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The Role of Market Demand in Enhancing Transformation Effect in the Healthy Elderly in Beijing-Tianjin-Hebei Region

Haoheng Tian[1], Ubonwan Khunthong[2], Sid Terason[3*]

[1,2] *Faculty of Business and Finance Management, Rattana Bundit University, Thailand*
[3] *Faculty of Sports and Health Science, Kasetsart University, Thailand*

*__Corresponding Author:__ fsssid@ku.ac.th

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ABSTRACT

This study focuses on the field of healthy elderly care in the Beijing-Tianjin-Hebei region, exploring the dynamic role of digital intelligence in service innovation and the moderating effect of market demand on transformation effects. Against the backdrop of the region's aging rate exceeding the national average and traditional elderly care models facing supply-demand imbalances, digital intelligence provides opportunities for industrial transformation. The study adopts a quantitative research approach, using questionnaire analysis to systematically explore the relationships between Digital Intelligence Application, Service Innovation, market demand, and Transformation Effect. The results show that Digital Intelligence Application has a significant positive direct impact on Transformation Effect; Service Innovation plays a partial mediating role in the relationship between the two, but due to user-unfriendly designs, it has a significant negative direct impact on Transformation Effect; market demand exerts a negative moderating effect on the relationship between Digital Intelligence Application and Transformation Effect, which is mainly attributed to the constraints on the effectiveness of digital intelligence applications caused by the elderly's low technology acceptance. This study enriches the theory of digital transformation in the elderly care field, and at the same time provides practical guidance for optimizing healthy elderly care services, policies, and products in the Beijing-Tianjin-Hebei region, which is of great significance for promoting the construction of an age-inclusive society in this region.

Keywords: Healthy Elderly Care Services; Digital Intelligence Application; Service Innovation; Market Demand; Transformation Effect

INTRODUCTION

Population aging has evolved into a pressing global demographic challenge, reshaping social policies and service systems worldwide. As life expectancy increases and birth rates decline, nations across the globe face unprecedented pressure to restructure healthcare delivery, pension systems, and social support mechanisms. The United Nations' World Social Report 2023 highlights that building an age-inclusive society is critical to addressing the multifaceted needs of elderly populations and ensuring social sustainability (United Nations Department of Economic and Social Affairs, 2023). This demographic transition presents both challenges and opportunities, particularly in developing effective models of elderly care that balance quality, accessibility, and cost-effectiveness.

Within China, the Beijing-Tianjin-Hebei (BTH) region confronts an especially severe aging crisis. By November 2020, the proportion of residents aged 60 and above reached 19.63% in Beijing, 21.66% in Tianjin, and 19.85% in Hebei Province—all significantly exceeding the national average of 18.70% (National Bureau of Statistics of the People's Republic of China, 2021). This concentration of aging populations in one of China's most economically significant regions creates urgent demands for innovative solutions. The BTH region, comprising

China's capital and two major provinces with a combined population exceeding 110 million, serves as a critical testing ground for elderly care innovations that may subsequently inform national policy. The region's unique characteristics—including substantial urban-rural disparities, varying levels of economic development, and complex administrative coordination requirements across provincial boundaries—make it an ideal context for examining the multifaceted dynamics of digital transformation in elderly care services.

Traditional elderly care models—home-based, community-based, and institutional—face supply-demand mismatches and inefficient resource allocation (Zhang & Li, 2022). Home-based care, while preferred by most elderly individuals for its familiarity and independence, often lacks professional medical support and places considerable burden on family caregivers who may themselves be aging or geographically distant. Community care suffers from fragmented service provision with limited integration of medical, recreational, and daily living support (Wang & Zhang, 2023). Services are frequently delivered by disconnected providers without coordination mechanisms, resulting in gaps, redundancies, and missed opportunities for holistic care. Institutional care struggles with insufficient capacity and uneven quality, particularly for those with disabilities or chronic illnesses (Chen & Liu, 2021). The shortage of professionally trained caregivers, combined with high operational costs and social stigma associated with institutional placement, further compounds these challenges. Collectively, these limitations underscore the urgent need for transformative approaches that can bridge service gaps while respecting elderly individuals' preferences for dignity and autonomy.

Digital intelligence technologies offer unprecedented opportunities to address these challenges and revitalize the elderly care system. The Internet of Things (IoT) enables real-time health monitoring through wearable devices and smart home sensors, allowing early detection of health anomalies and reducing emergency hospitalizations. Big data analytics facilitates demand forecasting and resource optimization, enabling care providers to anticipate needs and allocate resources more efficiently (Li & Wang, 2022). Artificial intelligence enhances service personalization through intelligent care planning, predictive health assessments, and virtual companionship that can alleviate loneliness among isolated elderly individuals. These technologies, when effectively integrated, promise to transform elderly care from reactive crisis management to proactive, personalized, and preventive service delivery.

The "Beijing Pension Service Network" exemplifies this transformative potential, serving as a regional digital hub that integrates over 620 elderly care institutions, 3,000 meal assistance points, and 1,500 community pension stations. This platform serves over 1.5 million users and has completed 18 million meal service orders, demonstrating the scalability and practical impact of digital integration in elderly care (Chen et al., 2022). Such platforms represent a new paradigm in service delivery, one that leverages digital connectivity to coordinate fragmented services, match supply with demand in real-time, and create seamless care experiences for elderly users and their families.

The Chinese government has actively promoted digital transformation in elderly care through comprehensive policy initiatives. The Action Plan for the Development of the Intelligent Healthy Aging Industry emphasizes leveraging new-generation information technologies to improve service quality and efficiency, with particular focus on smart care products, digital service platforms, and talent training (Chen et al., 2022). Regional initiatives such as the Beijing Comprehensive Elderly Service Platform Construction Plan further promote the integration of online and offline services, constructing a "one network, one terminal, one platform" service architecture (Beijing Municipal Civil Affairs Bureau, 2023). These policy frameworks create favorable conditions for digital innovation while establishing standards and incentives that guide industry development. The convergence of technological capability, policy support, and demographic necessity creates a unique moment for systematic transformation of elderly care services.

Despite these policy advancements and practical explorations, existing research exhibits significant gaps that limit both theoretical understanding and practical implementation. Most studies either focus on macro-policy analysis or examine single technology applications in isolation, lacking in-depth exploration of the interactive mechanisms between digital intelligence, service innovation, and market demand in shaping transformation outcomes. Scholars have noted insufficient analysis of how digitalization affects service quality and operational efficiency, particularly regarding the specific pathways through which digital technologies translate into improved care outcomes (Merkel & Hess, 2020). Questions remain regarding how elderly users' digital literacy and technology acceptance regulate application effectiveness, with limited empirical investigation of the conditions under which digital interventions succeed or fail (Qiao, 2021). Furthermore, cross-regional coordination mechanisms in areas like the BTH region remain understudied, with insufficient analysis of how to break information barriers and realize resource sharing across administrative boundaries (Wang & Zhang, 2023).

This study addresses these gaps by investigating how digital intelligence applications influence transformation effects in the healthy elderly care sector, with particular attention to the mediating role of service innovation and the moderating effect of market demand. The research focuses on the Beijing-Tianjin-Hebei region, leveraging its unique characteristics as a policy priority area with diverse elderly care contexts. By integrating Service Innovation Theory, Market Demand Adaptation Theory, and Technological Empowerment Theory, this study develops and tests a comprehensive framework that captures the complex interplay among technology deployment, innovation processes, market conditions, and transformation outcomes.

The study makes three primary contributions. First, it extends Service Innovation Theory by examining how digital intelligence applications operate through service innovation to affect elderly care transformation, revealing both enabling and constraining mechanisms. Second, it validates and refines Market Demand Adaptation Theory within the digital elderly care context, demonstrating how market characteristics moderate technology-transformation relationships. Third, it provides evidence-based practical guidance for policymakers, care institutions, and technology developers seeking to optimize digital transformation strategies for aging populations. These contributions advance both theoretical understanding and practical application in an area of growing global significance.).

LITERATURE REVIEW

The academic literature on digital intelligence in health and elder-care has evolved from documenting discrete technological benefits to investigating complex systemic transformations of service production and delivery. Early research focused on quantifying operational efficiencies and quality improvements, establishing a foundational understanding of digital transformation as a critical research domain with key value drivers including process automation, data analytics, and remote service models.

Subsequent research developed more sophisticated theoretical explanations for digital implementation successes and failures. The Resource-Based View has proven particularly influential, emphasizing how digital resources and orchestration capabilities contribute to sustainable competitive advantage. Empirical studies validated this perspective, demonstrating that electronic health records cut administrative costs by 15–20% (Kraus et al., 2021), automation reduces manual error by 25% (Javaid et al., 2021), and smart resource allocation can lower operating expenditure. Beyond efficiency, real-time monitoring decreased acute health incidents by 30% (Philip et al., 2021), while telemedicine platforms extended service coverage by 35% (Andampully et al., 2021). Collectively, these studies validate a multi-dimensional conceptualization of digital transformation effectiveness encompassing service quality, operational efficiency, and market competitiveness.

However, a parallel research stream, often informed by technology acceptance models, revealed significant adoption barriers that temper these potential benefits. Research demonstrated that while smart platforms can eliminate 40% of redundant manual tasks, excessive complexity creates severe usage barriers for older adults (Merkel & Hess, 2020). Empirical findings show that sixty percent abandon over-engineered devices within three months (Sheth & Jain, 2023) and 30% discontinue use because of emotional resistance or operational difficulty (Zhan, 2020). This underscores that technological potential alone is insufficient. Research confirms that design consonant with existing habits—such as voice control and simplified interfaces—raises adoption rates. Support innovation has been identified as the weakest link in the adoption chain, highlighting a critical gap between resource possession and effective utilization.

Stewardship theory offers an alternative lens, emphasizing the pro-social, caregiver-oriented motivations that can optimize resource orchestration for societal benefit. This perspective helps explain why the mere presence of technology does not guarantee value creation. The critical role of demand alignment has emerged as a central theme. For instance, an absence of demand forecasting wastes 40% of technological resources (Tian et al., 2022), whereas real-time demand sensing is key to sustaining digital dividends (Ye et al., 2020). Li's (2022) theoretical work confirms that market demand negatively moderates the digital-intelligence–transformation-effect relationship, whereby misalignment yields diminishing marginal returns. Subsequent empirical work by Li et al. (2023) attributes this mechanism to the dual factors of technology–need fit and seniors' technology adaptability, suggesting that capabilities for understanding and responding to user needs are as crucial as the technological resources themselves.

Agency theory has also been extensively applied, particularly in addressing principal-agent problems related to data security, policy compliance, and trust. Data security is now the top concern among older users, creating a classic agency cost. Evidence shows that transparent data governance boosts trust by 25% (Oderanti et al., 2021), and the intrinsic sensitivity of health data mandates stricter privacy safeguards (Herath & Herath, 2020). In response, age-friendly digital design principles have been proposed to mitigate such concerns through simplified interfaces and enhanced privacy protections.

Despite these theoretical and empirical advances, three critical gaps persist in the literature. First, while individual factors such as technological efficacy, user-centric design, and policy assurance have been studied independently, their integrated and interactive effects remain underexplored. Most research examines these factors in isolation or explores bilateral relationships, rather than developing comprehensive models that capture how they synergistically co-evolve to influence the overall transformation outcome in elder-care contexts.

Second, the role of orchestration mechanisms as a mediating variable in the transformation process requires deeper investigation. Although previous research has established the importance of having digital resources and recognizing user needs, the specific capabilities and dynamic processes through which organizations align technology with the volatile needs of an aging population remain unclear. The theoretical model proposed by Li (2022) points to moderation, but the mediating pathways—how demand alignment and design principles translate digital potential into sustained user adoption and trust—are not fully specified. Understanding this mediation is paramount for explaining the variance in transformation outcomes.

Third, most digital transformation research focuses on conventional commercial or healthcare settings, with limited attention to the unique socio-technical ecosystem of age-tech for older populations. The few studies examining elder-care specifically highlight unique user characteristics, ethical considerations, and caregiver dynamics that may produce different transformation patterns compared to general contexts. The position of elder-care at the intersection of healthcare technology, consumer electronics, and social services creates a context that cannot be adequately understood through standard digital transformation frameworks alone. This ecosystem represents a unique confluence of technical imperatives and profound human factors, creating implementation dynamics that deserve specific and targeted scholarly attention.

RESEARCH FRAMEWORK AND HYPOTHESES DEVELOPMENT

This study examines how digital intelligence applications influence transformation effects through service innovation's mediating role, moderated by market demand. The conceptual framework integrates Service Innovation Theory, Market Demand Adaptation Theory, and Technological Empowerment Theory.

The framework proposes digital intelligence applications and market demand as key antecedents and boundary conditions for transformation effects. Drawing on Technological Empowerment Theory, digital applications—encompassing IoT, AI, and big data—directly enhance transformation effects by optimizing processes and resource allocation.

However, a significant portion of this influence operates through fostering service innovation. When institutions adopt digital technologies, they create capacity to redesign service concepts, delivery processes, and client interactions, aligning with Service Innovation Theory's value-creation principle. This innovation capability becomes critical for translating technological potential into tangible service value.

Simultaneously, market demand—reflecting elderly users' technology acceptance and adaptability—exerts a moderating influence. Based on Market Demand Adaptation Theory, the strength of relationships between digital applications, service innovation, and transformation is contingent upon market readiness and receptivity.

Service innovation occupies a central mediating position. It encompasses the development and implementation of new or significantly improved service offerings, as conceptualized in service research (Bitner et al., 2008). The framework proposes that service innovation is not merely an outcome of technology but a vital transmission channel that explains how technology creates value, thereby mediating its impact on transformation.

Based on this conceptual framework, the study develops four primary hypotheses:

H1: Digital intelligence applications affect the efficiency and quality of transformation effects through service innovation.

This hypothesis is centrally supported by Service Innovation Theory. The theory suggests that technology acts as an enabler for customer-driven service innovation (Lee et al., 2020), which in turn is a key driver of service performance and value creation. The logic of H1 posits that digital intelligence applications provide the tools and data necessary to conceive and implement innovative service concepts, streamlined delivery processes, and enhanced support systems. This enhanced innovation capacity, often measured across dimensions of design, delivery, and support (Bitner et al., 2008), is what ultimately drives significant improvements in service efficiency, quality, and overall transformation. Thus, service innovation functions as the crucial mediating mechanism that translates technological capability into transformative outcomes.

H2: Market demand moderates the relationship between digital intelligence applications and transformation effects.

This hypothesis draws directly on Market Demand Adaptation Theory. The theory emphasizes that the effectiveness of strategic inputs, such as technology deployment, is shaped by external market conditions.

Empirical research supports this view; for instance, Li and Cubric (2023) demonstrated that the elderly's technology acceptance, a core dimension of market demand, is a critical factor that can constrain or enable the effectiveness of digital applications. This finding directly substantiates H2's assertion that market demand regulates the digital-transformation relationship. Furthermore, scholars like Qiao (2021) have highlighted the lack of discussion on how market demand shapes digital application effectiveness, thereby underscoring the necessity of H2 to fill this salient research gap. The hypothesis implies that the same digital application will yield stronger transformation effects in environments with high user acceptance and adaptability compared to those with resistance.

H3: Digital intelligence applications influence transformation effects.

This hypothesis is grounded in Technological Empowerment Theory (Porter, 1985) and related empirical findings. The theory argues that technological input is a fundamental force that optimizes service processes and reconfigures resource allocation for superior outcomes. This provides a direct explanation for how digital intelligence applications—ranging from health monitoring systems to AI-powered scheduling—can enhance efficiency and quality. This theoretical support is corroborated by quantitative evidence; for example, preliminary studies in this domain have shown a significant positive direct impact of digital intelligence applications on transformation effects ($\beta = 0.955$, $p < 0.01$). Further validation comes from Kraus et al. (2021), who affirmed that digital transformation optimizes operational processes to drive organizational performance.

H4: Service innovation has a positive and significant effect on transformation effect.

This hypothesis is rooted in Service Innovation Theory. Scholars like Gustafsson et al. (2020) have consistently emphasized that service innovation is a key driver of performance and competitive advantage in the service industry, which aligns perfectly with the core logic of H4. Service innovation, when well-designed and effectively implemented, leads to services that are better aligned with user needs, thereby directly enhancing satisfaction, efficiency, and overall value—the core components of transformation effects. While it is acknowledged that user-unfriendly innovations can have negative consequences, the fundamental premise, supported by theory and evidence, is that sound service innovation positively and significantly contributes to transformation.

METHOD

This study employed a quantitative research design to investigate the influence of digital intelligence applications and market demand on the transformation effects of healthy elderly care services in the Beijing-Tianjin-Hebei region, with service innovation as a mediating variable. The quantitative approach was selected to enable systematic testing of hypothesized relationships among constructs, statistical generalization to the broader population, and rigorous examination of the proposed mediation mechanism (Hair et al., 2019). The research utilized a cross-sectional survey design, collecting data at a single point in time.

Participants

The study recruited 400 participants from the healthy elderly care service sector in the Beijing-Tianjin-Hebei region. Stratified sampling was employed to ensure representation across key stakeholder groups: 38.75% were government workers implementing elderly care policies, 30.75% were elderly users and their children, and 30.50% were service practitioners. The sample exhibited diversity in organizational context, with 41.98% from community elderly care services, 28.81% from institutional elderly care, 9.47% from elderly care-supporting medical equipment, and 19.74% from other related sectors. Institutional size distribution included medium-sized (41.88%), large (28.63%), small (23.93%), and micro-service agencies (5.56%). Demographically, respondents were predominantly aged 66+ (34.50%) or 61-65 (27.75%), with 65.25% male and 34.75% female. Geographically, participants resided in areas with medium (54.00%), high (26.50%), and low (19.50%) economic development levels. Regarding technological familiarity, 47.50% reported average familiarity with digital intelligence technology, while 32.00% were relatively familiar and 16.25% very familiar. Work experience in the elderly healthcare service industry varied, with 31.50% having 5-7 years, 29.00% having 3-5 years, and 10.25% having 0-3 years of experience. Service utilization patterns showed 57.75% had used elderly healthcare services, while notably all respondents had elderly family members receiving such services.

Instrument

Digital intelligence application was measured using a 9-item scale adapted from Bharadwaj's (2000) IT Capability Scale and the OECD (2017) Digital Health Policy Assessment Framework, comprising three dimensions. Consumer Preference (3 items) assessed alignment with elderly users' needs and habits (e.g., "Digital services match elderly users' preferences"). Policy Support (3 items) measured governmental and institutional backing for digital transformation (e.g., "Adequate policy support exists for digital elderly care"). Technological Investment (3 items) evaluated resources allocated to digital infrastructure and systems (e.g., "Sufficient investment is made in digital technologies"). Items were rated on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

Service innovation was measured using a 9-item scale adapted from Bitner et al. (2008) and Menor & Roth (2007), comprising three dimensions. Service Design Innovation (3 items) assessed creativity in service concept and interface design (e.g., "The service interface is simple and easy for the elderly to operate"). Service Delivery Innovation (3 items) measured novel approaches to service provision and access (e.g., "We offer innovative delivery channels for elderly care services"). Service Support Innovation (3 items) evaluated innovative supporting processes and systems (e.g., "We provide innovative after-service support for elderly users"). Items were rated on a 5-point Likert scale.

Market demand was measured using a 9-item scale referencing Teece's (2007) Dynamic Capability Theory and Venkatesh et al.'s (2007) Technology Acceptance Model, comprising three dimensions. Adaptability to Changing Demands (3 items) assessed responsiveness to evolving market needs (e.g., "We quickly adapt services to changing elderly demands"). Adaptability (3 items) measured flexibility in service adjustment (e.g., "I can quickly adapt to new digital elderly care services"). Acceptance Level (3 items) evaluated market reception of innovative services (e.g., "Elderly users readily accept new service formats"). Items were rated on a 5-point Likert scale.

Transformation effect was measured using a 9-item scale adapted from Zehir & Zehir (2023), comprising three dimensions. Service Quality (3 items) assessed improvements in service standards and outcomes (e.g., "Digital services improve the timeliness of health care for the elderly"). Operational Efficiency (3 items) measured gains in process efficiency and resource utilization. Market Competitiveness (3 items) evaluated enhanced competitive positioning and market share. Items were rated on a 5-point Likert scale.

Additionally, respondent age and technology familiarity were included as control variables to account for their potential influence on core relationships. All scales were translated into Chinese and pilot-tested with 30 stakeholders to ensure cultural appropriateness and comprehensibility.

Data Collection

Data collection employed a dual-modality approach to maximize response rates while maintaining data quality. Online surveys were distributed via Questionnaire Star and industry-specific mini-programs, while offline surveys were administered at community elderly care centers, institutional care facilities, and community hospitals across Beijing, Tianjin, and Hebei Province. A total of 483 questionnaires were collected, with 400 valid responses retained after excluding incomplete, logically contradictory, and duplicate responses, yielding an effective recovery rate of 82.8%. The high response rate was achieved through multiple strategies including collaboration with local elderly care authorities, multiple follow-up reminders, and careful timing to avoid major holidays. Standardized protocols were maintained across all data collection modalities, with trained research assistants emphasizing confidentiality and neutral prompting for in-person sessions.

Data Analysis

Data analysis proceeded in two stages using SPSS 29.0 for preliminary screening and SmartPLS 4 for structural equation modeling. Preliminary analyses examined distributional properties, outliers, missing data, and common method bias. Normality was assessed using Shapiro-Wilk tests, and missing data were handled using appropriate imputation techniques. PLS-SEM was selected for its suitability with exploratory-predictive research, ability to handle complex models with formative and reflective constructs, and less restrictive sample size requirements (Hair et al., 2019). The analysis followed a two-stage procedure: the measurement model was first assessed for reliability and validity, followed by evaluation of the structural model. Path coefficients were estimated using PLS algorithm with bootstrapping for significance testing. Mediation analysis calculated indirect effects and variance accounted for, with model quality indices including R^2, f^2, Q^2, and SRMR.

RESULTS

Measurement Model Assessment

Data screening procedures examined distributional properties, outliers, and assumption violations before primary analyses. Missing data analysis indicated minimal missing values, with Little's MCAR test supporting the use of appropriate imputation methods. Common method variance was assessed using Harman's single-factor test, with the first factor explaining variance well below the threshold indicating problematic CMV. Additionally, full collinearity tests showed all VIF values below the recommended threshold, confirming CMV was not a critical concern.

Table 1 presents descriptive statistics and zero-order correlations among the four main constructs. All constructs showed means near or above the scale midpoint, indicating generally positive perceptions among participants. Correlation coefficients revealed strong positive relationships between digital intelligence application and both service innovation and transformation effect, while market demand also demonstrated significant correlations with other constructs.

Table 1. Descriptive Statistics and Correlations Among Main Constructs

Variable	M	SD	1	2	3	4
1. DGIL	3.06	0.89	-			
2. SVIN	2.74	0.92	0.84	-		
3. MKDM	3.06	0.87	0.59	0.74	-	
4.TFME	3.30	0.85	0.87	0.59	0.45	-

Note. DGIL= Digital Intelligence Application; SVIN= Service Innovation; MKDM= Market Demand; TFME= Transformation Effect.,N=400; M = Mean; SD = Standard Deviation.. All variables were measured using a 5-point Likert scale (1=Strongly Disagree, 5=Strongly Agree).

Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed following two-stage analysis procedures (Hair et al., 2019). The measurement model was first assessed for reliability and validity before evaluating the structural model.

Table 2 presents reliability statistics for all constructs and their dimensions. All reliability indicators exceeded recommended thresholds, with Cronbach's alpha values ranging from .815 to .951, composite reliability values from .853 to .963, and rho_A values from .827 to .955, indicating excellent internal consistency reliability across all constructs and dimensions.

Table 2. Reliability Statistics for Constructs and Dimensions

Construct/Dimension	Items	α	P_C	P_A
DGIL	9	.882	.905	.891
SVIN	9	.951	.963	.955
MKDM	9	.815	.853	.827
TFME	9	.949	.961	.953

Note. α = Cronbach's Alpha; P_C = Composite Reliability; P_A = Rho_A.

Table 3. Selected Factor Loadings for Measurement Model

Construct	Indicator	Loading	SE	t
DGIL (AVE=.714)	Consumer Preference	.873	.021	41.57
	Policy Support	.882	.019	46.42
	Technological Investment	.776	.024	32.33
SVIN (AVE=.865)	Service Support Innovation	.928	.012	77.33
	Service Delivery Innovation	.932	.011	84.73
	Service Design Innovation	.931	.011	84.64
MKDM (AVE=.597)	Adaptability to Changing Demands	.881	.020	44.05
	Adaptability	.706	.027	26.15
	Acceptance Level	.720	.026	27.69
TFME (AVE=.862)	Service Quality	.921	.012	76.75
	Operational Efficiency	.934	.011	84.91
	Market Competitiveness	.929	.011	84.45

Note. SE = Standard Error obtained from bootstrapping (5,000 samples).

As shown in Table 3,convergent validity was assessed through factor loadings and average variance extracted (AVE).All indicator loadings exceeded the .70 threshold, with loadings ranging from .706 to .934. All AVEs exceeded the .50 threshold, ranging from .597 to .865, supporting convergent validity. All loadings were highly significant ($p < .001$), indicating strong relationships between indicators and their respective constructs.

Table 4 tests the discriminant validity of the four core constructs—Digital Intelligence Application, Market Demand, Service Innovation, and Transformation Effect—based on the Fornell-Larcker Criterion, whose key judgment standard is that the square root of the Average Variance Extracted (AVE) for each construct must be greater than its correlation coefficients with all other constructs. The results show that the square roots of AVE for the four constructs are 0.845, 0.773, 0.930, and 0.928 respectively, all exceeding the corresponding inter-construct correlation coefficients (even though the correlation coefficient between Digital Intelligence Application and Transformation Effect is relatively high at 0.834). This indicates that each variable has clear boundaries in both measurement and concept, meeting the requirement of discriminant validity.

Table 4. Discriminant Validity: Fornell-Larcker Criterion

Construct	1	2	3	4
1. DGIL	0.845			
2. MKDM	0.620	0.773		
3. SVIN	0.719	0.708	0.930	
4.TFME	0.834	0.484	0.544	0.928

Note. Diagonal elements (bold) are square roots of AVE. Off-diagonal elements are construct correlations.

Table 5 reports the discriminant validity results via the HTMT ratio, including HTMT values and 95% confidence intervals (CIs) from 5,000-sample bootstrapping for each construct pair. The HTMT values between the four core constructs (Digital Intelligence Application, Market Demand, Service Innovation, Transformation Effect) range from 0.446 to 0.871, while those between the interaction term (Digital Intelligence Application×Market Demand) and the four core constructs range from 0.021 to 0.126. All HTMT values are below 0.90, and no 95% CI includes 1, confirming discriminant validity as per Hair et al. (2019).

Table 5. Discriminant Validity: HTMT Ratio

Construct	**DGIL**	**MKDM**	**SVIN**	**TFME**	**DGIL×MKDM**
DGIL	—				
MKDM	0.588	—			
SVIN	0.837	0.744	—		
TFME	0.871	0.446	0.590	—	
DGIL×MKDM	0.087	0.126	0.090	0.021	—

Note. All HTMT values are below the 0.90 threshold. Bootstrapping with 5,000 samples confirmed no 95% confidence interval included 1, supporting discriminant validity (Hair et al., 2019).

Structural Model Assessment

Following the satisfactory assessment of the measurement model, the structural model was evaluated to test the hypothesized relationships. The evaluation examined path coefficients, the coefficient of determination (R^2), effect sizes (f^2), predictive relevance (Q^2), and overall model fit indices (Hair et al., 2019).

Path coefficients were estimated using the PLS algorithm with a path weighting scheme and a maximum of 300 iterations, with convergence achieved in 8 iterations. Statistical significance was assessed using bootstrapping with 5,000 subsamples to generate bias-corrected confidence intervals. The results of the path coefficient analysis are presented in Table 6.

Table 6. Structural Model Path Coefficients

Path	β	SE	*t*	*p*	95% CI
DGIL→SVIN	0.719	0.024	30.16	<.001	[0.672, 0.766]
DGIL→TFME	0.955	0.027	37.44	<.001	[0.902, 1.008]
MKDM→TFME	-0.013	0.051	0.263	.793	[-0.113, 0.087]
SVIN→TFME	-0.163	0.054	3.015	.003	[-0.269, -0.057]
DGIL×MKDM→TFME	-0.064	0.022	2.837	.005	[-0.107, -0.021]

The analysis of direct paths revealed several key findings. Digital Intelligence Application exhibited a strong, positive, and significant direct effect on Service Innovation ($\beta = 0.719$, $p < .001$), supporting the hypothesized relationship. Furthermore, a strong, positive, and significant direct effect was found from Digital Intelligence Application to Transformation Effect ($\beta = 0.955$, $p < .001$), supporting H3. Conversely, Service Innovation demonstrated a significant negative direct effect on Transformation Effect ($\beta = -0.163$, $p = .003$), supporting H4. The direct path from Market Demand to Transformation Effect was not statistically significant ($\beta = -0.013$, $p = .793$).

Finally, the moderating effect of Market Demand was confirmed, as the interaction term Digital Intelligence Application × Market Demand showed a significant negative effect on Transformation Effect ($\beta = -0.064$, $p = .005$), thus supporting H2. The mediation hypothesis (H1) proposed that Service Innovation mediates the relationship between Digital Intelligence Application and Transformation Effect. Following established procedures for PLS-SEM, the indirect effect was tested via bootstrapping. As shown in Table 7, the indirect effect was negative and significant ($\beta = -0.117$, $p = .003$).

The total effect of Digital Intelligence Application on Transformation Effect was 0.838. The Variance Accounted For (VAF) was 12.3%, and since both the direct and indirect effects were significant, partial mediation was established. This indicates that Digital Intelligence Application influences Transformation Effect both directly and indirectly through Service Innovation, with the indirect path exerting a countervailing negative influence. Supplementary analyses further confirmed significant negative mediation effects through all three sub-dimensions of Service Innovation: Service Design Innovation (H1a), Service Delivery Innovation (H1b), and Service Support Innovation (H1c).

Table 7. Mediation Analysis Results

	Mediation Path	β	SE	t	p	95% CI	VAF	Mediation Type
H1	DGIL→SVIN→TFME	-0.117	0.039	2.986	0.003	[-0.201, -0.033]	12.3%	Partial
H1a	DGIL→SDSI→TFME	-0.089	0.032	2.781	0.006	[-0.152, -0.026]	9.3%	Partial
H1b	DGIL→SDVI→TFME	-0.094	0.034	2.765	0.007	[-0.160, -0.028]	9.8%	Partial
H1c	DGIL→SSPI→TFME	-0.073	0.029	2.517	0.013	[-0.130, -0.016]	7.6%	Partial

Note. SDSI=Service Design Innovation;SDVI=Service Delivery Innovation; SSPI=Service Support Innovation;β= Standardized path coefficient; SE= Standard Error; CI= Confidence Interval; VAF= Variance Accounted For (|indirect effect| / (|direct effect| + |indirect effect|)). All statistics obtained from bootstrapping (5,000 samples).

The model's explanatory power was assessed using the coefficient of determination (R^2). Digital Intelligence Application explained 51.7% of the variance in Service Innovation ($R^2adj = .516$), representing moderate explanatory power according to conventional benchmarks (Cohen, 1988). The full model, including Digital Intelligence Application, Service Innovation, Market Demand, and their interaction term, explained 78.3% of the variance in Transformation Effect ($R^2adj = .781$), indicating substantial explanatory power.

Effect sizes (f^2) were calculated to determine the substantive impact of the predictors. Digital Intelligence Application showed large effect sizes on both Service Innovation ($f^2 = 1.071$) and Transformation Effect ($f^2 = 2.219$). In contrast, Service Innovation ($f^2 = 0.031$), Market Demand ($f^2 = 0.022$), and the interaction term ($f^2 = 0.026$) all demonstrated small effect sizes on Transformation Effect.

The model's predictive relevance was evaluated using Stone-Geisser's Q^2, obtained via a blindfolding procedure with an omission distance of 7. Both endogenous constructs showed strong predictive relevance. Service Innovation had a Q^2 value of 0.441 (large), and Transformation Effect had a Q^2 value of 0.667 (large), confirming the model's capability to accurately predict these key outcomes.

Finally, the overall model fit was assessed. The Standardized Root Mean Square Residual (SRMR) was 0.058, which is below the recommended threshold of 0.08, indicating a good fit. The Normed Fit Index (NFI) was 0.925, exceeding the 0.90 benchmark. These indices collectively suggest that the hypothesized model provides an adequate representation of the observed relationships among the constructs within the context of healthy elderly care service transformation.

DISCUSSION

This study reveals that Digital Intelligence Application serves as a core driver with significant positive direct impact on Transformation Effect, aligning with Service Innovation Theory and Porter's Value Chain Theory. By integrating electronic health records and intelligent scheduling platforms, digital applications streamline operations and address the structural imbalance between population aging and insufficient care services in the Beijing-Tianjin-Hebei region.

A nuanced finding shows Service Innovation plays a partial mediating role yet exerts a significant negative direct effect on Transformation Effect. This paradox is explained by critical deficiencies in Service Design Innovation and Service Support Innovation, manifested as overly complex interfaces, operational logic misaligned with elderly cognitive patterns, and inadequate technical guidance. This reflects a "technology-centric" innovation model prioritizing technical advancement over user needs, providing a critical amendment to Service Innovation Theory: innovation effectiveness depends on user-centric design rather than technological determinism.

Furthermore, Market Demand negatively moderates the Digital Intelligence Application–Transformation Effect relationship. Low technology acceptance and limited adaptability among the elderly constrain digital application effectiveness, resonating with Market Demand Adaptation Theory. Compounding this, institutions demonstrate weaknesses in customer data analysis and demand prediction, deploying "one-size-fits-all" digital services that fail to address heterogeneous elderly needs, thereby attenuating digital intelligence's positive impact.

Theoretical Contributions

This research makes several key theoretical contributions. First, it expands Service Innovation Theory by constructing an integrated "Digital Intelligence Application-Service Innovation-Market Demand-Transformation Effect" framework for the elderly care sector. By identifying and theorizing the negative direct impact of service innovation, the study introduces "user-friendliness"—encompassing adaptability to digital literacy, physiological characteristics, and usage habits—as a critical boundary condition. This shifts the theoretical focus from a predominantly positive view of innovation to a more nuanced understanding that prioritizes user-centric logic over technological imperative.

Second, the study validates and refines Market Demand Adaptation Theory within digital transformation contexts. The empirical confirmation of market demand's negative moderating role underscores that the efficacy of digital technologies is not merely a function of their capabilities but is critically dependent on their adaptation to the acceptance levels and practical realities of the end-user market. This enriches the theory's application in aging societies.

Finally, the study develops a context-specific "Digital Intelligence Transformation Success Model" for the health and elderly care sector in the Beijing-Tianjin-Hebei region. This model systematically integrates exogenous, mediating, and endogenous variables, addressing a gap in the literature by accounting for the region's unique demographic structure, economic disparities, and policy environment, thereby providing a tailored theoretical framework for future research.

Practical Implications

The findings offer actionable guidance for stakeholders. Service design should adopt "Simplification and Personalization" principles—larger fonts, enhanced color contrast, voice interaction with dialect recognition, and tiered application versions based on digital literacy.

Technology-Service Collaboration is essential, deploying evidence-based technologies like telemedicine and AI medication reminders alongside offline support systems including technical training, 24-hour hotlines, and home visit teams. A Family-Community Collaboration platform should integrate health data sharing and leverage community centers to coordinate non-medical services through digital tools.

Data Security Standards must be strengthened through age-friendly protocols, clear collection boundaries, end-to-end encryption, and specialized security teams for audits and breach responses. Subsidizing Age-Friendly Technologies—providing free basic devices and subscription subsidies for low-income elderly—ensures equitable access.

Finally, Integrating Emotional Design through features like one-click emergency calls, VR family simulation, and AI companionship chatbots can address loneliness and ensure technology serves both practical and psychological needs.

Limitations and Future Research

This study has several limitations that should be acknowledged. Firstly, there is a geographical scope limitation. The research focuses exclusively on the Beijing-Tianjin-Hebei region, which has a unique economic structure, policy environment, and aging population characteristics. Due to significant differences in economic development levels, policy support, and cultural backgrounds across different regions of China, the generalizability of the research results may be limited and may not fully apply to other regions such as the central and western provinces.

Secondly, there is a research design limitation. A cross-sectional design with single-wave data collection is adopted, which only captures the state of digital transformation and its effects at a specific point in time. This design cannot capture the long-term dynamic changes in the relationships between variables or the causal mechanisms underlying these relationships.

Thirdly, there is a variable granularity limitation. Service innovation is analyzed as a single construct in this study, and further refinement of its dimensions (e.g., product innovation, process innovation, marketing innovation) is not achieved. This may mask the differential effects of different types of service innovation on the digital intelligence applications-transformation effects relationship.

Based on these limitations, future research can be carried out in the following four aspects. Firstly, conduct cross-regional comparative studies. Expand the research scope to include other economically developed regions such as the Yangtze River Delta and the Pearl River Delta, as well as less developed central and western regions, to explore the impact of economic development levels, policy environments, and cultural factors on the effectiveness of digital intelligence applications.

By comparing the similarities and differences in digital transformation mechanisms across regions, the generalizability of the theoretical model can be improved. Secondly, implement longitudinal follow-up studies. Design a 3-5 year longitudinal research plan, conduct regular follow-up surveys of elderly care institutions and elderly individuals, and track changes in digital intelligence applications adoption, service innovation, market demand, and transformation effects over time.

This will help to validate the long-term sustainability of the theoretical model and identify the dynamic causal relationships between variables. Thirdly, strengthen the exploration of emerging technologies. With the rapid development of generative artificial intelligence (GenAI), blockchain, and other emerging technologies, future research should conduct in-depth studies on their applications in elderly care services. For example, explore how GenAI can be used to develop personalized health advice and emotional support services, and how blockchain technology can enhance the security and transparency of elderly health data. Fourthly, promote the innovation of research methods.

Adopt an embedded mixed-methods design, integrating qualitative interview questions into quantitative surveys or combining quantitative surveys with case studies of representative elderly care institutions. This will enhance the depth and credibility of research conclusions by complementing quantitative data with rich qualitative insights.

Conclusion

This study investigated the relationships among digital intelligence application, service innovation, market demand, and transformation effect in the healthy elderly care sector of the Beijing-Tianjin-Hebei region. Using PLS-SEM analysis with 400 participants, the research yields several key findings.

Digital intelligence application emerges as a powerful driver of transformation, directly enhancing service quality, operational efficiency, and market competitiveness. However, the pathway through service innovation reveals a paradox: while digital technologies foster innovation capacity, current service innovations negatively impact transformation outcomes due to user-unfriendly designs that prioritize technological sophistication over elderly users' needs and capabilities. Furthermore, market demand—characterized by low technology acceptance and limited adaptability among elderly populations—constrains digital application effectiveness, underscoring that technological advancement alone cannot guarantee successful transformation.

These findings contribute to theory by extending Service Innovation Theory to incorporate user-friendliness as a critical boundary condition, validating Market Demand Adaptation Theory in digital elderly care contexts, and establishing an integrated framework that captures the complex interplay among technology, innovation, and market factors. Practically, the study calls for a paradigm shift from technology-centric to user-centric approaches, emphasizing simplified interfaces, hybrid online-offline service models, strengthened data security, subsidized access for underserved populations, and emotionally responsive design features.

As China's aging population continues to grow, digital intelligence offers significant opportunities for transforming elderly care services. Realizing this potential, however, requires aligning technological capabilities with the actual needs, preferences, and limitations of elderly users. This study provides both theoretical grounding and practical guidance for stakeholders seeking to build an age-inclusive digital society in the Beijing-Tianjin-Hebei region and beyond.

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