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Bridging the Innovation Gap: The Mediating Role of Technological Adoption in Enhancing Elderly Care Service Quality in Zigong, China

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Abstract: As China transitions into a super-aged society, the demand for high-quality, technology-integrated elderly care services has increased substantially. Although the national government has invested heavily in smart healthcare infrastructure, regional disparities in technology adoption and service quality remain evident. This study examines the influence of Digital Readiness and Technological Infrastructure (DRTI), Citizen Participation and Engagement (CPE), and the Regulatory and Policy Environment (RPE) on Service Quality (SQ) in elderly care within Zigong, China, while emphasizing the mediating role of Adoption of Technological Innovation (ATI). Using survey data from 534 elderly residents across 174 care institutions and analyzed via Structural Equation Modeling (SEM), the results reveal that ATI has a substantial and significant direct effect on SQ ($\beta = 0.618$, $p = 0.001$). In contrast, CPE ($\beta = 0.167$, $p = 0.090$), DRTI ($\beta = 0.082$, $p = 0.303$), and RPE ($\beta = 0.029$, $p = 0.718$) do not directly predict SQ at statistically significant levels. However, all three antecedents significantly influence ATI: CPE ($\beta = 0.416$, $p < 0.001$), DRTI ($\beta = 0.247$, $p < 0.001$), and RPE ($\beta = 0.375$, $p < 0.001$). Furthermore, the indirect effects through ATI are statistically significant—CPE→ATI→SQ ($\beta = 0.257$, $p = 0.005$), DRTI→ATI→SQ ($\beta = 0.153$, $p = 0.027$), and RPE→ATI→SQ ($\beta = 0.232$, $p = 0.004$) indicating a full mediation effect. These findings underscore the pivotal role of ATI as the primary mechanism linking systemic and participatory factors to improved service outcomes. They suggest that investments in digital infrastructure must be complemented by strategies to enhance citizen involvement, regulatory alignment, and institutional capacity. The study offers valuable guidance for policymakers and care providers seeking to develop inclusive, resilient, and digitally empowered elderly care systems in rapidly transforming urban–rural settings.

Keywords: Adoption of Technological Innovation, Citizen Participation, Elderly Care, Public Service Quality, Structural Equation Modeling

1. Introduction

China is undergoing a profound demographic transformation. By 2035, it is projected that over 400 million citizens will be aged 60 and above, comprising more than 30% of the national population (Zhang *et al.,* 2025). This trajectory firmly places China among the ranks of "super-aged" societies, a demographic designation marked by a substantial proportion of elderly residents and accompanied by mounting challenges for healthcare, social support, and long-term care systems. The shift demands urgent and strategic planning to ensure that elderly care services are accessible, personalized, efficient, and equitable across diverse socio-economic contexts.

Technological innovation has been identified globally as a transformative tool for achieving such goals. In China, national and provincial authorities have invested heavily in digital public services, including e-health platforms, telemedicine, smart community care, and integrated elderly service systems (Li, 2024; Wheatley, 2024). These innovations aim to offset rising care burdens, labor shortages, and fiscal pressures in the aging services sector. However, the potential of digital technologies to close care gaps and enhance quality remains unevenly realized particularly when considering regional disparities and the digital divide.

The urban–rural gap in digital health infrastructure is especially concerning. Internet penetration, access to smart devices, and digital literacy levels in rural and mid-sized cities consistently lag behind those in their metropolitan counterparts (Zhu & Wang, 2023; Liu, 2024). This urban bias has generated inequities in access, quality, and responsiveness of elderly care services, despite formal inclusion in national strategies such as "Healthy China 2030" and "Smart Health and Elderly Care" initiatives (Shaw *et al.,* 2013; Zhang, 2023). For example, in mid-sized cities like Zigong, care facilities often lack sufficient IT infrastructure, and local personnel may have limited training in providing digital services. Policy support may exist in principle, but practical implementation is inconsistent and fragmented (Li, 2024; Siatan *et al.,* 2024).

This scenario is not unique to China. In fact, international evidence shows that even in high-income nations with robust digital ecosystems, digital health equity remains a persistent challenge. Studies from OECD countries, including Sweden, the UK, Canada, and Germany, reveal structural barriers such as low digital literacy among older adults, concerns about privacy and data security, and insufficient tailoring of services to diverse user needs (Greenhalgh *et al.,* 2020; Luijkx *et al.,* 2021; König *et al.,* 2022). In Southeast Asia, similar trends are evident, where digital aging strategies often overlook linguistic, cultural, and infrastructural variations between urban and rural communities (Onitsuka *et al.,* 2018; Mbanugo, 2020; Aung *et al.*, 2022). The World Health Organization (WHO) and the European Commission have both emphasized the need to move beyond techno-centric planning toward more inclusive, participatory, and context-sensitive digital health systems (WHO, 2021; EC, 2023).

Despite this growing body of global literature, current research on digital transformation in elderly care often centers on either national-level policy frameworks or large urban centers, leaving significant gaps in empirical evidence from second- and third-tier cities, especially in non-Western contexts (Tanev, 2014; Qi *et al.*, 2023; Zheng *et al.,* 2025). Furthermore, while studies have documented direct relationships between digital readiness and service outcomes, few have examined the mediating mechanisms such as the Adoption of Technological Innovation (ATI) through which policy, infrastructure, and user engagement interact to shape care quality in measurable ways (Shaw *et al.,* 2022; König *et al.,* 2022).

This study aims to address these critical gaps by empirically examining the impact of Digital Readiness and Technological Infrastructure (DRTI), Citizen Participation and Engagement (CPE), and the Regulatory and Policy Environment (RPE) on Service Quality (SQ) in elderly care facilities within Zigong, a mid-sized city in western China. Central to this analysis is the role of ATI as a mediating variable, which enables us to explore not only whether these systemic factors matter, but also how they exert their influence. ATI captures the extent to which care providers and institutions internalize, implement, and sustain technological innovations in daily service delivery—an area increasingly recognized as a key driver of value in both domestic and international elderly care systems (Greenhalgh *et al.,* 2020; Alhur, 2024).

Using survey data from 534 elderly residents across 174 long-term care facilities, the study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine both direct and indirect pathways. This methodological approach enables us to assess not only the significance of individual relationships but also the relative contribution of adoption as a mediating process. In doing so, the research provides insights that are both theoretically grounded, drawing on models such as the Technology Acceptance Model and Diffusion of Innovations Theory, and practically relevant for policymakers, service providers, and digital health designers operating in resource-constrained and transitional settings.

By situating Zigong as a case study within the broader context of digital aging strategies, this research aims to contribute to both the localized implementation science of smart elderly care and the global discourse on digital health equity. The findings are intended to inform not only China's evolving care systems but also offer comparative lessons for similarly positioned cities around the world that are grappling with the dual challenge of rapid aging and uneven digital capacity.

1.1 Literature Review

Service Quality (SQ) in elderly care is frequently defined through the SERVQUAL model, which includes five core dimensions: tangibles, reliability, responsiveness, assurance, and empathy. In contemporary service environments, a sixth element efficiency is often integrated to reflect the evolving expectations of service delivery (Parasuraman *et al.*, 1988). The addition of "Efficiency" as a sixth dimension is both theoretically grounded and empirically validated within the context of elderly care. While the traditional SERVQUAL model focuses on tangibles, reliability, responsiveness, assurance, and empathy, efficiency captures the timeliness, resource effectiveness, and coordination of service delivery—elements that are increasingly essential in technology-enabled care environments. The U.S. Agency for Healthcare Research and Quality (AHRQ, 2023) recognizes efficiency as a core domain of healthcare quality, alongside safety and patient-centeredness. In the field of smart senior care, Neuhüttler *et al.* (2017) integrated efficiency into their quality assessment framework, highlighting its importance in optimizing service workflows and ensuring continuity of care. Moreover, the inclusion of efficiency aligns with studies on digital health where process improvement is critical to service effectiveness and patient satisfaction (Iyamu *et al.*, 2021; Chak *et al.*, 2022). In the context of elderly care, these dimensions capture both the functional and emotional aspects of service provision, which are essential for ensuring dignity, trust, and satisfaction among older adults (Kabadayi *et al.*, 2020; Pageau *et al.*, 2024; Li, 2024). With the rise of digital transformation in public health, the measurement of SQ increasingly incorporates technological aspects, including the accessibility of digital platforms, ease of communication, and the integration of health records into service workflows (Iyamu *et al.*, 2021; Wang & Ma, 2022; Bachuk, 2024; Dobrovolska & Kolomiiets, 2024; Zhang *et al.*, 2025).

The integration of technology into elderly care services often referred to as competent healthcare—has demonstrated potential to improve care coordination, enhance patient engagement, and optimize resource allocation (Shaw *et al.*, 2013; KOÇ, 2023; Zhao, 2024; Shi & Zhou, 2024). Digital tools, including telemedicine platforms, wearable health monitoring devices, and electronic health records, enable both preventive and responsive care, thereby addressing the complex and chronic health needs of aging populations (Tanev, 2014; Taiwo *et al.*, 2021; Chak *et al.*, 2022; Wang, 2023; Wang *et al.*, 2024). However, the benefits of technology adoption in elderly care are not uniform, and disparities in infrastructure, digital literacy, and policy support often limit its potential (Hung, 2022; Li, 2024; Liu, 2024; Hepburn *et al.*, 2025). The theoretical foundations underpinning this relationship can be traced to models such as the Technology Acceptance Model (TAM), which emphasizes perceived usefulness and perceived ease of use as drivers of adoption (Davis, 1989), the Diffusion of Innovation theory, which highlights innovation characteristics and social system readiness (Rogers, 2003; Silva *et al.*, 2022; Guo & Huang, 2024), and Institutional Theory, which considers the role of policy, norms, and organizational structures in shaping adoption behavior (Tanev, 2014). Collectively, these frameworks offer a comprehensive understanding of how institutional preparedness, public involvement, and policy environments impact the adoption of technological innovations in elderly care services.

The literature highlights three principal determinants. First, Digital Readiness and Technological Infrastructure (DRTI) refers to the presence of digital tools, robust IT systems, cybersecurity protocols, and the digital competence of care staff. Studies have shown that care facilities with well-developed technological infrastructure are more adept at adopting and maintaining digital innovations (Shaw *et al.*, 2013; Avtalion *et al.*, 2024; Yue & Md Johar, 2024). Second, Citizen Participation and Engagement (CPE) encompasses factors such as public awareness, trust in digital platforms, channels for user feedback, and the inclusivity of service provision. These elements have been linked to higher adoption rates and long-term utilization of technology-driven services (Ma & Wu, 2020; Wang & Ma, 2022; Bvuma, 2024; Li, 2024). Third, the Regulatory and Policy Environment (RPE) including enabling policies, legal infrastructures, investments in e-governance, and the promotion of public-private partnerships serves as a foundational catalyst for fostering technological innovation (Tanev, 2014; Chorzempa & Huang, 2022; Wan & Wang, 2023).

Adoption of Technological Innovation (ATI) functions as a key mediating variable that connects the identified determinants to service quality outcomes. Evidence from healthcare and public service sectors indicates that adoption bridges the gap between technological readiness and actual service improvements, enabling organizations to convert digital capabilities into enhanced accessibility, responsiveness, and operational efficiency (Shaw *et al.*, 2013; Alhur, 2024; Mohammed, 2024). In the context of elderly care, this mediating role is especially critical, as advancements in service quality rely not only on the presence of technology but also on the readiness and engagement of stakeholders to utilize these tools effectively.

Building on the established theoretical and empirical framework, this study posits that Digital Readiness and Technological Infrastructure (DRTI) (H1), Citizen Participation and Engagement (CPE) (H2), and the Regulatory and Policy Environment (RPE) (H3) will each exert direct effects on Service Quality (SQ). Additionally, it is hypothesized that these three factors will each have a positive impact on the Adoption of Technological Innovation (ATI) (H4–H6). Furthermore, ATI is hypothesized to mediate the relationships between DRTI, CPE, and RPE with SQ (H7–H9), thus offering a comprehensive model of how readiness factors and contextual variables shape elderly care service outcomes in a mid-sized Chinese city.

2. Methodology

2.1 Participants

The study recruited 534 elderly residents from 174 elderly care facilities in Zigong City, Sichuan Province, China, using a stratified random sampling method. Facilities were first stratified based on key characteristics such as type (public/private), size, and geographic location (urban/suburban) to ensure broad representativeness, as illustrated in Table 1.

Table 1. Participant Characteristics

Characteristics	Frequency (n)	Percentage (%)
Gender		
Male	268	50.3
Female	265	49.7
Age (years)		
60–64	150	28.1
65–69	116	21.8
70–74	137	25.7
75–79	85	15.9
80 and above	45	8.4
Marital Status		
Single	197	37.0
Married	202	37.9
Widowed	82	15.4
Divorced	52	9.8
Highest Education Level		
No formal education	191	35.8
Primary school	165	31.0
Secondary school	128	24.0
Vocational training	34	6.4
College/University	15	2.8
Living Arrangement		
Living alone	87	16.3
Living with a spouse	166	31.1
Living with children/family	177	33.2
Living in an elderly care facility	103	19.3
Monthly Income (RMB)		
Less than 1,000 RMB	80	15.0
1,000–2,999 RMB	179	33.6
3,000–4,999 RMB	167	31.3
5,000–6,999 RMB	58	10.9
7,000 RMB and above	49	9.2
Use of Technology in Daily Life		
Never	0	0.0
Rarely	165	31.0
Sometimes	173	32.5
Often	131	24.6
Very often	64	12.0

Within each stratum, participants were then randomly selected to capture variation across institutional and demographic contexts. This approach was employed to minimize sampling bias and enhance the generalizability of the findings to similar mid-sized urban–rural settings. Participants were aged 60 years and above, with the majority falling within the 60–64 age group (28.1%), followed by the 65–69 age group (21.7%), and smaller proportions in the older categories, up to 80 years and above. The gender distribution among respondents was pretty even, comprising 51.3% females and 48.7% males. In terms of marital status, the most significant proportion was married (43.8%), followed by widowed (27.3%), single (18.2%), and divorced (10.7%). Educational attainment varied, with secondary school (34.1%) and primary school (27.2%) being the most common forms of education, while 15.5% had vocational training, 13.3% had no formal education, and only 9.9% had attended college or university. Regarding living arrangements, 38.6% lived with children or family, 31.1% lived with a spouse, 18.8% resided in elderly care facilities, and 11.5% lived alone. Monthly income levels showed that most participants earned between 1,000–2,999 RMB (33.5%) or 3,000–4,999 RMB (31.3%), with smaller shares in the lowest (<1,000 RMB, 16.5%) and highest (>7,000 RMB, 4.9%) income brackets. In terms of technology usage in daily life, 26.4% reported using technology "sometimes," 24.3% "often," 18.6% "rarely," 16.2% "very often," and 14.5% "never." This indicates a moderate baseline of digital engagement among the elderly population in Zigong, with notable variation in technological readiness.

2.1 Measures

Digital Readiness and Technological Infrastructure (DRTI) evaluated the technological preparedness of the environment for delivering elderly care services. This construct was measured across five key dimensions: Availability of Digital Tools and Platforms (ADTP), IT Infrastructure Readiness (ITIR), Cybersecurity and Data Privacy Policies (CDPP), Digital Literacy of Service Providers and Users (DLSPU), and Government Investment in Digital Transformation (GIDT). The measurement items were adapted from established scales in e-governance and digital readiness literature and rated using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). An example item is: "I have noticed that more public services are now available online." The Cronbach's alpha for ADTP was 0.913, reflecting excellent internal consistency for the broader DRTI construct.

Citizen participation and engagement were measured using five sub-dimensions: Public Awareness and Willingness to Adopt Digital Services (PAWA), Citizen Involvement in Co-Creation of Services (CICS), Feedback Mechanisms for Service Improvement (FMSI), Trust in Digital Public Service Platforms (TDPSP), and Accessibility and Inclusivity in Service Delivery (AISD). Items evaluated the extent to which elderly citizens are aware of, engaged with, and able to contribute to digital public services. Responses were measured using a five-point Likert scale, featuring items like "I am willing to try using digital tools if they help me access services more easily." The Cronbach's alpha for Citizen Participation and Engagement (CPE) was 0.915, demonstrating high internal reliability.

The Regulatory and Policy Environment (RPE) construct comprises five dimensions: Policies Supporting Public Sector Innovation (PSPSI), Legal Framework for Digital Transformation (LFDT), Government Investment in E-Governance (GIE), Public-Private Partnerships for Innovation (PPPI), and Standards and Compliance with Digital Governance (SCDG). Items captured participants' perceptions of the policy and regulatory environment's ability to facilitate digital innovation in elderly care services. All items were rated using a five-point Likert scale, with sample statements such as "I believe the government has clear plans to improve public services using new ideas." The Cronbach's alpha for the Regulatory and Policy Environment (RPE) was 0.910, indicating strong internal consistency.

Adoption of Technological Innovation (ATI) was conceptualized as a mediating variable with four sub-dimensions: Management Innovation (MI), Service Innovation (SI), Technological Innovation (TI), and Collaborative Innovation (CI). Items measured the extent to which innovative practices, technologies, and collaborative approaches are adopted within elderly care services. A representative item is "I think new technologies help make public services faster and easier." All indicators were assessed using a five-point Likert scale, and the Cronbach's alpha for Adoption of Technological Innovation (ATI) was 0.893, signifying robust internal reliability.

Service Quality (SQ) was measured using the SERVQUAL framework, enhanced with an additional Efficiency dimension, resulting in six subcomponents: Tangibles (TAN), Reliability (REL), Responsiveness (RES), Assurance (ASS), Empathy (EMP), and Efficiency (EFF). Respondents rated various aspects of service quality 534 such as the condition of facilities, dependability of services, staff responsiveness, sense of security, empathy, and operational efficiency on a five-point Likert scale. A representative item is: "Public services are delivered in a timely and streamlined manner." The overall Cronbach's alpha for the SQ construct was 0.941, reflecting excellent internal consistency.

2.2 Data Analysis

This study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS to investigate the interrelationships among the core constructs and evaluate the mediating effect of Adoption of Technological Innovation (ATI). PLS-SEM was selected due to its appropriateness for analyzing complex, prediction-focused models and its robustness in handling datasets that may violate the assumption of multivariate normality. The analysis adhered to the conventional two-stage process, encompassing the evaluation of both the measurement and structural models. In evaluating the measurement model, internal consistency reliability was assessed using both Cronbach's alpha and composite reliability (CR), with threshold values set at 0.70 or higher to indicate acceptable reliability. Convergent validity was determined through the average variance extracted (AVE), where values exceeding 0.50 suggest that the constructs account for more than half of the variance in their respective indicators. Discriminant validity was tested using the Fornell–Larcker criterion, which requires the square root of each construct's AVE to be greater than its correlations with other constructs, as well as the Heterotrait–Monotrait (HTMT) ratio, with acceptable values being below 0.85 for a strict criterion or 0.90 for a more lenient standard. For the structural model assessment, the statistical significance of the hypothesized paths was examined by calculating path coefficients (β) along with their t-values and p-values, using a bootstrapping procedure with 5,000 resamples. The coefficient of determination (R^2) was used to evaluate the model's predictive accuracy, with benchmarks of 0.75 (substantial), 0.50 (moderate), and 0.25 (weak). To assess the impact of individual predictors on endogenous constructs, effect sizes (f^2) were calculated and interpreted as 0.02 (small), 0.15 (medium), and 0.35 (large). Additionally, model fit was assessed using the standardized root mean square residual (SRMR), where values below 0.08 indicate an acceptable fit. This multi-faceted analytical approach ensured a robust evaluation of both measurement reliability and the theoretical structure of the model.

3. Results

3.1 Measurement Model Assessment

Table 2 indicates a solid measurement model for all constructs. Internal consistency is acceptable to good, with Cronbach's alpha ranging from .761 (ATI) to .843 (SQ), exceeding the benchmark of .70 (Hair et al., 2019). Composite reliability falls within recommended bounds (.70–.95) for both rho_a (.763–.847) and rho_c (.761–.844); note that rho_a is often preferred in PLS-SEM as a consistent reliability estimate and closely tracks rho_c here, suggesting stable indicator sets (Dijkstra & Henseler, 2015; Hair *et al.,* 2019). Convergent validity is supported because AVE values exceed .50 across constructs (ATI=.544; CPE=.588; DRTI=.572; RPE=.559; SQ=.575), meaning indicators explain more than half of their latent variance (Fornell & Larcker, 1981). Among the predictors, CPE shows the strongest convergence (AVE = .588), while RPE has the lowest reliability (rho_c = .807) and AVE (.559), yet remains acceptable. Overall, the reflective measures for DRTI, CPE, RPE, ATI (mediator), and SQ (dependent) meet conventional reliability and convergent validity criteria, supporting subsequent structural path testing (Hair *et al.,* 2019).

Table 2. Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATI	0.761	0.763	0.761	0.544
CPE	0.825	0.829	0.826	0.588
DRTI	0.817	0.819	0.817	0.572
RPE	0.810	0.815	0.807	0.559
SQ	0.843	0.847	0.844	0.575

As presented in Table 3, all indicators exhibit their highest loadings on their respective intended constructs, thereby providing evidence of discriminant validity based on the cross-loadings criterion (e.g., CPE: AISD=.744, PAWA=.747, TDPSP=.709 exceed their correlations with other latents; DRTI: ITIR=.749, DLSPU=.709; RPE: SCDG=.790, PPPI=.702; SQ: REL=.758, RES=.730), while off-diagonal loadings are meaningfully lower (typically ≥.10 less), which aligns with Chin's (1998) rule of thumb. Several loadings are slightly below .70 (e.g., ATI: CI=.674, MI=.683, SI=.688, TI=.618; RPE: GIE=.580, PSPSI=.617; DRTI: ADTP=.659, CDPP=.623), but their retention is defensible because the construct reliabilities and AVEs in Table 2 meet recommended thresholds, indicating adequate indicator communality at the construct level (Hair *et al.,* 2019; Fornell & Larcker, 1981). Conceptually adjacent constructs (e.g., ATI with SQ and CPE) show moderate cross-loadings (≈.50–.61), which is theoretically plausible in public-service digitalization but still lower than each item's primary loading. Nonetheless, best practice is to corroborate discriminant validity with HTMT (<.85) rather than relying solely on cross-loadings (Henseler, Ringle, & Sarstedt, 2015; Hair *et al.,* 2019).

Table 3. Cross Loadings

	ATI	CPE	DRTI	RPE	SQ
CI	**0.674**	0.559	0.405	0.496	0.570
MI	**0.683**	0.544	0.528	0.473	0.562
SI	**0.688**	0.529	0.549	0.544	0.537
TI	**0.618**	0.453	0.397	0.464	0.540
AISD	0.600	**0.744**	0.394	0.489	0.519
CICS	0.519	**0.630**	0.499	0.351	0.428
FMSI	0.498	**0.654**	0.397	0.355	0.485
PAWA	0.569	**0.747**	0.459	0.389	0.554
TDPSP	0.547	**0.709**	0.451	0.387	0.519
ADTP	0.464	0.423	**0.659**	0.355	0.423
CDPP	0.436	0.434	**0.623**	0.351	0.402
DLSPU	0.509	0.461	**0.709**	0.392	0.447
GIDT	0.510	0.433	**0.689**	0.369	0.418
ITIR	0.508	0.408	**0.749**	0.360	0.501
GIE	0.419	0.355	0.259	**0.580**	0.375
LFDT	0.491	0.397	0.421	**0.678**	0.437
PPPI	0.513	0.406	0.359	**0.702**	0.448
PSPSI	0.443	0.396	0.344	**0.617**	0.403
SCDG	0.624	0.373	0.403	**0.790**	0.454
ASS	0.560	0.465	0.427	0.396	**0.661**
EFF	0.533	0.432	0.379	0.376	**0.618**
EMP	0.560	0.497	0.407	0.446	**0.679**
REL	0.607	0.558	0.503	0.480	**0.758**
RES	0.606	0.528	0.465	0.449	**0.730**
TAN	0.557	0.485	0.455	0.434	**0.682**

Table 4 indicates satisfactory discriminant validity among all constructs using the HTMT criterion: every inter-construct ratio is comfortably below the conservative .85 guideline (range = .527–.783), with the highest associations observed between ATI–CPE (.783) and ATI–SQ (.730), which remain within acceptable bounds for conceptually related but distinct constructs (Henseler, Ringle, & Sarstedt, 2015; Hair, Risher, Sarstedt, & Ringle, 2019). These magnitudes are theoretically plausible e.g., stronger digital readiness and citizen engagement can co-occur with greater innovation adoption and perceived service quality yet the HTMT values still suggest the constructs are empirically separable. For completeness, best practice is to supplement point estimates with HTMT-inference (bootstrapped confidence intervals) and confirm they do not include 1.00, thereby reinforcing discriminant validity beyond threshold checks (Henseler *et al.,* 2015; Hair *et al.*, 2019).

Table 4. HTMT Matrix

	ATI	CPE	DRTI	RPE	SQ
ATI					
CPE	0.783				
DRTI	0.704	0.633			
RPE	0.734	0.567	0.527		
SQ	0.730	0.718	0.637	0.624	

Table 5 applies the Fornell–Larcker criterion: the diagonal elements are the square roots of each construct's AVE (e.g., ATI = 0.783; CPE = 0.767; DRTI = 0.756; RPE = 0.748; SQ = 0.758), which should exceed the construct's correlations with other latent variables shown off-diagonal (Fornell & Larcker, 1981). This condition is met across the matrix, supporting discriminant validity. The closest case is RPE versus ATI (√AVE_RPE = 0.748 vs. r_ATI,RPE = 0.742), which is acceptable but leaves a narrow margin and suggests conceptual proximity; nevertheless, it remains below the diagonal, and HTMT results (reported separately) further substantiate discriminant validity when < .85 (Henseler, Ringle, & Sarstedt, 2015; Hair *et al.,* 2019). Overall, the results demonstrate that each construct explains more variance in its own indicators than in those of other constructs, thereby fulfilling the Fornell–Larcker criterion for discriminant validity.

Table 5. Fornell-Larcker Criterion

	ATI	CPE	DRTI	RPE	SQ
ATI	**0.783**				
CPE	0.704	**0.767**			
DRTI	0.707	0.627	**0.756**		
RPE	0.742	0.566	0.531	**0.748**	
SQ	0.728	0.719	0.639	0.626	**0.758**

3.2 Structural Model Assessment

After confirming the reliability and validity of the measurement model, the structural model was evaluated to test the proposed relationships among constructs. This assessment involved analyzing the significance and magnitude of path coefficients, the model's explanatory power as measured by the coefficient of determination (R^2), the effect size (f^2) to gauge the relative influence of each predictor, and the overall model fit using the standardized root mean square residual (SRMR). To ensure robustness in hypothesis testing, bootstrapping with 5,000 resamples was conducted to estimate t-values and p-values.

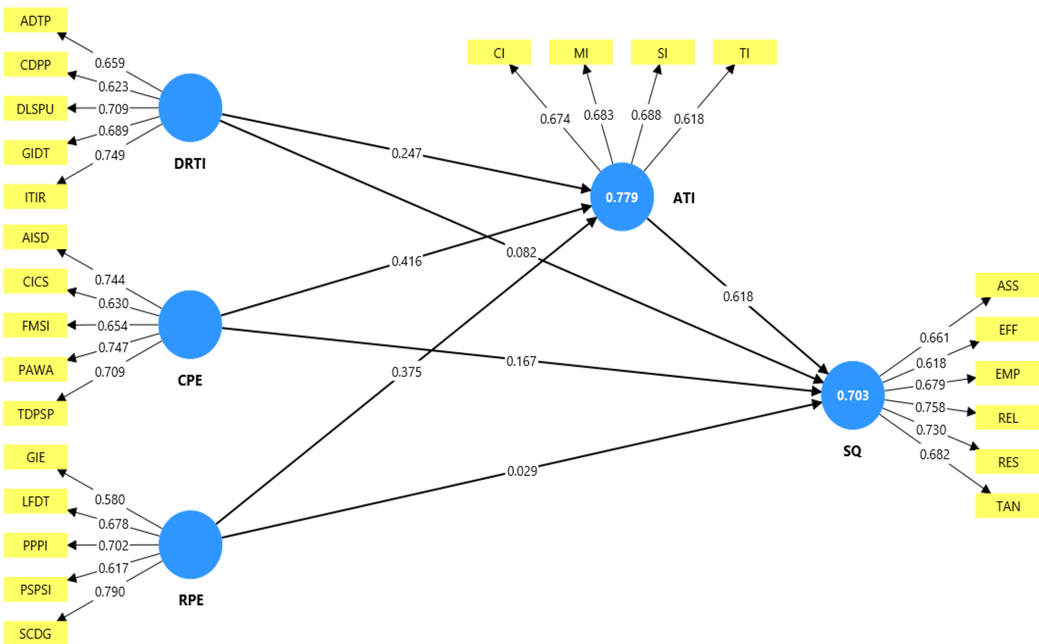

Figure 1. SEM model.

Figure 1 shows SEM analysis results, and Table 6 suggests excellent overall model fit for a PLS-SEM context. The SRMR is 0.035 (saturated and estimated), which is well below the conservative threshold of 0.08 and even the stricter threshold of 0.05 indicating an excellent approximation of the empirical correlation matrix (Henseler, Hubona, & Ray, 2016; Hair, Risher, Sarstedt, & Ringle, 2019). The discrepancy measures d_ULS = 0.408 and d_G = 0.177 are small; while absolute cutoffs are not universal, best practice is to verify that these values fall below their bootstrapped 95% quantiles to formally conclude a good fit (Henseler *et al.,* 2016). NFI = 0.912 exceeds the commonly cited 0.90 benchmark for an acceptable fit. However, researchers should interpret NFI cautiously, given its sample-size sensitivity, and complement it with predictive assessments (e.g., PLSpredict) rather than relying solely on absolute-fit indices (Bentler & Bonett, 1980; Hair *et al.,* 2019). The chi-square value (492.341) is reported for completeness; however, it is not central to variance-based SEM, as the distributional assumptions differ from those in covariance-based ML chi-square testing (Hair *et al.*, 2019). Notably, the equality of the saturated and estimated model values suggests that imposing the structural relations does not degrade fit relative to the unconstrained measurement model, consistent with a well-specified model (Henseler *et al.,* 2016).

Table 6. Model Fit

	Saturated model	Estimated model
SRMR	0.035	0.035
d_ULS	0.408	0.408
d_G	0.177	0.177
Chi-square	492.341	492.341
NFI	0.912	0.912

Table 7 reveals that the model exhibits strong explanatory power for both endogenous constructs, with exogenous variables accounting for 77.9% of the variance in ATI and 70.3% of the variance in SQ. The adjusted R^2 values (0.778 for ATI and 0.700 for SQ) are nearly identical to the unadjusted values, indicating minimal risk of overfitting in relation to the model's complexity. Using standard PLS-SEM benchmarks, ATI's $R^2 = .779$ is substantial ($\geq .75$), while SQ's $R^2 = .703$ is high, sitting between moderate (.50) and substantial (.75) explanatory power (Hair, Risher, Sarstedt, & Ringle, 2019). Substantively, this implies that digital readiness, citizen engagement, and the regulatory environment (as modeled) are potent predictors of innovation adoption, and, together with ATI, also explain a significant share of perceived service quality. For completeness, inference should be complemented with f^2 effect sizes and Stone–Geisser Q^2 to assess incremental and predictive relevance, respectively (Cohen, 1988; Hair *et al.,* 2019; Stone, 1974; Geisser, 1974).

Table 7. R-square

	R-square	R-square adjusted
ATI	0.779	0.778
SQ	0.703	0.700

Table 8 reports f^2 effect sizes, which quantify each predictor's incremental contribution to an endogenous construct's R^2 when included versus omitted. Using Cohen's (1988) benchmarks $\approx.02$ small, $\approx.15$ medium, $\approx.35$ large ATI as criterion shows CPE ($f^2=.417$) and RPE ($f^2=.401$) as significant effects and DRTI ($f^2=.156$) as medium, indicating that citizen participation/engagement and the regulatory–policy environment are primary drivers of innovation adoption, with digital readiness adding moderate explanatory power. When evaluating Service Quality (SQ) as the dependent variable, Adoption of Technological Innovation (ATI) demonstrates a medium-to-large effect size ($f^2 = 0.283$), underscoring its substantive role in shaping perceived service quality. In comparison, the effect sizes of Citizen Participation and Engagement (CPE) at 0.035, Digital Readiness and Technological Infrastructure (DRTI) at 0.011, and the Regulatory and Policy Environment (RPE) at 0.001 are notably smaller ranging from minor to trivial. These results suggest that enhancing SQ primarily depends on strengthening ATI. Moreover, the model indicates that ATI is most effectively improved through interventions targeting CPE and RPE. Given the relatively weak direct effects of the exogenous variables on SQ, these findings should be interpreted in conjunction with path significance, variance inflation factor (VIF), and predictive validity metrics (Hair, Risher, Sarstedt, & Ringle, 2019).

Table 8. f-square

	ATI	CPE	DRTI	RPE	SQ
ATI					0.283
CPE	0.417				0.035
DRTI	0.156				0.011
RPE	0.401				0.001
SQ					

Table 9 presents the MV-level Q²_predict results from the PLS-Predict procedure, demonstrating the model's out-of-sample predictive performance for individual measurement variables. All Q²_predict values are positive (ranging from 0.196 to 0.362), indicating acceptable predictive relevance for each indicator (Shmueli *et al.,* 2019). Moreover, for most indicators, the PLS-SEM model yields lower RMSE and MAE values compared to both the linear model (LM) and individual average (IA) benchmarks, indicating that the structural model exhibits superior predictive accuracy. Notably, indicators such as SI ($Q^2 = 0.362$) and REL ($Q^2 = 0.331$) exhibit extreme predictive power. These results reinforce the model's robustness and validate its practical relevance for policy and service planning in technology-enabled care for the elderly.

Table 9. MV-level Q²_predict

	Q²predict	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE	IA_RMSE	IA_MAE
CI	0.306	0.652	0.498	0.655	0.504	0.783	0.641
MI	0.328	0.658	0.511	0.651	0.507	0.803	0.653
SI	0.362	0.657	0.514	0.660	0.511	0.823	0.677
TI	0.239	0.708	0.533	0.719	0.546	0.811	0.661
ASS	0.230	0.691	0.556	0.697	0.558	0.787	0.644
EFF	0.196	0.706	0.568	0.711	0.573	0.787	0.650
EMP	0.256	0.781	0.629	0.790	0.637	0.906	0.782
REL	0.331	0.709	0.570	0.724	0.577	0.867	0.749
RES	0.291	0.653	0.503	0.661	0.512	0.776	0.657
TAN	0.261	0.689	0.547	0.700	0.555	0.801	0.676

Table 10 highlights the Adoption of Technological Innovation (ATI) as the central pathway through which the antecedent variables influence Service Quality (SQ). The direct relationship between ATI and SQ is statistically significant ($\beta = 0.618$, $p = .001$), indicating a strong positive effect. Furthermore, the paths from Citizen Participation and Engagement (CPE) to ATI ($\beta = 0.416$, $p < .001$), Digital Readiness and Technological Infrastructure (DRTI) to ATI ($\beta = 0.247$, $p < .001$), and Regulatory and Policy Environment (RPE) to ATI ($\beta = 0.375$, $p < .001$) all demonstrate that these factors significantly contribute to fostering the adoption of technological innovations. By contrast, the direct effects of CPE (β=0.167, p=.090), DRTI (β=0.082, p=.303), and RPE (β=0.029, p=.718) on SQ are not significant once ATI is included. Still, their indirect effects via ATI are significant and practically meaningful—CPE → ATI → SQ (β=0.257, p=.005), DRTI → ATI → SQ (β=0.153, p=.027), and RPE → ATI → SQ (β=0.232, p=.004). The close agreement between "Original sample" and "Sample mean" estimates suggests stable bootstrap results. Taken together, these findings support a comprehensive mediation model, wherein improvements in Service Quality (SQ) are largely contingent upon strengthening Adoption of Technological Innovation (ATI). ATI itself is primarily influenced by Citizen Participation and Engagement (CPE) and the Regulatory and Policy Environment (RPE). At the same time, Digital Readiness and Technological Infrastructure (DRTI) plays a supportive but less influential upstream role.

Table 10. Relationship between Constructs

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
ATI -> SQ	0.618	0.637	0.193	3.195	0.001
CPE -> ATI	0.416	0.416	0.041	10.053	0.000
CPE -> SQ	0.167	0.158	0.099	1.695	0.090
DRTI -> ATI	0.247	0.246	0.050	4.936	0.000
DRTI -> SQ	0.082	0.078	0.080	1.031	0.303
RPE -> ATI	0.375	0.376	0.043	8.688	0.000
RPE -> SQ	0.029	0.021	0.080	0.362	0.718
CPE -> ATI -> SQ	0.257	0.266	0.091	2.823	0.005
DRTI -> ATI -> SQ	0.153	0.158	0.069	2.209	0.027
RPE -> ATI -> SQ	0.232	0.240	0.080	2.900	0.004

4. Discussion

The findings of this study reaffirm that the Adoption of Technological Innovation (ATI) is the central mechanism through which Digital Readiness and Technological Infrastructure (DRTI), Citizen Participation and Engagement (CPE), and the Regulatory and Policy Environment (RPE) influence Service Quality (SQ) in elderly care services in Zigong, China. While these systemic enablers are essential, their direct effects on SQ were not statistically significant. Instead, their influence is realized indirectly through ATI, demonstrating that readiness, engagement, and policy support must be translated into actual usage and integration of technologies to drive measurable service improvements. This aligns with prior evidence suggesting that digital infrastructure and policy environments, while foundational, are insufficient without active and sustained adoption by end-users and providers (Shaw *et al.*, 2013; Alhur, 2024; Mohammed, 2024).

This study conceptualizes SQ using the SERVQUAL model, expanded to include efficiency as a sixth dimension, acknowledging the increasing importance of timeliness and process optimization in technology-mediated care delivery (Parasuraman *et al.*, 1988; Kabadayi *et al.,* 2020; Pageau *et al.,* 2024). In elderly care settings, these dimensions tangibles, reliability, responsiveness, assurance, empathy, and efficiency encompass both the operational and emotional facets of care that are critical to maintaining dignity, trust, and satisfaction among older adults (Li, 2024; Koç, 2023; Chak *et al.,* 2022). With the acceleration of digital transformation in public health, these elements now increasingly reflect users' interactions with digital platforms, integration of health data, and service accessibility (Iyamu *et al.,* 2021; Dobrovolska & Kolomiiets, 2024; Wang & Ma, 2022).

The results are theoretically grounded in three major frameworks. The Technology Acceptance Model (TAM) emphasizes perceived usefulness and ease of use as core determinants of adoption (Davis, 1989), while the Diffusion of Innovation theory highlights the importance of innovation characteristics and social system readiness (Rogers, 2003; Guo & Huang, 2024; Pašti, 2022). Institutional Theory complements these by underscoring the role of regulatory frameworks, norms, and organizational practices in shaping the uptake of technology (Tanev, 2014). The full mediation effect observed in this study supports an integrated view, wherein systemic readiness and policy support must be internalized through actual adoption before improvements in service quality can be realized especially in urban–rural transitional cities like Zigong, where digital ecosystems remain underdeveloped.

The demographic data show that only 2.8% of participants held a college degree, which reflects the broader socio-demographic context of mid-sized Chinese cities, where older cohorts had limited access to higher education due to historical and economic factors. While this distribution aligns with regional trends, it has significant implications for digital literacy and the capacity for adoption. Lower education levels are often associated with reduced confidence in technology use, limited exposure to digital tools, and a greater risk of exclusion from innovation-driven services (Luijkx *et al.,* 2015; Mannheim *et al.,* 2019; Hung, 2022). To address this variation, policy interventions must go beyond infrastructure development and focus on targeted, inclusive strategies that address the needs of marginalized groups. These may include community-based digital literacy programs tailored to older adults with lower educational attainment, participatory co-design approaches that involve users in shaping interfaces and workflows, and trust-building initiatives that improve confidence in digital care tools (Aung *et al.,* 2022; König *et al.,* 2018; WHO, 2021). Additionally, simplified and culturally sensitive digital applications, as well as multilingual or audio-assisted features, can enhance accessibility for elderly users with limited literacy or cognitive challenges.

The findings contribute to a growing body of literature that emphasizes the importance of inclusive digital transformation in aging societies. They suggest that while systemic factors, such as DRTI, CPE, and RPE, are necessary enablers, the real impact on service quality emerges only when these conditions foster meaningful and widespread adoption. This insight is particularly relevant for rapidly aging, digitally transitioning regions where social inequality, low digital skills, and fragmented institutional capacities may hinder the realization of smart elderly care systems. In sum, this study provides empirical support for a mediated model in which technological adoption serves as the pivotal bridge between institutional readiness and service outcomes. At the same time, it highlights the need to embed digital transformation strategies within a broader social equity framework that accounts for subgroup differences in education, income, and digital access. For policy and practice, this means designing interventions that are not only technically sound but also socially inclusive, ensuring that the benefits of innovation in elderly care are equitably distributed across diverse aging populations.

This study has several limitations that merit consideration. First, the analysis is restricted to elderly care facilities in Zigong, which may limit the generalizability of findings to regions with differing socio-economic profiles or levels of digital maturity. Second, the cross-sectional research design constrains causal inference, as temporal changes and behavioral evolution cannot be observed. Third, the study relies on self-reported data to assess technological adoption and service quality. While PLS-SEM is relatively robust against common method bias (CMB), Harman's single-factor test was also conducted and showed no dominant factor, reducing concern about inflated relationships. However, self-report measures are inherently subject to social desirability bias and potential misinterpretation particularly among elderly respondents who may face cognitive decline, literacy limitations, or language-related comprehension issues. Although the survey was pilot-tested and items were simplified for clarity, residual bias cannot be entirely excluded. Additionally, the model does not incorporate potentially influential organizational variables such as leadership style, institutional culture, or inter-agency collaboration, which may also shape technology adoption and service quality outcomes.

Future research should adopt longitudinal designs to capture the dynamics of technological adoption and service improvements over time, thereby strengthening causal interpretation. Comparative analyses across cities with varying levels of digital infrastructure and economic development would offer insights into the contextual determinants of successful adoption. Furthermore, to enhance robustness and reduce reliance on subjective perceptions, future studies should triangulate self-reported data with complementary sources such as administrative records, ethnographic observations, or digital trace data. Incorporating qualitative methods can also help uncover the nuanced socio-cultural and organizational factors that influence adoption behaviors. Expanding the conceptual model to include moderating influences such as funding structures, leadership characteristics, or stakeholder engagement mechanisms would further deepen our understanding of digital transformation in elderly care.

5. Conclusion

This study examined the impact of digital readiness and technological infrastructure, citizen participation and engagement, and the regulatory and policy environment on the quality of elderly care services in Zigong, China, with a particular focus on the mediating role of technological innovation adoption. The findings indicate that these structural and contextual factors do not have a direct, significant impact on service quality; instead, their influence is primarily channeled through the effective adoption and integration of digital technologies. This underscores the central role of technological adoption (ATI) as a critical mechanism linking systemic enablers to measurable service improvements. The results also highlight the interdependence between infrastructure and citizen engagement—

neither alone is sufficient, but together they foster a more conducive environment for adoption. The study contributes to the existing literature by providing empirical support for frameworks such as the Technology Acceptance Model and the Diffusion of Innovations theory, demonstrating that adoption effectiveness relies on both perceived usability and institutional readiness. On a practical level, the findings underscore the importance of inclusive digital literacy initiatives, especially for vulnerable elderly populations, alongside cross-sector collaboration and participatory service design. In conclusion, the research advocates for a comprehensive, equity-oriented approach to modernizing elderly care one that integrates technological, social, and policy elements to ensure digital transformation is sustainable and accessible across diverse settings.

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Authors' Contributions

YiFei Yan: Conceptualization, Methodology, Data collection, Writing original manuscript. Chaimongkhon Supromin: Methodlogy, Data collection, Formal analysis, Vaidation, Supervision, Writing Review and Editing. Pattama Pasitpakakul: Writing Review and Editing. All the authors read and approved the final version of the manuscript.

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The authors declare that ChatGPT-5.1 (OpenAI) was used solely for language polishing, grammar correction, and enhancing clarity and readability of the manuscript. All scientific content, experimental data, analyses, interpretations, and conclusions in this study are entirely original and generated by the authors.

Conflict of Interest

The authors have no conflicts of interest to declare. There is also no financial interest to report. The author certifies that the submission is original work and is not under review at any other publication.

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