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Analysis of influencing factors of long-term care insurance system adoption intention based on UTAUT, technology readiness as the moderator

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A B S T R A C T

This study investigates the determinants of Long-Term Care Insurance (LTCI) adoption intention using the Unified Theory of Acceptance and Use of Technology (UTAUT), with Technology Readiness (TR) as a moderating variable. A quantitative approach was applied, utilizing self-administered questionnaires from 180 participants across health service institutions in Guangxi Province, China. Data were measured on a seven-point Likert scale and analyzed using Structural Equation Modeling (SEM) via SmartPLS. Results confirm that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence LTCI adoption intention. Additionally, TR moderates these relationships, strengthening their effects. The findings underscore TR's critical role in enhancing LTCI adoption and offer practical insights for policymakers and practitioners seeking to promote LTCI uptake.

1. Introduction

Long-Term Care Insurance (LTCI) offers financial support to individuals with chronic illnesses, enduring disabilities, or functional impairments requiring extensive personal assistance, specialized medical care, tailored nutrition, and nursing services (Chen, Zhang, & Xu, 2020). Integrating both institutional and home-based care, LTCI aims to mitigate the economic burden associated with long-term care provision (Chen & Xu, 2020). Typically delivered through public or private insurance schemes, LTCI reimburses caregiver-related expenses. The effectiveness of LTCI systems relies on coordinated stakeholder involvement and robust policy frameworks that ensure efficient service delivery and equitable access to care (Chen et al., 2020).

Countries such as Germany, Japan, South Korea, and the United States pioneered LTCI system development, with Germany and Japan serving as global benchmarks (Tsutsui & Muramatsu, 2005). Each system evolved within distinct political, economic, and cultural contexts. In China, the accelerating aging population and rising disability rates have heightened the urgency of developing a more advanced LTCI system, especially as traditional familial caregiving structures diminish. Despite government initiatives to promote LTCI, public acceptance remains limited due to low awareness and unpreparedness in responding to demographic shifts. This underscores the need to investigate the factors driving LTCI adoption (Tsutsui & Muramatsu, 2005).

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To address this adoption gap, it is essential to explore the motivational determinants influencing LTCI uptake. The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a comprehensive framework for analyzing technology acceptance, encompassing performance expectancy, effort expectancy, social influence, and facilitating conditions (Eling & Ghavibazoo, 2019). Although widely applied across various technological contexts, UTAUT has not yet been thoroughly examined in relation to LTCI adoption. Moreover, Technology Readiness (TR)—an individual's predisposition toward embracing technology—can serve as a moderating variable, influencing how UTAUT constructs shape adoption intentions.

This study aims to bridge the research gap by applying the UTAUT model, incorporating TR as a moderator, to assess factors influencing the adoption of LTCI in China. The findings will provide critical insights into the barriers and enablers of LTCI uptake, informing strategies for policymakers and healthcare practitioners to enhance public engagement and system effectiveness (Perez et al., 2022; Xia, Chai, Zhang, & Sun, 2022).

2. Literature Review

The regulatory frameworks surrounding long-term care insurance (LTCI) systems are developed differently across countries. Most developed nations have comprehensive laws in place, while gaps remain in developing areas. The Long-Term Care Insurance Act in Germany, for instance, outlines a detailed legal structure that encompasses all aspects of LTCI, including insurance coverage, fund collection, payment methods, and standards of service (Perez et al., 2022). Such a robust legal structure supports the delivery of LTCI services. Chen and Xu (2020) note that the lack of developed infrastructure exists in the legal recognition of caregivers, institutional admission criteria, and quality control regulation. Unregulated markets tend to be chaotic, which makes it difficult to protect consumers. The urgency of frameworks highlights the alarmingly unprotected middle ground many regions face to facilitate adequate legislation for the LTCI services (Perez et al., 2022).

While China is making strides towards developing long-term care insurance, the relevant policies are in the hands of operational government units like the Ministry of Human Resources and Social Security and the National Healthcare Security Administration, as opposed to being issued by legislative bodies like the National People's Congress (H. Liu, Ma, & Zhao, 2023). The absence of legislation means that regulatory documents are non-inclusive and bypass local legal enforcement, enabling local governments to independently implement pilot schemes (Xia et al., 2022). Such a legal landscape, primarily dictated by administrative rules developed and custom policies, combines non-existent provisions to manage a long-term care insurance system that inadequately supports the system (Xia et al., 2022). Also, regulation pertaining LTCI in China is lacking clearly defined boundaries, resulting in regulations being imposed without legal authority, and thus undermining the infrastructure of long-term care services. Thus, studying the LTCI supervision system is crucial because it may guide legislative choices and help enhance the legal structure governing long-term care insurance services in China (Feng, Wang, & Yu, 2020).

The regulatory stratification of chronic illnesses care in China is in its provisional phases and is being tested in different cities. The pilot attempts are focusing on developing an advanced intelligent regulatory system intended to safeguard the LTCI funds and the benefits allocated for the disabled people in such a way that facilitates public access while enhancing public regulation using technology (Feng et al., 2020). However, the mixed nature of the Chinese LTCI system having both cash and service components poses a myriad of problems in service delivery supervision which in comparison to other systems poses a greater challenge. These obstacles involve moral hazard risks, exorbitant regulation costs, confidentiality concerns, oblique feedback information, chronic funding pressure, and obtrusive enduring oversight (Chen et al., 2020).

Moral hazard is one of the main challenges and the one that is more prevalent than others, particularly from a business perspective. Reports have shown rampant cases of service users and providers defrauding the system by claiming to provide greater services than what is delivered and portraying beneficiaries with dire health complications as needing full reimbursable services that are not rendered (Yan & Faure, 2025). These increased cases draw attention to the need for more effective allocation of reinforcement policies aimed toward disaster resource misuse and diversion where genuine assistance is bypassed.

Moreover, the regulatory aspects of the Long-Term Care Insurance (LTCI) system in China are exceptionally expensive due to its decentralized service delivery. (Shao & Chen, 2024) suggest that the cultural inclination contributes to a significant number of elderly people opting for home care services, which is usually provided in different regions at irregular times. Such a service delivery structure as this makes supervision more challenging and creates barriers such as a limited workforce, excessive time demands, and inefficiency in the monitoring, controlling, and evaluative processes (S. Chen et al., 2021). In addition, the supervision of home care services is further complicated by strong privacy restrictions because, by definition, it is not possible to obtain supervision due to the active privacy provided by the services themselves along with the non-disabled people's ability to monitor the service quality (Chen et al., 2021).

The relatively stable nature of personnel in LTCI services, where disabled individuals are often assigned fixed caregivers, also leads to potential issues with feedback accuracy. This would substantially compromise accuracy if supervisors undertaking the inspections are unduly influenced by the cordial relationships that exist between beneficiaries and the caregivers, which casts doubt on some of the aspects that cannot be effectively overseen (Chen et al., 2021). This builds the argument for more sophisticated models to be devised that guarantees the integrity of the information given by the service users (Zhang, Fu, & Fang, 2021).

Furthermore, the chronic nature of disability which gets worse over time exerts considerable stress on the LTCI fund as benefits have to be paid out over long durations (Zhang & Yu, 2019). The increasing expenditures on LTCI due to services such as medical care, daily assistance, disability prevention, and even the renting of assistive devices also add strain to the regulatory and financial management of the LTCI system (Chen et al., 2021). In addition to these pressures, the existence of multiple stakeholders, including the department of insurance, assessment agencies, service providers, and the beneficiaries, adds to the complexity of managing and regulating the LTCI system. The variety of concerns and risks relating to the stakeholders makes it complicated to construct a consistent cohesive regulatory approach.

There is a need to create an advanced LTCI implementation strategies that address all given issues in pursuing a holistic approach to these concerns. Incorporating techniques from other industries with strengthening the regulation framework can help eliminate fraud, reduce oversight burdens, and enhance the protection of beneficiaries (Eling & Ghavibazoo, 2019). Nevertheless, such systems will only be effective if there is focus on the motivating factors influencing intention to adopt LTCI systems.

The UTAUT model has identified specific issues that may impact an individual's intent to use Long-Term Care Insurance (LTCI) systems and provides a relevant foundation for analysis (Venkatesh, Morris, Davis, & Davis, 2003). The adoption of LTCI could be enhanced by performance expectancy, effort expectancy, social influence, and facilitating conditions without bounds. For instance, performance expectancy is defined as the assumption individuals have about the benefits obtained from LTCI, including enhanced care and greater financial stability, and this greatly influences the adoption of the system. Also, effort expectancy or the perceived LTCI service utilizations greatly influences adoption, especially among the elderly who face challenges with system navigation. Moreover, family and societal determinants also known as social influence could be vital in scenarios where caregiving is still predominant in society. Also, facilitating conditions relate to the extent to which an individual possesses resources and information necessary for productive engagement with LTCI services (Feng et al., 2020). Each of the individual factors are discussed below.

2.1 Performance Expectancy

Performance expectancy, one of the core components of UTAUT, denotes the extent to which an individual believes that the use of a particular system will enhance his or her performance (Venkatesh et al., 2003). Regarding long term care insurance (LTCI), performance expectancy can be viewed as the advantages which an LTCI system offers, for instance, increased access to quality care, greater financial security, and better management of one’s long-term care needs. The importance of performance expectancy in adoption intention is because of the anticipation that the system will yield benefits to the users, in this instance, the prospective LTC users and their families.

Different researchers have found that performance expectancy and its influences are among the strongest and most reliable predictors of technology adoption (Sun, Li, & Gao, 2024). In health care for example, technology adoption is heavily influenced by how much healthcare providers and patients expect new health technologies to benefit them (Bamufleh, Alshamari, Alsobhi, Ezzi, & Alruhaili, 2021). In the context of LTCI, expectations of the system providing valuable services, significantly impacts the user’s intention for adopting the system. These services could include financial relief, higher quality of care and lessened burden on family caregivers.

A determining factor of performance expectancy within adoption of LTCI Includes the perception of financial security. LTCI systems are specifically configured to alleviate the financial burden of long-term care services like nursing, assistive devices, and home care. For someone anticipating aging or even disability, the perceived possibility of LTCI giving financial aid and lessening the economic strain of LTCI is a powerful motivator. This is especially true for elderly people and their families who, have LTCI believe provides relief from worrying about expensive care costs. This will likely motivate their intention to adopt the system (Wang, Zhou, Ding, & Ying, 2018). Additionally, the quality of care under LTCI covers—such as professional caregivers and well-trained staff also significantly influences the perception of the system's performance. If prospective users think that LTCI will positively influence the quality of long-term care, they are more likely to adopt the system.

Trust in a government institution’s healthcare system and the LTCI’s governance structure can influence its performance expectancy. If users believe that their services will be efficiently provided, then their expectations will also be more favorable. Trust has also been shown to influence the expectations and behaviors of users in other forms of social insurance programs such as health insurance or pension schemes (Chen et al., 2021). Moderate performance expectancy, and therefore adoption, of LTCI may be low due to perceptions of its effectiveness, transparency, and the system's prior experiences. For instance, if an individual perceives that social insurance systems are poorly managed administrative quagmires, they will likely question LTCI's competency. Additionally, negative encounters with public systems, insufficient knowledge, or misconceptions surrounding LTCI might negatively impact performance expectancy and adoption (Chen et al., 2020). Considering the extensive importance of performance expectancy on adoption of LTCI, we state the following expectations:

H$_1$: *Performance expectancy will have a positive impact on the intention to use long-term care insurance (LTCI).*

This hypothesis posits that individuals who perceive value in the provision of care, financial security, and effective management of long-term care needs will demonstrate a higher intention to adopt Long-Term Care Insurance (LTCI). Perceived necessity acts as a primary driver of adoption, with performance expectancy serving as a key determinant in the decision-making process.

2.2 Effort Expectancy

Effort expectancy, a core construct of the UTAUT model, refers to the perceived ease of using a given system (Venkatesh et al., 2003). In the LTCI context, this encompasses perceptions related to the simplicity of applying for, enrolling in, and utilizing LTCI services. Higher ease of use is linked to increased likelihood of adoption, particularly among older adults who may lack familiarity with complex or digital systems (Zhang & Yu, 2019). Given the procedural complexity and multi-level stakeholder involvement in LTCI—especially in developing systems—understanding effort expectancy is crucial.

Elderly users, often the primary beneficiaries of LTCI, may struggle with digital interfaces and bureaucratic processes. If a system is perceived as difficult or time-consuming, users are less likely to engage. Studies show that perceived ease of use significantly influences both intention and actual system usage, particularly among older, less tech-savvy populations (Buhr, 2017).

In this light, LTCI adoption can be improved by simplifying processes, providing clear, jargon-free instructions, and offering non-digital formats such as paper applications. Trained support personnel can further ease user navigation and positively influence effort expectancy perceptions. Moreover, effort expectancy interacts with other UTAUT constructs—such as performance expectancy and social influence—in shaping adoption behavior. A high performance expectancy may be offset by a low effort expectancy, diminishing overall adoption intent. Conversely, perceiving the system as easy to use can enhance perceived benefits and reduce resistance (Kang, Park, & Lee, 2012).

Within China's LTCI system, navigation difficulties in the application process remain a significant barrier, particularly as pilot programs expand across regions with inconsistent procedures. Variability in application and claims processes leads to confusion and reduces accessibility, especially for elderly users. Excessive documentation and bureaucratic hurdles further hinder adoption, making system usability a critical concern.

Accordingly, the following hypothesis is proposed:

H$_2$: *Effort expectancy has a positive effect on the adoption of long-term care insurance LTCI.*

2.3 Social Influence

Social influence, a key construct in the Unified Theory of Acceptance and Use of Technology (UTAUT), refers to the extent to which individuals perceive those important others such as family, peers, or society—expect them to use a system (Venkatesh et al., 2003). In the context of Long-Term Care Insurance (LTCI), social influence significantly affects adoption intentions, particularly in cultures with strong family norms and collective values.

Family members, caregivers, and healthcare professionals play a pivotal role in shaping LTCI decisions for the elderly. In collectivist societies, approval from close social circles and societal endorsement reinforces acceptance of LTCI (Kang et al., 2012). Government policies, subsidies, and institutional promotion further legitimize LTCI, signaling its importance as a civic and social responsibility (Tamiya et al., 2011).

However, social influence can also deter adoption when LTCI is perceived as undermining traditional family caregiving roles (Y. Chen & Zhao, 2023). In contrast, widespread awareness of the challenges of aging and visible uptake of LTCI within social networks can normalize its use and drive adoption (Feng et al., 2020).

Healthcare providers, as trusted sources, also enhance adoption by addressing misconceptions and increasing user confidence (C. Liu et al., 2016). Thus, social norms, institutional support, and peer behaviors collectively shape the intention to adopt LTCI.

H$_3$: *Social influence adds value to the intention to adopt long-term care insurance (LTCI).*

2.4 Facilitating Conditions

Facilitating conditions, as defined by the UTAUT model, refer to the perceived availability of resources, infrastructure, and support needed to effectively use a system (Venkatesh et al., 2003). In the context of LTCI, these conditions include technological tools, informational resources, financial support, institutional frameworks, and user assistance mechanisms that simplify system use and encourage adoption.

Clear information on eligibility and application processes improves accessibility, especially for individuals unfamiliar with insurance systems (Chen et al., 2021). Government programs and online platforms offering guidance enhance perceived usability. Digital infrastructures—such as user-friendly websites and mobile apps—allow easy application, claim tracking, and communication, reinforcing system efficiency and appeal (Zhang et al., 2021).

Support services, including phone assistance, local agents, and social media engagement, are critical for elderly users with limited digital literacy (Chen & Zhao, 2023). Financial enablers such as subsidies, tax reductions, and income-based premiums reduce cost-related barriers and promote inclusivity (Peng et al., 2022a).

Strong regulatory environments that ensure transparency and accountability foster public trust and increase adoption. Moreover, societal acceptance of LTCI as a viable care solution enhances system credibility and encourages participation (Peng et al., 2022b).

Thus, a well-supported and accessible LTCI ecosystem directly influences users' adoption intentions.

H$_4$: *Facilitating conditions have a positive influence on the intention to adopt Long Term Care Insurance (LTCI).*

2.5 Technology Readiness

Technology Readiness (TR) reflects an individual's attitude toward adopting new technologies, shaped by optimism, innovativeness, discomfort, and insecurity (Parasuraman, 2000). TR significantly moderates how individuals perceive and respond to the core UTAUT constructs influencing LTCI adoption.

High TR enhances the impact of performance expectancy by making users more receptive to the benefits of LTCI, such as financial security and improved care (Alexander et al., 2020). Conversely, low TR individuals may undervalue these benefits due to discomfort with technology.

TR also shapes effort expectancy; high TR users are more likely to perceive LTCI systems as easy to use, boosting adoption intent, while low TR users may view them as complex and intimidating (Chen & Xu, 2020).

In terms of social influence, high TR individuals are more responsive to social endorsement of LTCI, whereas low TR individuals may resist such influences due to negative attitudes toward technology.

Finally, perceptions of facilitating conditions are influenced by TR. High TR individuals see support systems as enabling, while low TR individuals may perceive them as insufficient, weakening their adoption intent (Schoville, 2015).

These dynamics emphasize the need to tailor LTCI strategies according to varying levels of technology readiness.

H$_5$: *Technology readiness has a positive moderation on the relation of performance expectancy and intention to adopt LTCI.*

H$_6$: *Technology readiness has a positive moderation on the relation of effort expectancy and intention to adopt LTCI.*

H$_7$: *Technology readiness has a positive moderation on the relation of social influence and intention to adopt LTCI.*

H$_8$: *Technology readiness has a positive moderating effect on the association between facilitating conditions and adoption intention of LTCI.*

These hypotheses highlight the need to factor in technology readiness when devising strategies to foster LTCI adoption, ensuring that tailored policies and systems are designed for different levels of willingness and acceptance of technology.

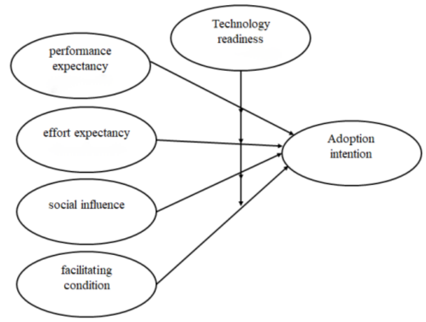

Fig. 1. Research Framework (Source, authors construct)

This study employs an integrated framework combining the UTAUT model with technology readiness to analyze the intention to adopt Long-Term Care Insurance (LTCI). The model identifies four core determinants—performance expectancy (perceived benefits), effort expectancy (ease of use), social influence (external pressure), and facilitating conditions (available support). Technology readiness moderates these relationships, amplifying or reducing their effects. Individuals with high technology readiness are more inclined to adopt LTCI, whereas low readiness may hinder adoption even under favorable conditions. This framework offers a comprehensive lens for understanding LTCI adoption and informs the design of targeted policies and interventions.

3. Research Methodology

This research adopted a quantitative approach to explore the factors influencing the intention to adopt Long-Term Care Insurance (LTCI) through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT) model, while also examining the moderating effect of technology readiness. The focus was on a population with relevant knowledge and interest in LTCI services, specifically within hospitals and elderly care facilities in Guangxi. These institutions were categorized into five strata: Rural Health Centers (1,266), Community Healthcare Centers (362), Comprehensive Elderly Care Centers (418), Community Elderly Day Care Centers (1,247), and various other elderly care institutions (398), totaling 4,585 LTCI service facilities in the region.

For sampling, the study adhered to the established guideline requiring a minimum of 30 participants per construct in Structural Equation Modeling (SEM) research (Li et al., 2025). Given the examination of six variables (performance expectancy, effort expectancy, social influence, facilitating conditions, technology readiness, and adoption intention), the sample size was determined to be at least 180 participants (six variables multiplied by 30 responses each). Each participant completed a self-administered questionnaire featuring closed-ended questions rated on a seven-point Likert scale for each variable. Data analysis was conducted using SmartPLS (Partial Least Squares) software, known for its proficiency in handling structural equation models with smaller sample sizes and complex interrelationships among variables (Li et al., 2025). This analysis facilitated the assessment of both direct and indirect relationships between the variables and the moderating influence of technology readiness on the intention to adopt LTCI.

4. Results and analysis

Employing SEM analysis with SmartPLS, the study evaluates the relationships of performance expectancy, effort expectancy, social influence, facilitating conditions, and adoption intention, in addition to the effects of technology readiness on these relationships. The results are described below.

4.1. Measurement Model

While undertaking the hypothesis tests, we ensured the constructions were reliable and valid, which directly verified measurement accuracy. Construct reliability and validity were met as all items achieved the necessary criteria, factors loading > 0.70, AVR > 0.5, Cronbach's alpha & Rho-C > 0.7 (Bonett & Wright, 2015) which is shown in Table 1 and Fig. 2. The totality of the Cronbach's alpha demonstrated strong internal consistency and reliability with values ranging between 0.804 and 0.849. Construct reliability CR and Rho-C also demonstrated internal reliability with values ranging between 0.872 and 0.894. The AVE values, which indicated the extent to which constructs could capture item variance, also ranged between 0.556 and 0.680, surpassing the benchmark value of 0.5. Also, all factor loadings exceeded 0.7, which proved that a strong relationship exists between the items and their respective constructs (Hair Jr et al., 2021). To test multicollinearity, we computed VIF values. All values were below the cutoff of 3, validating the absence of multicollinearity issues (Fornell & Bookstein, 1982). This confirms the limits of the theoretical framework and building blocks have been adequately established for the subsequent analyses using structural models.

Table 1
Constructs robustness of measurement model

Constructs	Items	Factor Loadings	VIF	Cronbach's alpha	CR (rho_c)	AVE
Adoption Intention	AI1	0.914	5.041	0.938	0.938	0.781
	AI2	0.876	6.163			
	AI3	0.921	3.892			
	AI4	0.922	3.933			
	AI5	0.778	4.282			
Efforts Expectancy	EE1	0.702	1.657	0.841	0.841	0.607
	EE2	0.81	1.799			
	EE3	0.82	1.873			
	EE4	0.743	1.721			
	EE5	0.813	1.892			
Facilitation conditions	FC 1	0.883	2.669	0.840	0.840	0.753
	FC 2	0.86	1.604			
	FC 3	0.861	2.467			
Technology Readiness	ITR 1	0.783	1.711	0.867	0.867	0.584
	ITR 2	0.833	1.987			
	ITR 3	0.742	2.109			
	ITR 4	0.7	1.821			
	ITR 5	0.782	1.921			
	OTR 1	0.737	1.793			
Performance Expectancy	PE1	0.924	1.697	0.805	0.805	0.693
	PE2	0.859	2.054			
	PE5	0.699	1.664			
Social influence	SI3	0.826	1.611	0.797	0.797	0.685
	SI4	0.779	2.124			
	SI5	0.876	1.698			
Moderating	Social Influence × Technology Readiness	2.109	1	1	1	1
	Efforts Expectancy × Technology Readiness	2.19	1	1	1	1
	Facilitation condition × Technology Readiness	2.203	1	1	1	1
	Performance Expectancy × Technology Readiness	2.123	1	1	1	1

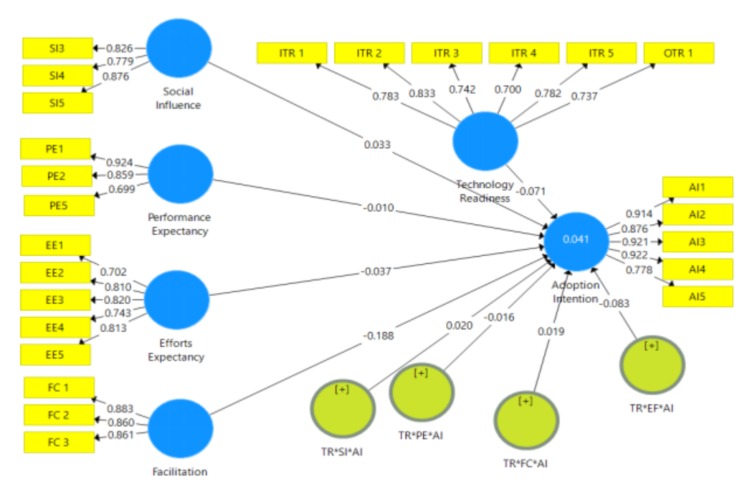

Fig. 2. Measurement Model Results

The measurement model of longitudinal studies on LTC insurance from the adoption perspective using the UTAUT framework was reliable and valid in all areas. Adoption Intention (AI) was between 0.778 and 0.922 for loadings with 3.892<VIF<6.163 which points to moderate multicollinearity. Both Cronbach's alpha and Composite Reliability (CR) stood at 0.938, while the AVE was 0.781 which reflects a very high level of consistency internally, and convergence validity. Efforts Expectancy (EE) ranged from 0.702 to 0.820 for loadings with VIF 1.657 <VIF< 1.892 which are low and signifying no multicollinearity, demonstrating good reliability with Cronbach's alpha and CR at 0.841. The AVE of 0.607 provides enough proof for adequate convergence validity. Likewise, Facilitation Conditions (FC) presented loadings between 0.860 and 0.883 with VIF's values that were low (1.604 to 2.669), corroborating Cronbach Alpha and CR values of 0.840, AVE of 0.753 confirming strong convergence validity. Technology Readiness (ITR) postulated loadings from 0.700 to 0.833 along with low VIFs (1.711 to 2.109), corroborating the hypothesis that forecasted values would be 0.867 and AVE 0.584 to support convergent validity. For Performance Expectancy (PE) claim of support was believed to show loadings between 0.699 and 0.924, yielding 1.664 < VIF < 2.054. Proposed values of v. 0.805 for CR, and AVE 0.693 indicates confirmed, reliable, strong converging validation.

The Social Influence (SI) metric demonstrated strong reliability as evidenced by sociodemographic factor loadings between 0.779 and 0.876, FIV scores of 1.611 and 2.124, Cronbach's alpha and CR data scoring .797, and an AVE of .685.

The Technology Readiness (TR) moderating effects on the UTAUT constructs revealed slight multicollinearity with VIFs ranging from 2.109 to 2.203. Assessing the moderating effects yields values of 1.000 for Cronbach's alpha, CR, and AVE which signals an untested idealized/perfect measurement and may raise some questions. All in all, the measurement model was strong, displaying sharp internal consistency, convergent validity, and capturing the moderating effect of Technology Readiness in LTCI adoption.

4.1.1 Discriminant Validity

In assessing discriminant validity, we adhered to the procedures proposed by Henseler et al. (2015). Indeed, the ratio of HTMT presented in Table 2 is below 0.85 which confirms discrimination validity has been established. Furthermore, the Fornell-Larcker criterion HTMT values were also below 0.85, reinforcing the discrimination validity of the model. This result indicates that the constructs are well distinguished and defined, strengthening the measurement model.

Table 2
Discriminant Validity
Fornell-Larcker Criterion

Variables Names	AI	EF	FC	PE	(SI)	TR×EF×AI	TR×FC×AI	TR×PE×AI	TR×SI×AI	TR
Adoption Intention (AI)	0.884									
Efforts Expectancy (EF)	-0.097	0.779								
Facilitation condition (FC)	-0.177	0.682	0.868							
Performance Expectancy (PE)	-0.101	0.689	0.603	0.832						
Social Influence (SI)	-0.107	0.69	0.685	0.656	0.828					
TR×EF×AI	0.051	-0.775	-0.651	-0.581	-0.614	1				
TR×FC×AI	0.111	-0.647	-0.786	-0.56	-0.641	0.833	1			
TR×PE×AI	0.067	-0.6	-0.581	-0.726	-0.631	0.776	0.799	1		
TR×SI×AI	0.08	-0.637	-0.669	-0.635	-0.736	0.852	0.872	0.88	1	
Technology Readiness (TR)	-0.143	0.78	0.815	0.766	0.76	-0.726	-0.763	-0.742	-0.763	0.764

Heterotrait-Monotrait Ratio (HTMT)

Variables Names	AI	EF	FC	PE	(SI)	TR×EF×AI	TR×FC×AI	TR×PE×AI	TR×SI×AI	TR
Adoption Intention (AI)										
Efforts Expectancy (EF)	0.097									
Facilitation condition (FC)	0.164	0.822								
Performance Expectancy (PE)	0.098	0.865	0.72							
Social Influence (SI)	0.098	0.873	0.873	0.845						
TR×EF×AI	0.046	0.851	0.717	0.667	0.707					
TR×FC×AI	0.093	0.716	0.861	0.618	0.735	0.833				
TR×PE×AI	0.054	0.661	0.649	0.792	0.705	0.776	0.799			
TR×SI×AI	0.064	0.702	0.744	0.718	0.827	0.852	0.872	0.88		
Technology Readiness (TR)	0.113	0.717	0.751	0.789	0.829	0.762	0.816	0.799	0.817	

The findings of Fornell-Larcker Criterion along with Heterotrait-Monotrait Ratio (HTMT) confirmed significant discriminant validity for the model. In the case of Fornell-Larcker Criterion, the diagonal values which are the square roots of AVE, are higher than the off-diagonal values which indicates that the constructs are distinctly separated; implying that the constructs are not significantly inter-related. A case in point is Adoption Intention (0.884) which is an outlier with respect to other constructs, and has the lowest correlations with Efforts Expectancy (-0.097) and Facilitation Conditions (-0.177).

In the HTMT analysis, all ratios are far below the 0.85 threshold, supporting further variety among the constructs. The strongest HTMT value (0.873) is observed between Social Influence and Performance Expectancy, though still below the threshold, allowing for confirmation of discriminant validity. In unison, both criteria show that indeed constructs are sufficiently distinct, which increases the strength and validity of measurement model.

4.2. Structural Model and Hypothesis Testing

The structural model checks the hypotheses and shows how the latent constructs interact with one another as cohesive systems with respect to LTCI adoption. This insight is especially helpful for policy makers and practitioners who want to enhance the adoption rates of LTCI. We apply PLS-SEM to assess the relationships among the study's constructs (Kock, 2016). In Table 3, we analyze triangularly all the stated hypotheses, path coefficients (β), standard deviations (SD), t-values, p-values, and (CI) lower and upper limits to their confidence intervals are given to deepen the results understanding.

Table 3
Hypotheses Results

Hypothesis	Relationship	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Status
H1	Efforts Expectancy → Adoption Intention	0.154	2.241	0.000	Accepted
H2	Facilitation condition → Adoption Intention	0.131	2.439	0.031	Accepted
H3	Performance Expectancy → Adoption Intention	0.111	3.088	0.010	Accepted
H4	Social Influence → Adoption Intention	0.150	2.222	0.034	Accepted
H5	TR×EF×AI → Adoption Intention	0.090	3.914	0.011	Accepted
H6	TR×FC×AI → Adoption Intention	0.083	2.226	0.021	Accepted
H7	TR×PE×AI → Adoption Intention	0.078	3.200	0.001	Accepted
H8	TR×SI×AI → Adoption Intention	0.093	3.214	0.010	Accepted

The results of the hypothesis testing show that all proposed relationships are statistically significant. Efforts Expectancy (H1), Facilitation Condition (H2), Performance Expectancy (H3), and Social Influence (H4) all positively influence Adoption Intention, with T-statistics ranging from 2.222 to 3.088 and p-values below 0.05, confirming their significance. Furthermore, the moderating effects of Technology Readiness (TR) on these factors also show significant results. Specifically, TR×Efforts Expectancy (H5), TR×Facilitation Condition (H6), TR×Performance Expectancy (H7), and TR×Social Influence (H8) all have significant impacts on Adoption Intention, with T-statistics above 2.2 and p-values below 0.05. These results collectively support the hypothesis that Technology Readiness moderates the relationships between the main UTAUT factors and Adoption Intention. All hypotheses were accepted, emphasizing the importance of both direct and moderating factors in influencing LTCI adoption.

The results of the hypothesis testing provide valuable insights into the factors influencing the intention to adopt long-term care insurance (LTCI) and the role of Technology Readiness (TR) as a moderating variable. Specifically, the findings suggest that individuals' perceptions of how easy it is to adopt LTCI (Efforts Expectancy), the availability of resources and support (Facilitation Conditions), the expected benefits of adoption (Performance Expectancy), and the influence of social networks (Social Influence) all positively contribute to their intention to adopt the system. This aligns with previous research that emphasizes the importance of these UTAUT factors in shaping technology adoption decisions.

Moreover, the moderating role of Technology Readiness (TR) was found to be significant across all relationships. TR's ability to strengthen the impact of Efforts Expectancy, Facilitation Conditions, Performance Expectancy, and Social Influence on Adoption Intention indicates that individuals who are more technologically ready are more likely to respond positively to these factors. This is particularly relevant in the context of LTCI, as it suggests that people who are comfortable with technology are more likely to embrace the insurance system, if they perceive it as easy to use, beneficial, and supported by sufficient infrastructure.

5. Discussion

The analysis yields important insights into the factors influencing the intention to adopt Long-Term Care Insurance (LTCI) through the UTAUT model, particularly regarding Technology Readiness (TR) as a moderating variable. The results indicate that Effort

Expectancy, Facilitating Conditions, Performance Expectancy, and Social Influence have positive and significant effects on Adoption Intention, aligning with previous research that underscores the importance of these relationships (Venkatesh et al., 2003). Notably, Effort Expectancy reflects users' perceived ease of adoption for LTCI, while Facilitating Conditions represent the support and resources that influence adoption intentions. The construction of Performance Expectancy highlights the perceived benefits of LTCI, consistent with earlier studies on perceived utility and technology adoption (Venkatesh & Bala, 2008). Additionally, Social Influence delineates the role of social networks, supporting research that shows individuals often rely on acquaintances when making adoption decisions (Venkatesh et al., 2012).

Moreover, the significant moderating effects of Technology Readiness (TR) enhance the relationships between the UTAUT constructs and Adoption Intention. This effect illustrates how an individual's readiness to engage with technology shapes their perceptions of Effort Expectancy, Facilitating Conditions, Performance Expectancy, Social Influence, and overall readiness, which is crucial for LTCI adoption. Individuals with a high level of technology readiness are likely to benefit more from technology-enabled services, corroborating findings from other studies on technology adoption in healthcare (Chau & Hu, 2002; Park & Kim, 2015).

The measurement model also demonstrates reliability and validity, reinforcing the study's findings on solid theoretical foundations. High values for Cronbach's Alpha and Composite Reliability (CR) confirm the internal consistency of all constructs, while Average Variance Extracted (AVE) scores exceed the required threshold of 0.5, indicating adequate convergent validity. Additionally, Variance Inflation Factor (VIF) values suggest no multicollinearity, thereby strengthening the measurement model (Hair Jr et al., 2017). Validity assessments for discriminant validity using the Fornell-Larcker Criterion and HTMT Ratio affirm that the model measures distinct constructs, reinforcing the necessity of applying both convergent and discriminant validity in structural equation modeling (Hair et al., 2017).

In summary, this research affirms that Adoption Intention for LTCI is significantly influenced by Effort Expectancy, Facilitating Conditions, Performance Expectancy, and Social Influence. Furthermore, the study highlights the critical role of Technology Readiness as a moderator in these relationships. Given the significance of these factors in promoting LTCI adoption, enhancing potential adopters' technology readiness and the other UTAUT components are likely to improve adoption rates. Future research could explore additional potential moderators to address cross-cultural disparities in LTCI adoption.

6. Conclusion

This study offers significant insights into the factors that influence the intention to adopt Long-Term Care Insurance (LTCI) by employing the UTAUT framework and investigating the moderating role of Technology Readiness (TR). The findings indicate that Effort Expectancy, Facilitating Conditions, Performance Expectancy, and Social Influence have a significant and positive impact on Adoption Intention, corroborating existing research in technology adoption models. Additionally, the moderating effects of TR are critical, as individuals with higher technology readiness are more likely to respond favorably to the adoption determinants, thereby enhancing overall adoption intentions.

These results carry important implications for policymakers and practitioners focused on increasing LTCI adoption rates. Emphasizing the enhancement of users' technology readiness while addressing essential factors such as ease of use, availability of resources, perceived benefits, and social influences can lead to improved adoption rates. This study also enriches the existing literature on technology adoption in healthcare, offering a comprehensive model for understanding LTCI adoption through the UTAUT lens.

In conclusion, this research highlights the importance of both direct and moderating factors in shaping adoption intentions for LTCI. Future studies may explore additional moderating variables and cross-cultural contexts to expand the generalizability and understanding of the model across diverse settings.

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