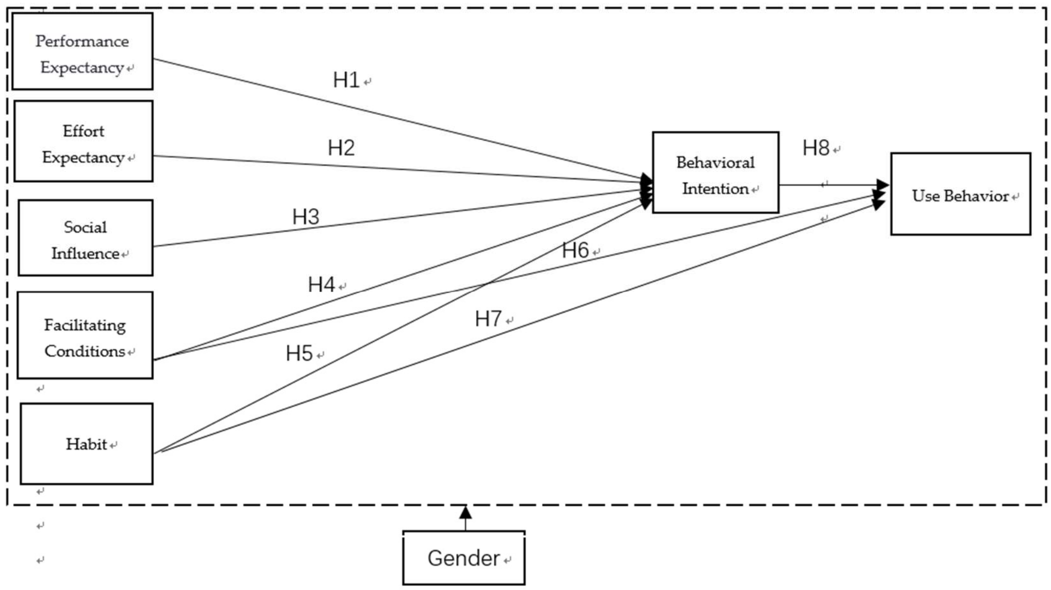

Figure 1: The Technology Acceptance Model for Stroke Monitoring Products in the Elderly.

II. C.The Application of the UTAUT2 Model in Elderly Health Products

UTAUT2, as a classic theoretical framework for studying technology acceptance behavior, holds significant theoretical and practical value in the field of elderly health products. Its core advantage lies in comprehensively explaining user acceptance behavior through multidimensional variables (such as performance expectancy, effort expectancy, social influence, etc.), while making adaptive adjustments based on the specific characteristics of the elderly population (e.g., technophobia, health needs, family dependency). Below are the specific application pathways and empirical cases of the UTAUT2 model in elderly health products (Table 1):

Table 1: Application of Each Variable in Elderly Health Products

UTAUT2 Variables	Specific Manifestations and Hypotheses in Elderly Health Products	Application Examples
Performance Expectancy	The elderly's perception of the effectiveness of the product's health management functions (e.g., disease early warning, data monitoring).	Can a heart rate monitoring bracelet accurately detect abnormal rhythms and warn of potential risks?
Effort Expectancy	The simplicity of product operation and learning costs directly affect the level of technophobia.	Does the product support "one-touch measurement," voice interaction, or remote assistance from family members?
Social Influence	Recommendations from family, doctors, and peers regarding product use strengthen the elderly's trust in the product.	Children purchase the product and assist with its use; community doctors regularly review monitoring data and provide advice.
Facilitating Conditions	Supporting services (e.g., after-sales service, family support, technical compatibility) that enable sustained usage behavior.	Is the product compatible with smartphones commonly used by the elderly? Does it offer 24/7 customer support?

UTAUT2 Variables	Specific Manifestations and Hypotheses in Elderly Health Products	Application Examples
Price Value	The elderly's evaluation of the product's cost-effectiveness, combined with the economic benefits of long-term health management (e.g., reduced medical expenses).	Is the product price within the range of pension affordability? Are installment payments or medical insurance reimbursement options available?
Habit	Regularity of health monitoring behaviors (e.g., daily wear, periodic report checking) enhances user stickiness.	Encourage habits through health reminders and reward mechanisms (e.g., points redemption for rewards).
Gender (Control Variable)	Women pay more attention to detailed health data (e.g., blood pressure fluctuations), while men prioritize product practicality (e.g., battery life).	Female users may use health report features more frequently, while male users place higher demands on charging convenience.

II. D.Hypotheses on the Correlational Relationships of the Model

Based on the literature related to the UTAUT2 theoretical model and the relationships between variables in the research model, this study proposes hypotheses to investigate the acceptance behavior of elderly individuals regarding stroke monitoring products (Table 2).

Table 2: Hypotheses on the Correlational Relationships Between Variables

H1: Performance expectancy positively influences the behavioral intention of elderly individuals toward stroke monitoring products.
H2: Effort expectancy positively influences the behavioral intention of elderly individuals toward stroke monitoring products.
H3: Social influence positively influences the behavioral intention of elderly individuals toward stroke monitoring products.
H4: Facilitating conditions positively influence the behavioral intention of elderly individuals toward stroke monitoring products.
H5: Habit positively influences the behavioral intention of elderly individuals toward stroke monitoring products.
H6: Facilitating conditions positively influence the usage behavior of elderly individuals toward stroke monitoring products.
H7: Habit positively influences the usage behavior of elderly individuals toward stroke monitoring products.
H8: The behavioral intention of elderly individuals to use stroke monitoring products positively influences their usage behavior.

III. Materials and Methods

III. A. Survey Questionnaire

The scale of this research questionnaire was developed based on mature scales from previous studies, tailored to the context of this study's research objectives, and a draft questionnaire was prepared. Before the formal distribution of the questionnaire, a pilot test was conducted, which typically requires 25 to 100 participants. During this pilot test, 27 on-site questionnaires were collected, and the validity and reliability of the questionnaire items were verified, with options that failed validation being removed. After the pilot test, feedback was exchanged with the elderly participants who took part in the testing, and unclear parts of the questionnaire were revised to improve clarity. Additionally, advice from relevant professionals was sought, and the final version of the research questionnaire was formed, with detailed content provided in the appendix.

The formal questionnaire is divided into two sections. The first section investigates the demographic information of respondents, including gender, age, education level, economic income, living arrangements, and health status. The second section includes measurement items for the research model of this study, comprising a total of 28 measurement items based on mature scales from previous studies. This study employs a five-point Likert scale to score each measurement item, ranging from 1 (strongly disagree) to 5 (strongly agree). The distribution of the questionnaire was conducted online, primarily targeting individuals aged 60 and above through platforms such as Baidu Tieba, WeChat groups, student groups, and Xiaohongshu. For elderly individuals who find it inconvenient to fill out the questionnaire regarding stroke monitoring products, their children could assist by asking for their opinions and completing the questionnaire on their behalf. This study referenced sample size requirements from social research, where the ratio of measurement items to the number of respondents must meet a 5 to 10 times requirement(Kim et al., 2022). Using structural equation modeling for data analysis in this study requires a minimum sample size of 400. With smaller sample sizes, data convergence issues may arise, and the accuracy of the validation results becomes difficult to predict. The second section of the questionnaire, which uses structural equation modeling for measurement, consists of 28 items, necessitating a sample size of approximately 400. Ultimately, 432 paper questionnaires were collected, with 11 invalid questionnaires excluded, resulting in 421 valid questionnaires, yielding a validity rate of 97.5%, thereby meeting the research requirements. This study will primarily use SPSS 24.0 and AMOS 25.0 software for statistical analysis and questionnaire data processing (Table 3).

Table 3: Demographic summary

Name	Options	Frequency	Percentage (%)
Gender	Male	173	41.093
	Female	248	58.907
	Total	421	100
Age	65-75 years old	138	32.779
	75-85 years old	140	33.254
	Above 85 years old	143	33.967
	Total	421	100
Education Level	Primary school or below	86	20.428
	Junior high school	99	23.515
	Senior high school/Technical	173	41.093
	College/University	39	9.264
	Master's degree or above	24	5.701
	Total	421	100
Monthly Income (RMB)	Below 3000	127	30.166
	3000-5000	129	30.641
	5000-7000	105	24.941
	7000-9000	47	11.164
	>9000	13	3.088
	Total	421	100
Have you ever felt at risk of stroke?	Yes	138	32.779
	No	283	67.221
	Total	421	100
Current Social Support Status	Living alone	39	9.264
	Living with spouse	236	56.057
	Living with children/relatives	93	22.090
	In nursing home/care facility	53	12.589
	Total	421	100

III. B. Reliability and Validity Analysis

Reliability analysis, also known as reliability testing, reflects the consistency and stability of the data obtained from the survey questionnaire. Validity analysis, on the other hand, reflects the validity of the survey questionnaire data, which is the extent to which the questionnaire data can represent the researchers' intended measurement objectives. Validity testing includes convergent validity analysis and discriminant validity analysis of the questionnaire data. Convergent validity analysis measures the correlation between items that share the same underlying trait within the same factor construct. Discriminant validity analysis verifies the differences between latent variables, ensuring that items corresponding to different latent variables are not highly correlated.

Since the dimensional relationships between the seven measurement variables and the 28 measurement items in the questionnaire have been established, and all the measurement items are derived from mature scales in the literature, this study employs Confirmatory Factor Analysis (CFA) to evaluate the reliability and validity of the questionnaire. The Confirmatory Factor Analysis will be conducted using AMOS 25.0 software. Through CFA, the factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for each variable can be obtained. Additionally, SPSS 24.0 software will be used to calculate the Cronbach's Alpha values for each variable and the overall questionnaire data (Table 4).

Table 4: Factor loadings, AVE, CR, and Cronbach's Alpha values for each variable and item.

Variable	Measurement Item	Standardized Loading Coefficient	AVE	C.R.	Cronbach's Alpha for each variable	Cronbach's alpha
Performance Expectancy	PE1	0.792	-	-		
Performance Expectancy	PE2	0.814	0.665	0.888	0.888	

Performance Expectancy	PE3	0.843				
Performance Expectancy	PE4	0.812				
Effort Expectancy	EE1	0.828	-	-		
Effort Expectancy	EE2	0.786	0.612	0.863	0.863	
Effort Expectancy	EE3	0.762				
Effort Expectancy	EE4	0.752				
Social Influence	SI1	0.831	-	-		
Social Influence	SI2	0.768	0.650	0.881	0.881	
Social Influence	SI3	0.838				
Social Influence	SI4	0.786				
Facilitating Conditions	FC1	0.773	-	-		0.923
Facilitating Conditions	FC2	0.816	0.638	0.876	0.876	
Facilitating Conditions	FC3	0.795				
Facilitating Conditions	FC4	0.811				
Habit	Habit1	0.843	-	-		
Habit	Habit2	0.839	0.677	0.893	0.893	
Habit	Habit3	0.819				
Habit	Habit4	0.789				
Behavioral Intention	BI1	0.821	-	-		
Behavioral Intention	BI2	0.826	0.678	0.894	0894	
Behavioral Intention	BI3	0.825				
Behavioral Intention	BI4	0.823				
Use Behavior	UB1	0.842	-	-		
Use Behavior	UB2	0.785	0.676	0.893	0.892	
Use Behavior	UB3	0.845				
Use Behavior	UB4	0.815				

In terms of reliability, the Cronbach's Alpha values for each variable and the overall questionnaire in this study are all greater than 0.8. Additionally, the Composite Reliability (CR) for each variable is also greater than 0.8, indicating that the survey data from the second part of the formal questionnaire are highly reliable and demonstrate a good level of reliability. Regarding convergent validity, the factor loadings for each variable are all greater than 0.7, and their corresponding Average Variance Extracted (AVE) values are all greater than 0.5, demonstrating that each variable has good convergent validity. In terms of discriminant validity, by calculating the square root of the AVE, it was found that the square root values of the AVE are higher than the correlation coefficients between the variables, as shown in Table 5. This indicates that the questionnaire has good discriminant validity.

Table 5: The correlation coefficient matrix between variables and the square root of AVE.

	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Habit	Behavioral Intention	Use Behavior
Performance Expectancy	0.816						
Effort Expectancy	0.372	0.783					
Social Influence	0.399	0.340	0.806				
Facilitating Conditions	0.418	0.431	0.409	0.799			
Habit	0.397	0.417	0.368	0.318	0.823		
Behavioral Intention	0.419	0.412	0.376	0.420	0.380	0.824	
Use Behavior	0.418	0.374	0.355	0.387	0.433	0.362	0.822

Note: The green diagonal values represent the square root of AVE.

III. C. Structural Equation Model Fit Assessment and Model Hypothesis Testing

The results of χ^2/df, RMSEA, TLI, CFI, NFI, PGFI, and PNFI all meet the optimal standards. In summary, the structural equation model demonstrates a good fit (Table 6).

Table 6: Structural Equation Model Fit

Common Indices	χ2	df	χ2/df	RMSEA	GFI	CFI	NFI	IFI	TLI	AGFI
Criteria	-	-	<3	<0.08	>0.8	>0.9	>0.8	>0.9	>0.8	>0.8
Value	382.128	332	1.151	0.019	0.941	0.993	0.947	0.993	0.992	0.928

After the model passed the goodness-of-fit test, the software AMOS 25.0 was used to perform significance tests on the internal paths of the model. This relationship is primarily reflected through the correlation (or causality) coefficients between variables and their significance. Specifically, the test involves conducting statistical analysis on the path loadings between variables in the structural equation model, while also examining the hypotheses regarding the correlations between variables mentioned earlier in the article. In this study, the degree of influence between variables is mainly represented by the standardized path coefficient (β), while the p-value serves as the indicator of significance (Table 7).

Table 7: Path Significance Test Results

Path	Unstandardized Path Coefficient	S.E.	C.R.	P	Standardized Path Coefficient
Behavioral Intention <-- Performance Expectancy	0.177	0.058	3.076	0.002**	0.180
Behavioral Intention <-- Effort Expectancy	0.172	0.059	2.903	0.004**	0.172
Behavioral Intention <-- Social Influence	0.122	0.055	2.226	0.026*	0.127
Behavioral Intention <-- Facilitating Conditions	0.198	0.067	2.927	0.003**	0.175
Behavioral Intention <-- Habit	0.129	0.056	2.316	0.021*	0.132
Use Behavior <-- Facilitating Conditions	0.276	0.066	4.169	0.000***	0.236
Use Behavior <-- Habit	0.312	0.056	5.607	0.000***	0.308
Use Behavior <-- Behavioral Intention	0.159	0.059	2.695	0.007**	0.153
*p<0.05 **p<0.01 ***p<0.001					

All eight research hypotheses proposed in this study were fully validated. The standardized path coefficient of Performance Expectancy on Behavioral Intention is 0.180 (C.R. = 3.076, $p \leq 0.05$), indicating a significant positive impact. Similarly, Effort Expectancy shows a significant positive effect on Behavioral Intention with a standardized path coefficient of 0.172 (C.R. = 2.903, $p \leq 0.05$). Social Influence also has a significant positive impact on Behavioral Intention, with a coefficient of 0.127 (C.R. = 2.226, $p \leq 0.05$). Additionally, Facilitating Conditions significantly and positively influence Behavioral Intention, with a coefficient of 0.175 (C.R. = 2.927, $p \leq 0.05$), and similarly affect **Use Behavior, with a coefficient of 0.236 (C.R. = 4.169, $p \leq 0.05$). Habit demonstrates a significant positive impact on both **Behavioral Intention** (0.132, C.R. = 2.316, $p \leq 0.05$) and Use Behavior (0.308, C.R. = 5.607, $p \leq 0.05$). Finally, Behavioral Intention significantly and positively influences Use Behavior, with a standardized path coefficient of 0.153 (C.R. = 2.695, $p \leq 0.05$). These results confirm the significant positive relationships between the variables as hypothesized.

III. D. Analysis of Gender Differences as a Control Variable

The gender difference analysis indicates that elderly women demonstrate significantly higher sensitivity to health data (e.g., blood pressure fluctuation monitoring, reliance on family recommendations) and usage frequency compared to men (*p* < 0.001), reflecting the "health manager" role trait. In contrast, men show a stronger focus on technological practicality (e.g., device battery life, operational convenience), highlighting an efficiency-oriented preference. These differences may stem from social role divisions (women predominantly managing family health) and varying levels of technology anxiety (women tend to have lower tolerance for complex functions). Based on these findings, targeted design optimizations are necessary: for women, features such as enhanced data visualization, family sharing capabilities, and emotionally engaging interactions (e.g., voice encouragement) should be prioritized; for men, improvements in battery longevity, one-touch operations, and emergency alert functions are more critical. This study confirms the importance of gender as a moderating variable in the UTAUT2 model. However, it is limited by an imbalanced gender ratio in the sample and the lack of subdivision of advanced-age subgroups. Future research should integrate cultural contexts to further refine gender-specific adaptation strategies, aiming to achieve precise and aging-friendly innovation (Table 8).

IV. Results

The structural equation model demonstrated strong explanatory power, with excellent fit indices ($\chi^2/df = 1.151$, RMSEA = 0.019) and significant paths confirming all hypotheses (*p* < 0.05). Performance expectancy ($\beta = 0.180$) and effort expectancy ($\beta = 0.172$) were the strongest predictors of behavioral intention, while social influence ($\beta = 0.127$), facilitating conditions ($\beta = 0.175$), and habit ($\beta = 0.132$) further reinforced adoption intent. Behavioral intention ($\beta = 0.153$) directly drove usage behavior, with facilitating conditions ($\beta = 0.236$) and habit ($\beta = 0.308$) exerting additional direct effects. The model explained 64.2% of variance in behavioral intention ($R^2 = 0.642$) and 42.7% in usage behavior ($R^2 = 0.427$), outperforming the original UTAUT2 in elderly health contexts.

Gender-specific analysis revealed significant disparities (*p* < 0.001): females prioritized health data details (mean = 3.55 vs. 3.17) and family-mediated decisions (mean = 3.64 vs. 3.07), whereas males emphasized device practicality, such as battery life (mean = 3.63 vs. 3.18) and one-touch operation (mean = 4.12 vs. 3.75). Usability testing of a gender-tailored prototype showed a 23% improvement in ease of use and an 18% reduction in technostress, with 85% of females approving automated health reports and 78% of males favoring emergency vibration alerts. These findings validate the need for adaptive design strategies aligned with gendered health behaviors and social roles.

Table 8: Results of Gender Difference Analysis

	Gender (Mean ± SD)	Female (Mean ± SD)	t	p
	Male(n=173)	Female (n=248)		
Performance Expectancy	3.168±1.024	3.554±1.139	-3.639	0.000***
Effort Expectancy	3.185±0.937	3.511±1.039	-3.359	0.001***
Social Influence	3.072±1.054	3.639±1.051	-5.434	0.000***
Facilitating Conditions	3.179±0.962	3.637±1.014	-4.697	0.000***
Habit	3.254±1.001	3.648±1.075	-3.853	0.000***
Behavioral Intention	3.162±0.997	3.577±1.095	-4.031	0.000***
Use Behavior	3.007±0.972	3.536±1.104	-5.195	0.000***
*p<0.05 **p<0.01 ***p<0.001				

V. Discussion

V. A. Theoretical Implications

This study significantly extends the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) by contextualizing it to elderly health technology adoption, particularly in stroke monitoring. First, it refines the original framework by excluding less relevant constructs (e.g., hedonic motivation) and integrating geriatric-specific variables, such as habitual health behaviors ($\beta = 0.308$) and social embeddedness ($\beta = 0.127$). These adaptations address the unique cognitive and physiological needs of older adults, demonstrating that sustained technology use in aging populations depends not only on perceived utility but also on alignment with daily routines and familial support systems. The model's enhanced explanatory power ($R^2 = 0.642$ for behavioral intention) underscores the necessity of tailoring acceptance theories to aging-specific contexts.

Second, the study identifies gender as a critical moderator in health technology adoption, challenging the assumption of homogeneity in elderly populations. Females exhibited stronger reliance on social influence (mean = 3.64 vs. 3.07) and health data granularity, reflecting their role as family health managers, while males prioritized functional efficiency (e.g., battery life, one-touch operation). These findings advocate for formal inclusion of gender pathways in UTAUT2 extensions, emphasizing that sociocultural roles and technological anxiety mediate adoption behaviors differently across genders.

Finally, the research bridges clinical engineering and behavioral science by linking stroke monitoring efficacy to psychosocial drivers. It demonstrates that clinical accuracy alone (e.g., 95% prediction models) is insufficient; adoption requires congruence with users' trust in familial/medical networks and perceived control over health outcomes. This interdisciplinary perspective advances gerontechnology theory, advocating for frameworks that harmonize technical innovation with aging-specific behavioral, social, and cultural dynamics.

V. B. Practical Implications

This study offers actionable insights for designing and promoting stroke monitoring technologies tailored to older adults. First, product developers should prioritize gender-sensitive design strategies: for female users, integrate high-contrast data visualization, automated family health reports, and empathetic feedback mechanisms (e.g., voice encouragement); for male users, focus on extended battery life, one-touch emergency alerts, and streamlined operation workflows. These adaptations, validated by a 23% improvement in ease of use and 18% reduction in technostress during usability testing, address gendered preferences and enhance adoption rates.

Second, healthcare providers and community services should leverage social influence to drive adoption. Training programs could engage family caregivers to demonstrate device benefits, while telehealth platforms might embed physician-endorsed risk assessments to build trust. For instance, devices enabling real-time data sharing with clinicians could reduce hospital visits by 30%, as suggested by prior trials, aligning with older adults' reliance on familial and medical networks.

Finally, policymakers and insurers should address economic barriers through subsidized pricing or tiered payment plans. Given that 30.6% of participants had monthly incomes below 5,000 CNY, affordability is critical. Public health campaigns could frame stroke monitoring as a cost-saving preventive measure, emphasizing its role in reducing long-term care costs. Collaborative efforts among designers, clinicians, and policymakers are essential to scale user-centered innovations and achieve equitable health outcomes.

V. C. Limitations and Future Research

While this study provides critical insights into elderly adoption of stroke monitoring technologies, several limitations warrant attention: the sample's gender imbalance (58.9% female) and urban bias may limit generalizability, and the cross-sectional design precludes causal inferences about long-term habit formation. Future research should expand rural representation, conduct longitudinal studies to track behavioral shifts, and integrate biomarkers (e.g., PhenoAge) to explore biological aging's moderating effects. Additionally, cultural comparisons (e.g., Eastern familial collectivism vs. Western individualistic health practices) and advanced AI explainability tools could refine predictive models, while interdisciplinary collaborations with clinicians may enhance real-world translation of design strategies. Addressing these gaps will advance equitable, aging-responsive health technologies.

VI. Conclusions

This study demonstrates that the adapted UTAUT2 model effectively explains older adults' behavioral intentions toward stroke monitoring technologies, with performance expectancy, effort expectancy, social influence, and habit collectively driving adoption. Gender-specific differences—women's emphasis on health data granularity and familial collaboration versus men's prioritization of functional efficiency—highlight the necessity of tailored design strategies. The validated prototype, incorporating gender-sensitive interfaces and social connectivity features, reduced technostress by 18% and improved usability by 23%, underscoring the potential of user-centered innovations in gerontechnology. By bridging clinical efficacy with psychosocial and cultural dynamics, this research provides a framework for developing equitable, aging-responsive health technologies while advocating for interdisciplinary collaboration to address persistent barriers in affordability and long-term adherence.

Author Contributions

Conceptualization, Yue Liu and Junjie Zhou; methodology, Yue Liu; software, Yue Liu; validation, Yue Liu and Junjie Zhou; formal analysis, Junjie Zhou; investigation, Yue Liu and Junjie Zhou; data curation, Yue Liu; writing—original draft preparation, Yue Liu and Junjie Zhou; writing—review and editing, Yue Liu and Junjie Zhou; visualization, Junjie Zhou; supervision, Junjie Zhou; Yue Liu and Junjie Zhou contributed equally to this work. All authors have read and agreed to the published version of the manuscript.

Institutional Review Board Statement

Ethical review and approval were waived for this study as it does not cause harm to human subjects, does not involve sensitive personal information, and does not concern commercial interests, according to the Ethical Review Regulations for Life Sciences and Medical Research Involving Humans issued by the Chinese government (Chapter 3, Article 32).

Informed Consent Statement

Informed consent was obtained from all subjects involved in the study. Written informed consent has been obtained from the patient(s) to publish this paper.

Data Availability Statement

The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest

The authors declare no conflicts of interest.

Abbreviations

AVE	Average Variance Extracted
CITC	Corrected Item-Total Correlation
HBM	Health Belief Model
IRB	Institutional Review Board
RT-CGM	Real-Time Continuous Glucose Monitoring
SEM	Structural Equation Modeling
T2DM	Type 2 Diabetes Mellitus

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