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Exploring the adoption intention of long-term care regulatory systems in Guangxi, China: The role of innovation attributes and perceived risk

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A B S T R A C T

This study examines the adoption intention of the Long-Term Care (LTC) regulatory system in Guangxi, China, emphasizing the influence of innovation attributes and perceived risk. It analyzes how relative advantage, compatibility, complexity, trialability, and observability positively affect healthcare providers' and elderly care institutions' willingness to adopt the system. The study further explores the moderating role of perceived risk in strengthening the relationship between these innovation attributes and adoption intention. Data were collected through a survey of 370 professionals from hospitals, rural health centers, and elderly care institutions and analyzed using SPSS and structural equation modeling (SEM). Results indicate that all five innovation attributes significantly enhance adoption intention, with perceived risk amplifying these effects. The findings underscore the need for supportive policies, technological advancement, and coordinated stakeholder engagement to ensure successful LTC system implementation. This research provides actionable insights for policymakers and industry leaders to support the expansion of LTC insurance systems amid China's aging population.

1. Introduction

With China's rapidly aging population, the provision of high-quality elderly care has become a critical concern for policymakers and healthcare institutions (Feng et al., 2020). The rising demand for long-term care (LTC), particularly in regions such as Guangxi, underscores the urgent need for innovative and effective regulatory frameworks (Feng et al., 2012). In response, the Chinese government has initiated healthcare reforms aimed at integrating comprehensive LTC services (Lobanov-Rostovsky et al., 2023). This study investigates the determinants of LTC regulatory system adoption in Guangxi, focusing on innovation attributes—relative advantage, compatibility, complexity, trialability, and observability—and the moderating role of perceived risk. While global demographic trends are transforming healthcare infrastructure (Penno & Gauld, 2017), China faces intensified challenges, with projections estimating over 300 million citizens aged 60 and above by 2050 (Feng et al., 2019). Such trends amplify the need for robust LTC systems, especially for seniors with chronic conditions or sustained care needs (Singer & Manton, 1998). China's LTC system aims to merge medical and social care within a unified regulatory framework, enhancing service quality and access (Wong & Leung, 2012). In Guangxi, implementation efforts are ongoing, yet adoption is hindered by operational, financial, and technological challenges faced by healthcare institutions (Chai & Yeo, 2012). Decision-makers in hospitals, rural health centers, and

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elderly care facilities must evaluate system integration within constraints of resource availability and technological readiness (Özkaytan et al., 2023). This research addresses these gaps by examining how innovation attributes influence adoption intention and how perceived risk moderates these effects. Despite growing demand and policy emphasis, limited research has examined LTC adoption in rural China, particularly in the context of healthcare institutions (Ehrenhard et al., 2014; Lai-Ming Tam, 2012). Moreover, existing studies rarely explore how perceived risk interacts with innovation attributes in determining adoption outcomes.

The study draws on innovation diffusion theory, which highlights the significance of perceived innovation characteristics in adoption decisions (Hirunyawipada & Paswan, 2006; Albertsen et al., 2020). However, the role of perceived risk—especially in rural, resource-limited healthcare settings—remains underexplored (Wei et al., 2023). This research thus offers a novel framework by incorporating perceived risk as a moderator, addressing the specific context of rural healthcare in Guangxi.

The study's objectives are threefold: (1) to assess how innovation attributes affect LTC system adoption intention; (2) to evaluate the moderating role of perceived risk in these relationships; and (3) to inform policy frameworks that address structural barriers while enhancing adoption facilitators in rural LTC implementation.

A survey of decision-makers in hospitals, rural clinics, and elder care facilities in Guangxi will be conducted. Data will be analyzed using structural equation modeling (SEM), following established methodological approaches (Arif et al., 2020). By integrating literature from healthcare, innovation studies, and policy implementation, this study contributes to a more comprehensive understanding of LTC system adoption in developing contexts.

The novelty of this research lies in its integrative approach, bridging innovation theory with healthcare policy and focusing on the under-researched rural Chinese setting. Its findings will support evidence-based policymaking and strategic planning for LTC implementation, with broader implications for regions facing similar demographic and infrastructural challenges.

2. Theoretical Foundation and Hypothesis development

2.1 Diffusion of Innovation Theory

This study is anchored in the Diffusion of Innovations (DOI) Theory, which explains how innovations spread within a social system—here, the healthcare sector (Iqbal & Zahidie, 2021). According to DOI, five core attributes influence innovation adoption: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage reflects the perceived benefits of the LTC regulatory system over current practices, such as enhanced care quality and efficiency. Compatibility assesses how well the LTC system aligns with existing values, policies, and operations in Guangxi's healthcare institutions (Du et al., 2020). Complexity refers to the perceived difficulty of implementing the LTC system, especially in resource-limited rural settings (Zhang et al., 2020, 2023). Trialability captures the extent to which healthcare providers can pilot the system before full implementation (Alcouffe et al., 2024). Observability concerns how visible the outcomes of system adoption are to other institutions and stakeholders (El-Yafouri et al., 2022). Perceived risk acts as a moderator, influencing how innovation attributes affect adoption intention. It includes financial, operational, and technological uncertainties tied to adopting the LTC system (Kaur & Arora, 2020). DOI provides a structured lens for understanding how these elements shape adoption behavior in Guangxi's healthcare landscape.

2.2 Hypothesis Development

2.2.1 Attributes of Innovation and Adoption Intention

Adopting healthcare innovations is complex and context-dependent (Milella et al., 2021). Drawing from DOI, this study examines how the five innovation attributes influence the adoption intention of the LTC system in Guangxi (Deng et al., 2021).

Relative advantage relates to the perceived improvement over existing elderly care systems. It includes benefits such as improved care delivery, regulatory compliance, and operational performance (Chokphukhiao et al., 2024; Lin et al., 2020). We hypothesize:

H_1: *Relative advantage is positively associated with adoption intention.*

Compatibility refers to the fit between the LTC system and the existing healthcare environment. High compatibility reduces resistance and eases integration (Bygstad & Øvrelid, 2020; Huang et al., 2021, 2024). Thus:

H_2: *Compatibility is positively associated with adoption intention.*

Complexity reflects perceived difficulty. While typically seen as a barrier, complexity may have a neutral or even positive effect if mitigated by training and support (Dehghani et al., 2022; Y. Du et al., 2022). Therefore:

H_3: *Complexity is positively associated with adoption intention.*
Trialability enables organizations to assess innovations on a limited scale. Higher trialability reduces uncertainty and builds confidence (Outcault et al., 2022; Wu et al., 2023). Hence:

H4: *Trialability is positively associated with adoption intention.*

Observability involves the visibility of innovation outcomes. Observable improvements can influence peer institutions to adopt (Wilson et al., 2022). We propose:

H5: *Observability is positively associated with adoption intention.*

2.2.2 The moderating effect of Perceived Risk between Attributes of Innovation and Adoption Intention

Perceived Risk (PR) plays a critical moderating role in the relationship between innovation attributes and Adoption Intention (AI), particularly regarding the adoption of the Long-Term Care (LTC) regulatory system in Guangxi, China (Cao, Dai, & Li, 2023).

PR significantly influences the effect of Relative Advantage (RA) on AI. While RA reflects perceived benefits compared to existing practices (Nwafor et al., 2023), concerns about financial cost, system reliability, and operational disruptions may diminish its impact (Featherman et al., 2021; Panichakarn et al., 2024).

Similarly, PR moderates the link between Compatibility and AI. Although alignment with institutional values and practices typically facilitates adoption (Salter et al., 2022), perceived risks—especially in under-resourced settings like Guangxi—may hinder uptake (Deng et al., 2023).

The influence of Complexity on AI is also shaped by PR. While complexity reflects perceived implementation difficulty, elevated risk perception may amplify resistance to adoption (Chen & Panichakarn, 2023; Fareed et al., 2024). However, adequate training and support can mitigate this effect.

For Trialability, PR affects the degree to which pilot testing reduces uncertainty. In risk-averse institutions, trial opportunities can increase confidence and facilitate adoption (Hasan et al., 2021; Kendall et al., 2022).

Lastly, PR moderates the relationship between Observability and AI. Although visible benefits observed in early adopters promote wider diffusion (Kaur & Arora, 2020), negative experiences or lack of observable outcomes may inhibit further adoption (Bylianto & Chan, 2023).

In summary, PR interacts with all five DOI attributes—RA, Compatibility, Complexity, Trialability, and Observability—shaping the likelihood of LTC system adoption. Effective risk management is therefore essential for successful implementation in healthcare settings.

Hypotheses:

H6: *Perceived Risk significantly moderates the relationship between Relative Advantage and Adoption Intention.*

H7: *Perceived Risk significantly moderates the relationship between Compatibility and Adoption Intention.*

H8: *Perceived Risk significantly moderates the relationship between Complexity and Adoption Intention.*

H9: *Perceived Risk significantly moderates the relationship between Trialability and Adoption Intention.*

H10: *Perceived Risk significantly moderates the relationship between Observability and Adoption Intention.*

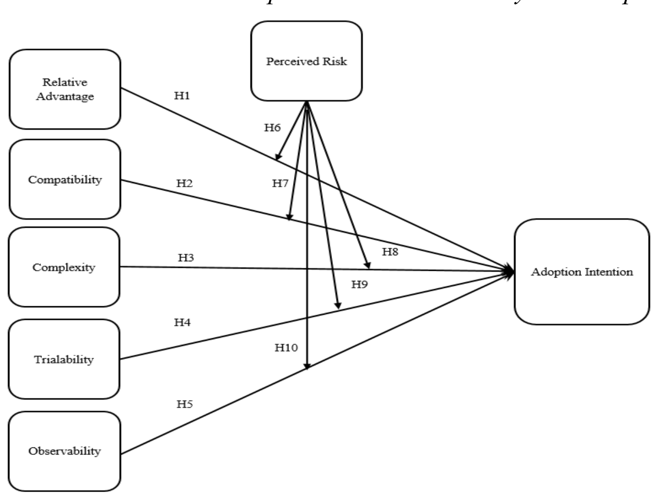

Fig. 1. Research Framework

3. Methodology

3.1 Research Design, Sampling & Data Collection Procedures

In this study, a cross-sectional survey was conducted among logistics managers and supply chain coordinators working in Hospitals, Rural Health Center, Community Healthcare Center , Comprehensive Elderly Care Center, Community Elderly Day Care Center , and other types of elderly care institutions in Guangxi China (Hunziker & Blankenagel, 2024). Respondents were chosen through an arbitrary sampling method using the filter of having a minimum of five years of experience dealing with the hospital activities and meeting legal obligations for braided reliability. Out of 1279 survey invitations that were sent out to industry specialists, 622 completed the questionnaires. However, only 541 cleaned and validated their data, which then enabled them to undergo the subsequent analysis. Data collection lasted six weeks using an online survey platform, resulting in a 48.63% response rate (Kurzhals, 2021). These were useful to collect the feedback in China's Hospital sector on the role of the relative advantage, compatibility, complexity, trialability, observability, perceived risk, adoption intention.

3.2 *Data Analysis Technique and Ethical Considerations*

We utilized IBM SPSS Statistics, which calculated central measures and variation in the data, specifically within the boundaries of hypothesis testing, and SEM with Smart PLS 4 for more intricate inter variable relationships (Hair Jr, Hult, Ringle, & Sarstedt, 2021; Chen et al., 2024) Prior to the commencement of the data-gathering tasks, each individual was provided relevant information concerning the intent of the study along with a consent form. Steps that were followed to privacy and confidentiality included file encryption and data anonymization as part of the ethical considerations of research conduct (Iversen et al., 2006).

3.3 Common Method Bias

In this study, we will employ certain procedural and statistical methods to minimize the impact of Common Method Bias (CMB). First steps will include ensuring that all items in the questionnaire are as straightforward and direct as possible in order to minimize participant misunderstanding. Also, to improve reliability and reduce response pattern biases, reverse-coded items will be added and spaced throughout the questionnaire. Statistically, I will utilize Harman's single-factor test and the partial correlation method, as (Kock, 2015, 2016), recommends, to account for CMB effects. These strategies will guarantee that the results of the study will be accurate and unbiased by systematic measurement errors.

4. Analysis and Results

A comprehensive quantitative analysis employs an investigation to explore the relationships shown in Figure 1 of the theoretical framework by statistical analysis and emphasizing data-driven rigor.

Table 1
Descriptive Statistics and Correlations for the Variables

	Mean	SD	Kurtosis (-7 to +7)	Skewness (-2 to +2)	1	2	3	4	5	6	7	8	9	10	11	12	13
[1]Institution Type	3.229	1.721	-1.475	0.153	1												
[2]Location	1.917	0.713	-1.031	0.123	.035	1											
[3]Years of operation	2.157	0.995	-0.777	0.505	-.049	.000	1										
[4]Number of Employees	2.383	0.932	-0.827	0.173	-.089*	-.016	.033	1									
[5]Number of elderly patients/clients served each	1.976	0.85	-0.403	0.535	.010	-.073	.002	.037	1								
[6]Institutional nature	2.105	0.726	-1.093	-0.163	.013	.006	.044	-.005	-.020	1							
7.Relative Advantage	5.073	1.534	-0.689	-1.022	.017	.046	.031	-.011	.021	.055	1						
8.Compatibility	5.289	1.462	-0.108	-1.219	-.024	.037	.029	.015	.107*	.021	.397**	1					
9.Complexity	3.284	1.783	-1.386	0.635	.039	-.028	.014	.014	.010	-.055	-.350**	-.287**	1				
10.Trialability	4.841	1.669	-1.332	-0.671	-.028	.001	-.002	.031	.088*	.026	.507**	.409**	-.357**	1			
11.Observability	4.942	1.652	-1.146	-0.76	.002	-.057	-.019	.027	.038	.030	.429**	.389**	-.306**	.406**	1		
12. Perceived Risk	5.166	1.575	-0.242	-1.195	-.068	.002	.049	-.068	.027	.063	.206**	.275**	-.134**	.256**	.255**	1	
13.Adoption Intention	4.838	1.895	-1.063	-0.73	-.007	.024	.011	-.018	.038	-.061	.414**	.428**	-.362**	.442**	.407**	.280**	1

Note: Sample size (n) = 541; α: Cronbach's alpha; SD: Standard deviation; AVE: Average Variance Extracted; CR: Composite Reliability, **. Correlation is significant at the 0.01 level (2-tailed).

1: Institution Type: Hospital (Total=105, 19.4%); Rular Health Centre (Total=148, 27.4%); Community Healthcare Center (Total=47, 8.7%); ; Comprehensive Elderly Care Center (Total=49, 9.1%); Community Elderly Day Care Center (Total=143, 26.4%); Other Types of Elderly Care Institutions (Total=49, 9.1%)
2 Location: City (Total=162, 29.9%); Community (Total=262, 48.4%); Rular (Total=117, 21.6%)
3Years of Operation: Less than 1 years (Total=159, 29.4%); 1-5 years (Total=211, 39.0%); 6-10 years (Total=98, 18.1%); More than 10 years (Total=73, 13.5%)
4Number of Employees: Less than 10 (Total=98, 18.1%); 10-50 (Total=211, 39.0%); 51-100 (Total=159, 29.4%); More than 100 (Total=73, 13.5%)
5Number of elderly patients/clients served each year: Less than 50 (Total=175, 32.3%); 50-100 (Total=231, 42.7%); 101-500 (Total=108, 20.0%); More than 500 (Total=27, 5.0%)
6Institutional Nature: Public (Total=117, 21.6%); Private (Total=250, 46.2%); NPO (Total=174, 32.2%)

4.1 Measurement model

Before conducting hypothesis testing, we ensured measurement accuracy by first assessing the reliability and validity of the constructs. All items achieved the necessary criteria, meeting construct reliability and validity, AVE > 0.5, Cronbach's alpha & Rho-C > 0.7 (Bonett & Wright, 2015), which is illustrated in Table 2 and Fig. 2. Strong internal consistency is indicated by the range of Cronbach's alpha values of 0.940 to 0.965. In addition, the range of composite reliability (CR) and rho-C values of 0.955 to 0.973 confirmed the reliability of the constructs. The AVE values ranging from 0.808 to 0.877 also surpassed the benchmark value of 0.5, illustrating that the constructs were able to adequately capture the variance in their items. As well, all factor loadings greater than 0.7 proved a strong relationship exists between the items and their constructs (Hair Jr et al., 2021). This finding confirms the boundaries of the theoretical framework and prepares the groundwork for the following structural model analysis.

Table 2
Construct robustness of measurement model

Constructs	Items	Factor Loadings	Cronbach's alpha	CR (rho_c)	AVE
Relative Advantage	RA1	0.912	0.942	0.955	0.811
	RA2	0.898			
	RA3	0.891			
	RA4	0.9			
	RA5	0.901			
Compatibility	CP1	0.905	0.940	0.955	0.808
	CP2	0.9			
	CP3	0.893			
	CP4	0.9			
	CP5	0.895			
Complexity	CX1	0.919	0.957	0.966	0.852
	CX2	0.92			
	CX3	0.923			
	CX4	0.93			
	CX5	0.922			
Trialability	TR1	0.906	0.947	0.959	0.825
	TR2	0.911			
	TR3	0.907			
	TR4	0.91			
	TR5	0.906			
Observability	OB1	0.911	0.948	0.960	0.828
	OB2	0.908			
	OB3	0.911			
	OB4	0.91			
	OB5	0.91			
Perceived Risk	PR1	0.889	0.941	0.955	0.808
	PR2	0.911			
	PR3	0.892			
	PR4	0.911			
	PR5	0.892			
Adoption Intention	AI1	0.938	0.965	0.973	0.877
	AI2	0.937			
	AI3	0.941			
	AI4	0.931			
	AI5	0.934			

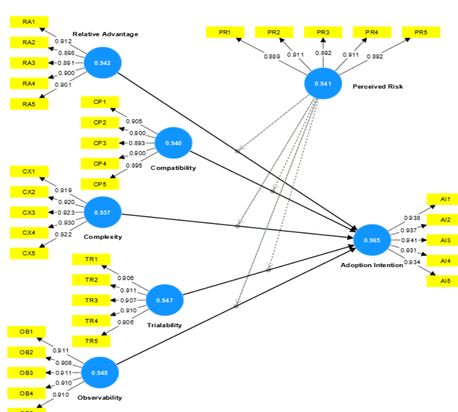

Fig. 2. Confirmatory factor analysis

4.2 Discriminant Validity

To test the discriminant validity, we used the Heterotrait-Monotrait (HTMT) ratio and the guidelines from Henseler et al. (2015), As stated in Table 3, all of the HTMT values are below 0.85, which means that discriminant validity has been achieved. Also, the Fornell-Larcker criterion confirmed that the HTMT values were below 0.85, which enhances the validity of the model that has been proposed. These results affirm that the constructs are well-defined, conceptually distinct, and part of a robust measurement model. The findings ensure that there is no significant overlap between constructs, confirming that each variable uniquely contributes to the model's overall explanatory power.

Table 3
Discriminant Validity

Variables	AI	CP	CX	OB	PR	RA	TR
Discriminant Validity (HTMT) ratio							
Adoption Intention							
Compatibility	0.449						
Complexity	0.377	0.303					
Observability	0.425	0.412	0.321				
Perceived Risk	0.293	0.293	0.141	0.27			
Relative Advantage	0.434	0.422	0.369	0.454	0.218		
Trialability	0.462	0.434	0.375	0.429	0.272	0.536	
Fornell-Larcker criterion							
Adoption Intention	0.936						
Compatibility	0.429	0.899					
Complexity	0.363	0.288	0.923				
Observability	0.409	0.39	0.307	0.91			
Perceived Risk	0.281	0.276	0.134	0.255	0.899		
Relative Advantage	0.415	0.398	0.351	0.428	0.206	0.901	
Trialability	0.443	0.411	0.358	0.407	0.255	0.506	0.908

Note: RA=Relative Advantage, CP=Compatibility, CX=Complexity, TR=Trialability, OB=Observability, PR=Perceived Risk, AI=Adoption Intention

4.3 Hypotheses Testing

Using PLS-SEM, we examined the structural model relationships among the study's constructs (Kock, 2016). Table 4 offers an in-depth analysis of the relationships between the hypotheses, evaluating their statistical significance using path coefficients (β), standard deviation (SD), t-value, p-value, and confidence intervals (CI). It is evident from the table that all ten hypotheses have been confirmed in the research, each having significant relationships concerning the variables governing the Adoption Intention (AI) of regulatory frameworks in Long-Term Care (LTC) in Guangxi, China's healthcare institutions. In H1, the Adoption Intention (AI) was found to be positively and strongly impacted by the Relative Advantage (RA) of LTC systems with $\beta=0.108$, $t=2.283$, and $p=0.022$, thus confirming advantages over existing practices drives adoption. H2, which analyzes Compatibility (CB) and Adoption Intention (AI), is also accepted with a β of 0.168, t of 3.699, and p of 0.000, reinforcing that where the system is congruent to practices, adoption is more probable. Similarly, H3 supports the positive impact of Complexity (CX) on adoption intention, with a β of 0.104, t-value of 2.419, and a p-value of 0.016, suggesting that even perceived complexity can have a positive influence on adoption, likely due to effective support systems and training. H4, examining the relationship between Trialability (TA) and Adoption Intention (AI), shows a positive effect ($\beta=0.119$, $t=2.737$, $p=0.006$), indicating that institutions are more willing to adopt the system when they can test it before full implementation. H5 confirms that Observability (OA) also positively influences Adoption Intention (AI) with a β of 0.160, t-value of 3.504, and a p-value of 0.000, suggesting that the visibility of benefits in early adopters encourages other institutions to follow suit. The study also validates the moderating role of Perceived Risk (PR), with H6 showing that Perceived Risk significantly moderates the relationship between Relative Advantage (RA) and Adoption Intention (AI) ($\beta=0.105$, $t=2.301$, $p=0.021$), indicating that while institutions see the benefits of the LTC system, perceived risks like financial and operational challenges impact their adoption decisions. H7 confirms that Perceived Risk (PR) also moderates the relationship between Compatibility (CB) and Adoption Intention (AI), with a β of 0.133, t-value of 3.342, and a p-value of 0.001, suggesting that institutions that perceive high compatibility but face high risks are less likely to adopt. H8, with Perceived Risk (PR) moderating the relationship between Complexity (CX) and Adoption Intention (AI) ($\beta=0.136$, t-value of 2.967, $p=0.003$), indicates that complex systems become harder to adopt when perceived risks are high. H9 confirms the moderating effect of Perceived Risk (PR) on the relationship between Trialability (TA) and Adoption Intention (AI), with a β of 0.161, t-value of 3.748, and a p-value of 0.000, further emphasizing the importance of testing systems before full adoption while managing risks. H10 confirms Perceived Risk (PR) moderates the relationship between Observability (OA) and Adoption Intention (AI) with a β of 0.137, t-value of 3.307 and p-value of 0.001 which indicates that the adoption is driven by visible benefits, but only when risks are sufficiently addressed. Such outcomes stress the importance of perceived innovation attributes and Perceived Risk concerning the adoption process of the LTC system, emphasizing the need for perceived risks to be addressed through pilot programs, support, and demonstrable success narratives to foster deeper integration within healthcare institutions.

Table 4
Hypothesis Result

						Confidence Interval		
Hypothesis	**Relationship**	**β**	**STDEV**	**t**	**p**	**2.50%**	**97.50%**	**Status**
H1	RA→AI	0.108	0.047	2.283	0.022	0.016	0.200	Accepted
H2	CB→AI	0.168	0.045	3.699	0.000	0.080	0.256	Accepted
H3	CX→AI	0.104	0.043	2.419	0.016	0.020	0.188	Accepted
H4	TA→AI	0.119	0.043	2.737	0.006	0.035	0.203	Accepted
H5	OA→AI	0.16	0.046	3.504	0.000	0.070	0.250	Accepted
H6	PR* RA→AI	0.105	0.046	2.301	0.021	0.015	0.195	Accepted
H7	PR* CB→AI	0.133	0.04	3.342	0.001	0.055	0.211	Accepted
H8	PR* CX→AI	0.136	0.046	2.967	0.003	0.046	0.226	Accepted
H9	PR* TR→AI	0.161	0.043	3.748	0.000	0.077	0.245	Accepted
H10	PR* OB→AI	0.137	0.041	3.307	0.001	0.057	0.217	Accepted

Note: RA= Relative Advantage, CB= Compatibility, CX= Complexity, TR=Trialability, OB= Observability, AI= Adoption Intention, PR= Perceived Risk

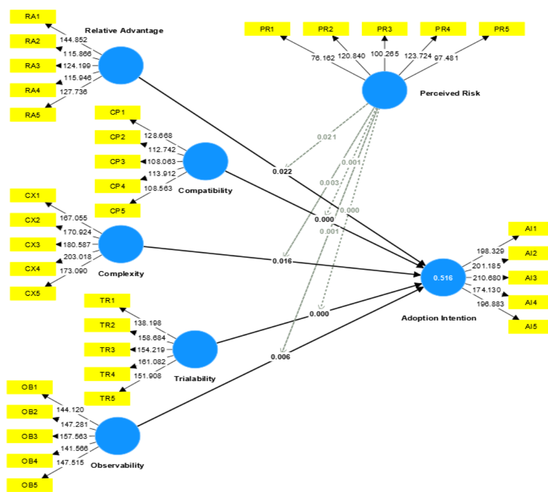

Fig. 3. Hypothesis Testing

5. Findings and discussion

This study has investigated the determinants of Adoption Intention regarding the Long-Term Care (LTC) regulatory system in healthcare institutions in Guangxi, China, using Rogers' Diffusion of Innovations (DOI) Theory and examining the moderating effect of Perceived Risk (PR).

The results support H1, confirming that Relative Advantage (RA) positively influences adoption. Institutions were more inclined to adopt the LTC system when its benefits—efficiency and enhanced care—outweighed those of existing practices. This aligns with Dearing and Cox (2018), who argue that innovations offering clear comparative benefits are more readily adopted.

H2 is also confirmed: Compatibility significantly impacts adoption. When institutions perceive the LTC system as aligned with existing values and workflows, adoption barriers are reduced (Bezboruah et al., 2014). This supports Khanagha et al. (2013), who assert that congruence with current systems facilitates innovation uptake.

Contrary to conventional assumptions, H3 shows that Complexity has a positive association with adoption. While complexity often deters implementation, institutions in Guangxi reported that, with adequate training, the LTC system is manageable. This supports Sterman (1994), who posits that complex innovations can be adopted when sufficient support exists.

H4, regarding Trialability, is validated. The ability to pilot the LTC system reduced uncertainty, built trust, and increased adoption likelihood. Bao (2009) emphasizes that trial opportunities mitigate hesitancy toward innovation.

H5 is also upheld: Observability positively affects adoption. Institutions were more likely to adopt the LTC system after observing successful implementation by early adopters, consistent with Cherry et al. (2011), who note that visibility of success promotes diffusion.

Moderating effects of Perceived Risk are also confirmed:

H6: PR significantly moderates the RA–AI relationship. Even when benefits are clear, concerns over cost and disruption reduce adoption intention (Berta et al., 2005).

H7: PR moderates the Compatibility–AI link. Despite alignment with existing practices, perceived resource constraints may inhibit adoption (Memar Zadeh & Haggerty, 2022).

H8: PR moderates Complexity's impact. High complexity paired with high risk reduces willingness to adopt, unless mitigated by training (Bezboruah et al., 2014).

H9: PR moderates the influence of Trialability. While trial phases enhance confidence, high perceived risk in testing may limit their use (Hayes et al., 2015).

H10: PR moderates the Observability–AI relationship. Visible benefits drive adoption, but uncertainty or negative early outcomes weaken this effect (Renn & Benighaus, 2013).

In summary, all five innovation attributes significantly influence adoption, with PR acting as a key moderator. Managing perceived risks through structured pilots, targeted training, and evidence from successful cases can improve adoption rates in Guangxi's healthcare institutions.

6. Conclusion

This study confirms that Relative Advantage, Compatibility, Complexity, Trialability, and Observability are critical drivers of adoption intention for the LTC regulatory system. Moreover, Perceived Risk significantly moderates these relationships. High perceived risk—due to financial burden, operational disruption, or implementation uncertainty—can weaken otherwise positive adoption drivers.

Findings suggest that strategic risk mitigation through pilot programs, training, and documented success stories can strengthen system adoption. These insights provide actionable guidance for policymakers and administrators aiming to promote effective integration of LTC systems in Guangxi.

7. Implication

7.1 Theoretical Implications

This research extends Rogers' DOI theory by empirically validating the role of innovation attributes and introducing Perceived Risk as a critical moderating construct. It expands the theoretical framework by illustrating how perceived risk alters the strength of innovation-adoption relationships in healthcare. The study also highlights the interplay between organizational resilience and innovation adoption, contributing to a deeper understanding of adoption processes in complex, resource-constrained environments.

7.2 Practical Implications

Findings offer clear implications for healthcare policymakers and administrators. Successful adoption of the LTC system depends on satisfying core innovation criteria and reducing perceived risks. Policymakers should ensure that LTC systems are seen as beneficial, compatible, and feasible. Supporting institutions through pilot programs, training, and transparent success stories is essential. Addressing concerns around financial cost, operational continuity, and implementation complexity will be crucial for building confidence and encouraging system-wide adoption.

8. Limitations and Future Research Directions

This study has several limitations. First, it focuses solely on Guangxi, China, which may limit generalizability. Future studies should include comparative analyses across regions or countries. Second, only Perceived Risk was considered as a moderator. Future research should examine other factors such as organizational culture, institutional readiness, or stakeholder involvement. Third, the cross-sectional design restricts insight into how adoption unfolds over time; longitudinal studies would offer deeper perspectives. Lastly, exploring healthcare professionals' experiences could provide valuable insights into end-user perceptions and resistance.

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