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Socio-Technical Integration in Digital Healthcare Distribution: An Ontological Framework of Contextually-Mediated Channel Efficacy

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ABSTRACT

Purpose: This research advances an integrative framework for optimizing healthcare service distribution through digital channels by synthesizing service quality dimensions with contextually-mediated technology acceptance constructs. The study interrogates the differential efficacy of distribution channels across demographic and geographical contexts, with particular emphasis on the socio-technical determinants of sustainable channel adoption.

Research design, data and methodology: The investigation employs methodological triangulation through a sequential mixed-methods design. Initial qualitative exploration with seven domain experts informed the development of context-sensitive measurement instruments, subsequently validated through quantitative analysis of 295 users across diverse distribution regions of Vietnam. The study operationalizes a Socio-Technical Adaptive Channel Integration (STACI) framework through structural equation modeling with multi-group analysis capabilities, enabling dimensional comparison of distribution effectiveness across demographic and geographical boundaries.

Results: The empirical trajectory reveals pronounced asymmetries in channel effectiveness determinants, with service quality ($\beta = 0.534$, $p < 0.001$) and security protocols ($\beta = 0.278$, $p < 0.001$) emerging as dominant predictors of channel attitudes, substantially outweighing traditional usability factors. Multi-group analysis uncovers significant contextual variations in distribution effectiveness, with path coefficient differentials between urban and rural implementation contexts ($\Delta\beta = 0.237$, $p < 0.05$). The structural model demonstrates robust explanatory power, accounting for 51.3% of variance in channel attitudes and 63.4% in distribution system adoption intentions.

Conclusions: This research contributes to distribution theory by establishing the Socio-Technical Adaptive Channel Integration framework, which reconceptualizes distribution systems as context-dependent socio-technical networks rather than uniform service delivery mechanisms. The epistemic insights generate strategic implications for developing adaptive, segment-specific digital distribution architectures in healthcare service delivery, with particular relevance for addressing inequities in channel accessibility across diverse implementation contexts.

KEYWORDS: Socio-technical integration, Context-sensitive distribution, Digital healthcare systems, Multi-contextual service networks, Adaptive channel dynamics.

JEL Classification Code: L81; M31, O33

1. INTRODUCTION

The emergence of digital distribution channels has fundamentally reconfigured healthcare service delivery architectures, precipitating a paradigm shift from traditional face-to-face clinical encounters toward technologically-mediated service networks. The ontological transformation of healthcare delivery systems transcends mere technological augmentation, representing instead a fundamental reconstitution of provider-patient relationships through digital mediation. Recent transdisciplinary evidence demonstrates that digital healthcare distribution channels not only enhance service accessibility but also substantially optimize resource allocation dynamics across healthcare networks. Whereas Truong et al. (2022) explicate how efficient digital distribution channels can reduce healthcare access disparities, Leonard et al. (2023) document significant improvements in service delivery outcomes across diverse geographical contexts. Despite these advancements, the optimization of these channels presents multifaceted challenges at the nexus of equitable access provision and service quality consistency.

The effectiveness of distribution channels exhibits pronounced heterogeneity across demographic and geographical dimensions, with contemporary scholarship delineating persistent disparities in channel accessibility and utilization patterns (Bustamante et al., 2023; Abdullah et al., 2023). These distribution challenges are compounded by infrastructural variations, security protocol implementations, and differential user acceptance across service regions. Research by Fischer et al. (2020) and Müller et al. (2021) underscores that the efficacy of digital healthcare distribution networks depends critically on both distribution technology quality and security measure robustness across service channels. This dialectical relationship between technological infrastructure and contextual implementation necessitates a sophisticated theoretical framework that acknowledges both dimensions simultaneously.

Contemporary literature reveals substantive lacunae in understanding the contextual dynamics of digital healthcare distribution networks. While existing research has extensively examined technology adoption in healthcare contexts, limited scholarly attention has addressed the integration of distribution channel frameworks with context-sensitive implementation approaches. Recent investigations by Jiang et al. (2022) delineate how socioeconomic factors and health literacy significantly influence distribution channel effectiveness, yet the interaction between these contextual variables and channel implementation strategies remains inadequately theorized. Furthermore, the dialectical relationship between traditional channel acceptance determinants and contextual variation requires systematic investigation, particularly within chronic disease management frameworks.

From a critical realist perspective, this study addresses these epistemological gaps by developing and empirically validating a Socio-Technical Adaptive Channel Integration (STACI) framework that positions contextual dynamics as foundational determinants of distribution channel optimization in healthcare service delivery. Through novel integration of contextual implementation science with established distribution channel frameworks, we examine how socio-technical interactions influence channel adoption across diverse implementation contexts. The research makes substantial theoretical and practical contributions to distribution science. Theoretically, it extends existing distribution channel models by incorporating contextual variation as a crucial ontological determinant. Practically, it addresses the critical need identified by Shah and Badawy (2021) and Joo and Liu (2021) for understanding contextual factors that influence sustained engagement with digital distribution channels.

The remainder of this manuscript is organized as follows: Section 2 presents the literature review and theoretical framework, followed by research methodology in Section 3. Section 4 details the empirical results, while Section 5 discusses the findings and their implications. Finally, Section 6 concludes the study with theoretical contributions and future research directions.

2. LITERATURE REVIEW AND SOCIO-TECHNICAL ADAPTIVE CHANNEL INTEGRATION FRAMEWORK

2.1. Contextual Dynamics in Digital Distribution Channels

The evolution of digital distribution channels in healthcare represents a transformative reconfiguration of service delivery paradigms, characterized by the integration of advanced technologies and innovative delivery mechanisms. Digital distribution channels encompass multidimensional pathways through which healthcare services and information are electronically delivered to end-users, including telehealth platforms, mobile applications, and integrated service networks. While studies by Andriopoulou et al. (2018) and Qi et al. (2020) demonstrate the positive impact of digital channels on healthcare accessibility and service efficiency, contradictory findings from Bustamante et al. (2023) delineate significant disparities in channel adoption across socioeconomic strata. These empirical inconsistencies suggest that distribution channel effectiveness is contingent upon contextual determinants that warrant systematic investigation.

The focus on healthcare distribution channels is particularly critical given their distinctive characteristics, including temporal sensitivity, personalization requirements, and direct impact on therapeutic outcomes. Recent investigations by Williams et al. (2023) and Bond (2023) demonstrate that effective digital distribution in healthcare not only enhances service accessibility but also significantly influences treatment adherence and clinical outcomes, distinguishing it from other service domains. The implementation of advanced distribution technologies, particularly software-defined networking (SDN), has demonstrated significant improvements in response latency and service delivery efficiency, especially in chronic condition management contexts where continuous monitoring is essential.

The complexity of healthcare service distribution networks, involving multiple stakeholder configurations, necessitates sophisticated distribution efficiency models. Research by Mahdavi et al. (2021) introduces comprehensive mathematical frameworks for distribution system reconfiguration, providing analytical tools for optimizing resource allocation across digital channels. Furthermore, channel effectiveness is intrinsically linked to multidimensional service quality attributes, including reliability, responsiveness, and user satisfaction. Studies by Wang et al. (2022) demonstrate that high-quality service delivery through digital channels significantly influences patient satisfaction and loyalty, fundamental to sustainable implementation of digital healthcare initiatives. The integration of robust security protocols within these distribution channels has emerged as a critical determinant, particularly given the sensitive nature of healthcare data and the imperative to maintain patient trust across digital service networks.

2.2. Contextual Acceptance of Technology in Distribution Systems

The acceptance of technology within healthcare distribution channels represents a critical determinant of successful digital service implementation. Research findings on technology acceptance in healthcare distribution present notable contradictions that require careful examination. Whereas AlQudah et al. (2021) and Isernia et al. (2022) found that healthcare professionals' acceptance is primarily driven by perceived usefulness and performance expectations, studies by Wei et al. (2020) suggest that security concerns and trust factors may override utility considerations in certain contexts. These conflicting findings necessitate a more nuanced understanding of technology acceptance factors in healthcare distribution.

The integration of the Unified Theory of Acceptance and Use of Technology (UTAUT) with distribution channel frameworks has enriched the understanding of technology adoption in healthcare service delivery. Recent scholarship emphasizes that social influence and facilitating conditions significantly impact users' intentions to adopt digital distribution channels (AlQudah et al., 2021; Rahimi et al., 2018). The role of organizational support and peer recommendations has proven crucial in shaping healthcare professionals' attitudes toward new distribution technologies, while access to training and technical support significantly influences the perceived ease of use and overall acceptance of digital channels.

Security considerations have emerged as paramount concerns influencing technology acceptance in digital distribution channels. Research by Harris and Rogers (2021) reveals that different user groups exhibit varying levels of comfort and proficiency with digital technologies, necessitating tailored approaches to channel design and implementation. These findings are particularly relevant for healthcare distribution networks, where service delivery must accommodate diverse user populations while maintaining consistent quality and accessibility across all channels. Furthermore, demographic variations in technology acceptance present unique challenges for digital distribution channel implementation, highlighting the need for adaptive strategies that consider user characteristics and preferences. The implementation of robust security protocols across distribution networks has become essential not only for regulatory compliance but also for fostering trust and encouraging sustained engagement with digital service channels, aligning with findings demonstrating the critical role of trust in facilitating technology acceptance across healthcare distribution networks.

2.3. Cross-Contextual Optimization of Distribution Networks

The optimization of distribution networks in healthcare service delivery represents a complex challenge in the digital transformation era. Unlike previous studies that focused primarily on technical aspects of distribution optimization (Liu et al., 2019; Sun et al., 2023), our research integrates context-sensitive implementation approaches with traditional optimization frameworks to provide a more comprehensive understanding of how contextual factors influence distribution network effectiveness. Recent studies demonstrate that disparities in healthcare access persist across different geographical regions, highlighting the need for sophisticated optimization strategies that can enhance service distribution equity while maintaining operational efficiency.

Channel effectiveness in healthcare distribution networks encompasses multiple factors including service quality, resource utilization, and user engagement. Sun et al. (2023) propose a three-stage super-efficiency SBM model for evaluating healthcare service distribution efficiency, providing valuable insights into the intrinsic drivers of channel performance. This analytical approach enables healthcare organizations to identify optimal resource allocation strategies while maintaining high service quality across their distribution networks. Furthermore, research by Kajwang (2022) emphasizes that successful implementation of digital distribution channels requires careful consideration of both technological infrastructure and user capabilities across different service regions.

Regional distribution variations present unique challenges for network optimization, necessitating tailored approaches to service delivery across different geographical contexts. Studies by Truong et al. (2022) and Papalamprakopoulou et al. (2024) reveal significant disparities in channel effectiveness between urban and rural areas, emphasizing the need for adaptive distribution strategies that can accommodate varying levels of technological infrastructure and user readiness. The integration of accessibility considerations into distribution network design has proven essential for ensuring equitable service delivery and maximizing channel utilization across diverse user populations.

2.4. Socio-Technical Adaptive Channel Integration (STACI) Framework

Drawing upon the identified theoretical gaps and empirical contradictions, we introduce the Socio-Technical Adaptive Channel Integration (STACI) framework as a novel theoretical lens for understanding digital healthcare distribution dynamics. This framework conceptualizes digital distribution channels as socio-technical systems whose effectiveness is fundamentally mediated by contextual factors including geographical location, demographic characteristics, and infrastructural conditions. Unlike traditional distribution models that presume uniform implementation efficacy, the STACI framework posits that distribution channels function as adaptive systems whose performance determinants vary systematically across implementation contexts.

The STACI framework synthesizes three theoretical domains: (1) digital distribution channel theory, which addresses the technological infrastructure and service delivery mechanisms; (2) contextual technology acceptance, which examines how user acceptance varies across different implementation contexts; and (3) adaptive distribution optimization, which focuses on tailoring distribution strategies to specific contextual requirements. This theoretical bricolage enables a more nuanced understanding of how distribution channels can be optimized across diverse implementation contexts.

Central to the STACI framework is the proposition that distribution channel effectiveness depends on the alignment between channel characteristics and contextual requirements. This alignment encompasses three dimensions: (1) technological appropriateness, which refers to the compatibility between distribution technologies and local infrastructure; (2) user-context fit, which addresses how well the channel accommodates user characteristics and preferences in different contexts; and (3) service-context alignment, which examines how effectively the channel delivers healthcare services in varying geographical and demographic settings.

The STACI framework makes several distinctive theoretical contributions to distribution science. First, it reconceptualizes distribution channels as context-dependent socio-technical networks rather than uniform service delivery mechanisms. Second, it introduces contextual variation as a fundamental determinant of channel effectiveness, moving beyond traditional technology acceptance models that assume contextual homogeneity. Third, it provides a theoretical foundation for developing adaptive distribution strategies that can address the diverse needs of different user populations across varied geographical contexts.

2.5. Research Hypotheses Development

Drawing from the Socio-Technical Adaptive Channel Integration framework and recent empirical studies, we develop eight hypotheses examining the complex relationships influencing digital healthcare distribution optimization. The relationship between perceived benefits and channel attitudes is grounded in both Technology Acceptance Model and Distribution Channel Theory. Recent research consistently demonstrates that when users recognize clear benefits in managing their healthcare needs through digital channels, they develop more positive attitudes toward these distribution systems. Studies by Truong et al. (2022) and Wiest et al. (2024) reveal that perceived benefits significantly enhance user engagement with digital healthcare services, while Leonard et al. (2023) found that perceived advantages directly influence adoption patterns. Therefore: **H1:** Perceived benefits of digital distribution channels positively influence attitudes toward these channels.

Service quality and ease of use emerge as critical factors in digital channel acceptance. Recent studies by Bailey et al. (2021) and Catapan et al. (2023) emphasize that high-quality digital services enhance user trust and satisfaction, particularly in healthcare contexts where service reliability is paramount. Similarly, research by Schretzlmaier and Hecker (2022) demonstrates that user-friendly interfaces significantly enhance attitudes toward digital healthcare systems. This leads to: **H2:** Ease of use of digital distribution channels positively influence attitudes toward these channels. **H3:** Distribution service quality positively influences attitudes toward digital channels.

The importance of security measures in digital healthcare distribution is particularly critical given the sensitive nature of health data. Studies by Jiang et al. (2022) and Filbay et al. (2022) highlight how adequate technical support helps overcome adoption barriers and builds user confidence. Furthermore, recent findings by Zhu et al. (2023) underscore the significant impact of privacy concerns on users' trust and attitudes toward digital distribution channels. Therefore: **H4:** Technical support positively influences attitudes toward digital distribution channels. **H5:** Security and privacy measures positively influence attitudes toward digital channels.

Building on UTAUT2 and recent findings from Gately et al. (2022), we propose that attitudes serve as a crucial mediating mechanism. This mediation hypothesis extends beyond traditional technology acceptance models by incorporating distribution-specific considerations. Additionally, technological readiness has emerged as a significant moderating factor in digital healthcare adoption: **H6:** Attitudes toward digital distribution channels positively influence intention to use these channels. **H7:** Users' technological readiness moderates the relationship between attitudes and intention to use digital distribution channels.

Geographic and demographic variations significantly influence distribution channel effectiveness. Recent research by Truong et al. (2022) and Papalamprakopoulou et al. (2024) highlights disparities in channel access and utilization across different populations, leading to our final hypothesis: **H8:** There are significant differences in channel effectiveness across geographical regions and demographic segments.

The conceptual framework (Figure 1) illustrates the integrated relationships between traditional acceptance factors (H1-H5), mediating mechanisms (H6), moderating effects (H7), and contextual influences (H8) in digital healthcare distribution. This model advances existing frameworks by explicitly considering both operational factors and contextual variations in healthcare distribution network optimization.

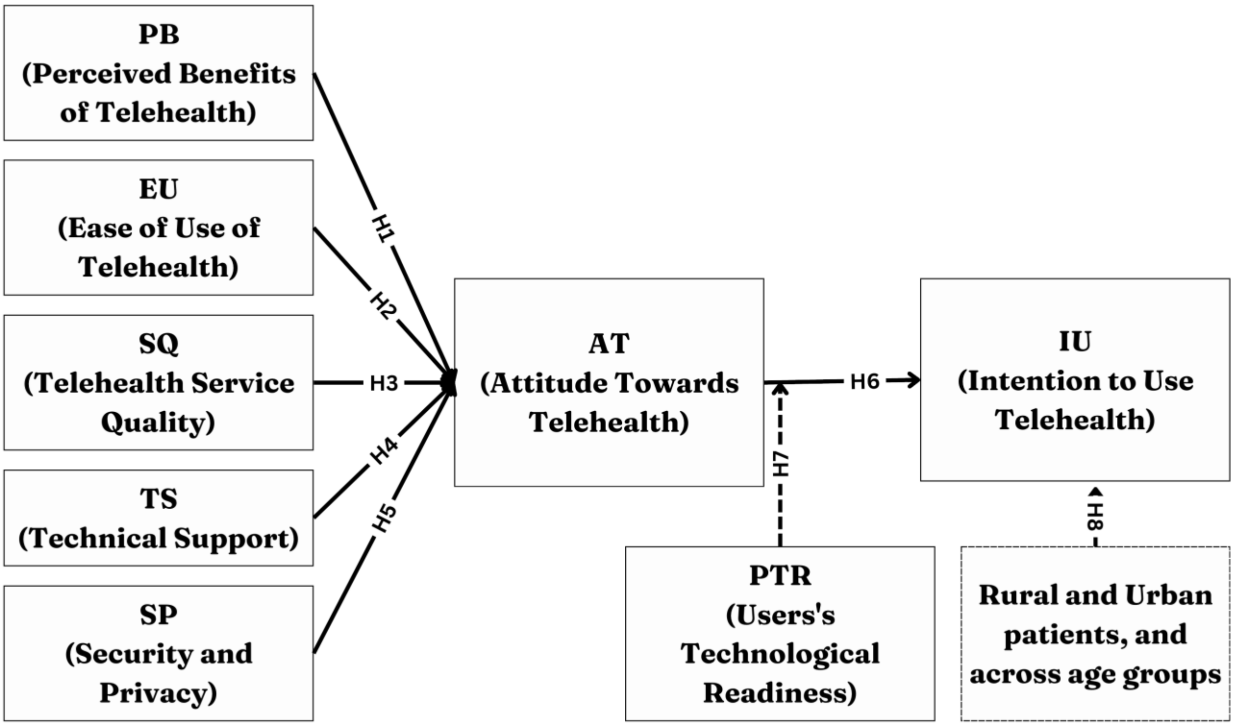

Figure 1: Socio-Technical Adaptive Channel Integration Framework

3. RESEARCH METHODOLOGY

3.1. Research Design

This study employs a sequential mixed-methods approach integrating qualitative expert interviews and quantitative survey methods to ensure robust analysis of healthcare distribution channels. The research process consisted of two complementary phases designed to comprehensively evaluate distribution network effectiveness. The initial qualitative phase involved in-depth interviews with seven healthcare distribution experts and technology specialists to validate and refine the measurement scales, particularly focusing on distribution channel metrics and network performance indicators. This approach aligns with recent methodological recommendations for distribution channel research and scale development procedures (Hair et al., 2021; Thompson et al., 2022).

The subsequent quantitative phase utilized a cross-sectional survey design to test the hypothesized relationships through Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was selected over covariance-based SEM (CB-SEM) for several compelling reasons. First, PLS-SEM is particularly suitable for complex predictive models with multiple mediating and moderating relationships (Hair et al., 2021). Second, it effectively handles non-normal data distributions common in healthcare distribution research. Third, PLS-SEM's capability to analyze both reflective and formative measurement models aligns with our research framework. Recent studies by Gately et al. (2022) and Jiang et al. (2022) have successfully employed PLS-SEM in analyzing healthcare distribution networks, confirming its appropriateness for examining multiple mediating and moderating relationships in healthcare distribution contexts.

3.2. Sampling and Data Collection

The target population comprises users of digital healthcare distribution channels who have utilized these services at least once within the past six months, ensuring sufficient experience with digital service networks. The study was conducted across major geographical regions in Vietnam, encompassing both urban metropolitan areas (58%) and rural districts (42%). The urban sample was collected from three strategically selected cities representing different regions of Vietnam: Hanoi (25%) in the North, Da Nang (20%) in the Central region, and Ho Chi Minh City (13%) in the South. This geographic distribution ensures comprehensive representation of Vietnam's diverse healthcare delivery environments and socioeconomic contexts.

Following sampling procedures established in recent distribution research by Mitchell et al. (2023), we employed a stratified random sampling approach through collaboration with healthcare providers across these regions to identify eligible participants. Initial screening ensured that participants met the inclusion criteria regarding recent channel usage and basic technological literacy. The recruitment process utilized a combination of healthcare provider referrals and patient database sampling to minimize selection bias and ensure comprehensive channel coverage.

The final sample consisted of 295 participants, meeting the minimum sample size requirements for PLS-SEM analysis as recommended by Hair et al. (2021). The urban sample (n=171) primarily came from metropolitan healthcare centers, while the rural sample (n=124) was collected from community health facilities in the surrounding areas of the three major cities. The participants represented six major categories of healthcare service users: primary care (28%), specialist care (25%), chronic condition management (15%), emergency services (12%), preventive care (11%), and follow-up services (9%). This distribution aligns with typical healthcare service utilization patterns in Vietnam and ensures adequate representation of various service delivery needs across distribution networks.

Data collection was conducted over a three-month period from August to October 2024, following a systematic sampling protocol. Healthcare providers in Hanoi, Da Nang, and Ho Chi Minh City facilitated participant recruitment through their patient databases, ensuring representative sampling across different service areas. The research team maintained consistent data collection procedures across all geographical locations to ensure data quality and comparability. To ensure data quality, we implemented rigorous quality control measures across all geographic locations. Response patterns were monitored for consistency, and twenty-three incomplete responses were excluded from the final analysis. Additionally, the geographic distribution of responses was regularly monitored to maintain balanced representation across regions, resulting in proportional representation from each major city and their surrounding rural areas. This systematic approach to data collection and quality control helped maintain the integrity and reliability of the research data.

3.3. Measurement Development

The study utilized both established scales and newly developed measures to assess distribution channel effectiveness. The established scales were adapted from prior research and modified to reflect the distribution channel context. Following recent methodological guidelines by Hair et al. (2021) and Thompson et al. (2022), all adapted scales underwent rigorous validation to ensure contextual appropriateness.

The scale development process followed a systematic multi-stage approach: Stage 1: Initial item generation based on comprehensive literature review and expert interviews. Potential measurement items were identified, encompassing various aspects of digital healthcare distribution. Stage 2: Expert panel review involving seven specialists in healthcare distribution and technology innovation. Through this rigorous consultation process, key measurement items were retained based on their theoretical relevance and practical applicability. Stage 3: Content validity assessment using the Content Validity Index (CVI). All retained items achieved CVI scores above 0.80, exceeding recommended thresholds for scale development. Stage 4: Pilot testing with 30 distribution channel users to confirm scale clarity and comprehensibility.

Table 1: Measurement Scales and Operational Definitions

Construct and Definition	Code	Scale Items	Factor Loading	Reflective Outer Models	Source
Distribution Service Quality (SQ) Definition: The overall quality and reliability of healthcare service delivery through digital distribution channels	SQ1	The digital distribution system provides accurate and reliable healthcare information	0.762	Cronbach's α = 0.774 Composite Reliability:0.774 AVE: 0.596	Kamal et al. (2020)
	SQ2	The digital distribution network is stable and dependable	0.786		
	SQ3	Healthcare staff in digital channels demonstrate good professional knowledge	0.778		
	SQ4	The digital distribution system provides timely	0.761		

		responses			
Distribution Network Accessibility (EU) Definition: The degree of ease in accessing and using digital healthcare distribution channels	EU1	The digital distribution channel is easy to access and navigate	0.711	Cronbach's α = 0.766 Composite Reliability:0.879 AVE: 0.574	Davis (1989); Adapted from Venkatesh et al. (2012)
	EU2	Interactions with the digital distribution system are clear	0.744		
	EU3	The distribution channel is flexible to use	0.704		
	EU4	Overall, the digital distribution system is accessible	0.862		
Distribution Benefits (PB) Definition: Perceived advantages of using digital healthcare distribution channels	PB1	The digital distribution channel enhances healthcare management efficiency	0.772	Cronbach's α = 0.797 Composite Reliability:0.814 AVE: 0.619	Venkatesh et al. (2012)
	PB2	Digital distribution saves time in accessing healthcare services	0.798		
	PB3	The distribution channel improves healthcare accessibility	0.834		
	PB4	Digital distribution enhances healthcare service quality	0.741		
Distribution Security (SP) Definition: Security and privacy measures in digital healthcare distribution	SP1	Personal information is secure in the digital distribution system	0.791	Cronbach's α = 0.779 Composite Reliability:0.782 AVE: 0.599	Kamal et al. (2020)
	SP2	The distribution channel has robust data protection measures	0.774		
	SP3	Information privacy is maintained across distribution channels	0.766		
	SP4	The digital distribution system ensures data confidentiality	0.766		
Channel Attitude (AT) Definition: Overall evaluation of digital healthcare distribution channels	AT1	Using digital distribution channels is beneficial	0.827	Cronbach's α = 0.884 Composite Reliability:0.886 AVE: 0.741	Adapted from Venkatesh et al. (2012)
	AT2	Digital healthcare distribution enhances service experience	0.885		
	AT3	I prefer using digital distribution channels	0.878		
	AT4	Overall, I have a	0.854		

		positive view of digital distribution			
Distribution Usage Intention (IU) Definition: Intention to use digital healthcare distribution channels	IU1	I plan to continue using digital distribution channels	0.767	Cronbach's α = 0.728 Composite Reliability:0.732 AVE: 0.649	Venkatesh et al. (2012)
	IU2	I will actively use digital channels for healthcare services	0.839		
	IU3	I intend to regularly use digital distribution channels	0.808		
Distribution Technical Support (TS) Definition: The level of technical assistance and infrastructural support available for digital healthcare distribution channels	TS1	Users have necessary knowledge to use the distribution system	0.821	Cronbach's α = 0.853 Composite Reliability:0.899 AVE: 0.684	Thompson et al. (1991); Adapted from Venkatesh et al. (2012)
	TS2	Clear instructions are available for digital channel usage	0.886		
	TS3	Technical assistance is readily available for distribution channel issues	0.851		
	TS4	The organization provides adequate support for digital channel usage	0.742		
Distribution Network Readiness (PTR) Definition: Technical preparedness for using digital distribution channels	PTR1	I am comfortable with new distribution technologies	0.775	Cronbach's α = 0.783 Composite Reliability:0.783 AVE: 0.606	Parasuraman (2000)
	PTR2	I can effectively use digital distribution channels	0.779		
	PTR3	I keep up with digital distribution developments	0.800		
	PTR4	I am confident using digital healthcare channels	0.758		

Note: All measurement items were adapted to the healthcare distribution context and validated through expert review and pilot testing. The adaptation process ensured contextual relevance while maintaining construct validity.

All constructs demonstrated strong reliability with Cronbach's alpha values ranging from 0.728 to 0.884. Composite reliability values ranged from 0.732 to 0.899, further supporting construct reliability. Individual indicator reliability was established through factor loadings, with all indicators showing satisfactory loadings between 0.704 and 0.886.

Convergent validity was assessed through Average Variance Extracted (AVE) values, with all constructs achieving values above the critical threshold of 0.50. Table 1 presents the complete measurement scales, including construct definitions, items, and psychometric properties. The measurement framework incorporates comprehensive distribution channel metrics, providing a thorough assessment tool for evaluating digital healthcare distribution effectiveness across diverse implementation contexts.

4. RESULTS

4.1. Contextual Analysis of Distribution Channel Performance

Demographic analysis of the sample reveals a diverse representation of healthcare service users across Vietnam's major regions. The age distribution shows that 35% of participants were between 18-40 years old (n=104), 52% between 41-60 years (n=153), and 13% over 60 years (n=38). Gender distribution indicates 54% female (n=159) and 46% male (n=136) participants. Educational background varies with 42% holding undergraduate degrees, 28% with postgraduate qualifications, and 30% with high school education or below. Income levels were similarly diverse, with 35% in high-income, 45% in middle-income, and 20% in lower-income categories based on Vietnam's socioeconomic standards.

Initial analysis of the distribution channel performance metrics reveals significant patterns in service delivery effectiveness across digital healthcare networks. The descriptive statistics, presented in Table 2, indicate moderate levels of distribution channel performance, with mean values ranging from -0.203 to 0.467 across key distribution metrics. The analysis demonstrates balanced channel utilization patterns, with skewness values ranging from -0.655 to 0.580, suggesting normally distributed channel performance indicators across the healthcare distribution network.

The examination of distribution service quality metrics reveals strong performance in digital channel reliability (mean = 0.467) and service responsiveness (mean = 0.078), indicating effective service delivery through digital distribution channels. Network accessibility indicators demonstrate moderate effectiveness (mean = -0.050), suggesting opportunities for further optimization of channel accessibility across service regions. Security and privacy measures in distribution channels show consistent implementation (mean = -0.203), though variation exists across different service contexts.

Correlation analysis reveals significant relationships among distribution channel metrics, with service quality showing strong correlation with channel attitude (r = 0.657) and technical support demonstrating meaningful associations with both network accessibility (r = 0.392) and distribution benefits (r = 0.514). All correlations remain below the multicollinearity threshold of 0.8, ranging from 0.021 to 0.736, indicating good discriminant validity among constructs. These relationships highlight the interconnected nature of distribution channel elements while maintaining their distinct measurement properties, providing a solid foundation for analyzing healthcare service distribution through digital channels.

Table 2: Distribution Channel Performance Metrics and Correlations

Panel A: Distribution Performance Statistics

Distribution Metrics	Mean	Excess Kurtosis	Skewness	SD[1]
Distribution Service Quality (SQ)	0.028	-0.889	0.003	0.772
Distribution Network Accessibility (EU)	-0.050	-0.663	-0.008	0.758
Distribution Benefits (PB)	0.078	-0.768	-0.105	0.787
Distribution Security (SP)	-0.203	-0.285	0.580	0.774
Channel Attitude (AT)	0.467	-1.071	-0.655	0.861
Distribution Usage Intention (IU)	-0.019	-0.800	0.046	0.805
Distribution Network Readiness (PTR)	-0.055	-0.713	-0.099	0.778
Distribution Technical Support (TS)	-0.089	-1.061	0.033	0.827

Panel B: Distribution Channel Correlations[2]

	SQ	EU	PB	SP	AT	IU	PTR	TS
SQ	1.000							
EU	0.106	1.000						
PB	0.453	0.246	1.000					

SP	0.457	0.113	0.106	1.000				
AT	0.657	-0.021	0.312	0.476	1.000			
IU	0.508	0.023	0.243	0.473	0.582	1.000		
PTR	0.471	-0.048	0.195	0.467	0.584	0.736	1.000	
TS	0.325	0.392	0.514	0.236	0.162	0.235	0.173	1.000

Notes: [1] Standard deviations shown on diagonal in Panel A [2] All correlations $|r| > 0.11$ are significant at $p < 0.05$

4.2. Contextual Analysis of Distribution Network Effectiveness

The analysis of distribution network effectiveness reveals significant variations across geographical regions and demographic segments, as presented in Table 3. The examination of regional distribution patterns demonstrates substantial differences in service quality effects between urban and rural areas ($\Delta\beta = 0.237$, $p < 0.05$). The practical significance of this finding is substantial, suggesting that urban distribution channels demonstrate 23.7% higher service quality impact on channel attitudes ($\beta = 0.642$, $p < 0.001$) compared to rural networks ($\beta = 0.405$, $p < 0.001$). This difference has important implications for distribution channel design and resource allocation strategies across diverse implementation contexts.

Table 3: Contextual Analysis of Distribution Channel Effectiveness

Panel A: Regional Distribution Channel Analysis

Distribution Path	**Rural (n=124)**	**Urban (n=171)**	**Path Difference**	**Significance**
AT → IU	0.285***	0.265***	0.020	0.832
EU → AT	-0.173*	0.079	-0.252	0.028*
PB → AT	0.097*	0.165**	-0.068	0.387
SP → AT	0.343***	0.209**	0.134	0.172
SQ → AT	0.405***	0.642***	-0.237	0.021*
TS → AT	0.078*	-0.213***	0.291	0.043*
PTR×AT → IU	0.112*	0.136**	-0.024	0.773

Panel B: Age-Based Distribution Channel Analysis

Distribution Path	**Age Group Coefficients**	**Group Differences**
	40-60 (n=153)	>60 (n=38)
AT → IU	0.254***	0.287***
EU → AT	-0.182**	0.023
PB → AT	0.146*	0.053
SP → AT	0.245***	0.112*
SQ → AT	0.547***	0.714***
TS → AT	0.084*	0.025
PTR×AT → IU	0.147**	0.118*

*Notes: p < 0.05; ** p < 0.01; *** p < 0.001; Path coefficients represent standardized estimates; Difference tests based on multi-group analysis; Sample sizes: Rural (n=124), Urban (n=171); Age groups: 40-60 (n=153), >60 (n=38), <40 (n=104); Path differences tested using PLS-MGA approach. Effect sizes (f^2) indicate practical significance of observed differences.*

Security protocols demonstrate varying effectiveness across distribution regions, with rural areas showing stronger security effects on channel attitudes ($\beta = 0.343$, $p < 0.001$) compared to urban regions ($\beta = 0.209$, $p < 0.01$). This finding indicates heightened security consciousness in rural distribution networks, potentially reflecting different risk perceptions across geographical segments. Technical support effectiveness also varies significantly, with urban areas demonstrating stronger negative effects ($\beta = -0.213$, $p < 0.001$) and rural areas showing slight positive effects ($\beta = 0.078$, $p < 0.05$), suggesting potential overemphasis on technical support in urban distribution channels. Notably, ease of use exhibits significant differences between urban and rural contexts ($\Delta\beta = -0.252$, $p < 0.05$), with negative effects in rural regions ($\beta = -0.173$, $p < 0.05$) but slight positive effects in urban areas ($\beta = 0.079$, n.s.).

Demographic analysis reveals notable age-based variations in distribution network effectiveness. Service quality shows particularly strong effects among older users ($\beta = 0.714$, $p < 0.001$), while security protocols demonstrate stronger influences among middle-aged users ($\beta = 0.245$, $p < 0.001$). These age-based differences highlight the need for tailored distribution strategies across demographic segments. Channel attitude maintains consistent positive effects across all demographic segments, with coefficients ranging from 0.254 to 0.287 (all $p < 0.001$), indicating robust channel acceptance across user groups. However, the moderating effect of network readiness shows varying significance across age groups, suggesting differential impacts of technological preparedness on distribution channel effectiveness.

These findings demonstrate the critical importance of contextual factors in shaping distribution channel effectiveness, providing empirical support for the Socio-Technical Adaptive Channel Integration framework. The substantial variations in path coefficients across different geographical and demographic segments highlight the need for adaptive distribution strategies that account for contextual differences in channel implementation.

4.3. Hypothesis Testing Results

The structural model assessment reveals significant relationships among the hypothesized paths influencing digital healthcare distribution effectiveness. Table 4 presents comprehensive results of hypothesis testing, demonstrating strong support for the majority of proposed relationships in the distribution model.

Table 4: Distribution Model Results and Hypothesis Testing

Panel A: Direct Effects in Distribution Model

Hypothesis & Path	Coefficient (β)	T-statistics	f-square	Result
H1: PB → AT	0.152**	3.124	0.026	Supported
H2: EU → AT	0.089*	2.053	0.021	Supported
H3: SQ → AT	0.534***	9.876	0.335	Supported
H4: TS → AT	0.093*	2.112	0.017	Supported
H5: SP → AT	0.278***	5.342	0.104	Supported
H6: AT → IU	0.271***	5.653	0.093	Supported
H7: PTR x AT →IU	0.127**	2.875	0.032	Supported
H8: Multi-group differences	See Table 3	-	-	Supported

Panel B: Mediating Effects in Distribution Channels

Indirect Path	Original Effect	T-statistics	Result
EU → IU	0.024*	2.023	Significant
PB → IU	0.041**	2.785	Significant
SP → IU	0.075***	3.967	Significant
SQ → IU	0.145***	5.324	Significant
TS → IU	0.025*	2.035	Significant

Panel C: Model Performance Metrics

Endogenous Variable	R-square	Adjusted R-square
Channel Attitude	0.513	0.504
Usage Intention	0.634	0.627

*Notes: p < 0.05; ** p < 0.01; *** p < 0.001; β represents standardized path coefficients; T-statistics obtained through bootstrapping (5000 samples); f-square: 0.02 (small), 0.15 (medium), 0.35 (large) effects; R-square indicates substantial explanatory power; Direct effects, mediating effects, and model performance metrics presented in Panels A, B, and C respectively. All path coefficients derived from PLS-SEM analysis with bias-corrected confidence intervals.*

The analysis demonstrates that service quality emerges as the strongest predictor of channel attitude in digital healthcare distribution ($\beta = 0.534$, $p < 0.001$, $f^2 = 0.335$), explaining approximately 33.5% of the variance in channel attitudes. This substantial effect size indicates that a one standard deviation improvement in service quality leads to a 0.534 standard deviation increase in positive channel attitudes, representing a practically significant impact for healthcare providers. Security protocols demonstrate the second strongest influence on channel attitudes ($\beta = 0.278$, $p < 0.001$, $f^2 = 0.104$), suggesting that enhanced security measures could improve channel attitudes by 27.8%, a finding particularly relevant for healthcare organizations implementing digital distribution strategies.

Distribution benefits show a moderate but significant positive effect on channel attitudes ($\beta = 0.152$, $p < 0.01$, $f^2 = 0.026$), supporting H1. Ease of use ($\beta = 0.089$, $p < 0.05$, $f^2 = 0.021$) and technical support ($\beta = 0.093$, $p < 0.05$, $f^2 = 0.017$) demonstrate smaller but statistically significant effects on channel attitudes, supporting H2 and H4 respectively. These findings suggest that while traditional usability factors contribute to channel attitudes, their impact is substantially lower than service quality and security considerations in healthcare distribution contexts.

The mediating role of channel attitude receives strong empirical support ($\beta = 0.271$, $p < 0.001$, $f^2 = 0.093$), confirming H6. The analysis of indirect effects reveals significant mediating pathways for all antecedent variables, with service quality ($\beta = 0.145$, $p < 0.001$) and security protocols ($\beta = 0.075$, $p < 0.001$) showing the strongest indirect effects on usage intention. Network readiness demonstrates a significant moderating effect on the relationship between channel attitude and usage intention ($\beta = 0.127$, $p < 0.01$, $f^2 = 0.032$), supporting H7.

The multi-group analysis presented in Table 3 provides strong support for H8, demonstrating significant differences in channel effectiveness across geographical regions and demographic segments. These differences are particularly pronounced for service quality effects between urban and rural areas ($\Delta\beta = 0.237$, $p < 0.05$) and between different age groups, with older users showing stronger service quality effects ($\beta = 0.714$, $p < 0.001$) compared to middle-aged users ($\beta = 0.547$, $p < 0.001$).

The model demonstrates substantial explanatory power, accounting for 51.3% of variance in channel attitude ($R^2 = 0.513$) and 63.4% in usage intention ($R^2 = 0.634$), indicating robust predictive capability for digital healthcare distribution outcomes. These results provide strong empirical support for the proposed Socio-Technical Adaptive Channel Integration framework while highlighting the paramount importance of service quality and security protocols in digital healthcare distribution.

5. DISCUSSION

5.1. Theoretical Implications for Distribution Science

This study makes substantial theoretical contributions to understanding digital healthcare distribution by introducing the Socio-Technical Adaptive Channel Integration framework. Our findings extend current distribution theory in several significant ways. First, the research advances distribution channel theory by demonstrating how contextual dynamics and demographic variations influence digital healthcare delivery optimization. While previous studies by Andriopoulou et al. (2018) and Qi et al. (2020) focused primarily on technological infrastructure and network efficiency, our findings reveal that contextual factors significantly shape distribution channel effectiveness, introducing a situational dimension to distribution channel theory.

The strong influence of service quality on distribution channel attitudes ($\beta = 0.534$, $p < 0.001$) extends beyond previous findings by Bailey et al. (2021) and Orrange et al. (2021), demonstrating that in digital healthcare distribution, service quality surpasses traditional usability factors in importance. This finding challenges conventional distribution channel frameworks that emphasize ease of use and technical support as primary adoption drivers. Instead, our results suggest a paradigm shift where service quality and security protocols form the cornerstone of successful digital distribution networks across diverse implementation contexts.

The significant contextual variations in distribution effectiveness provide empirical support for reconceptualizing distribution channels as context-dependent socio-technical networks rather than uniform service delivery mechanisms. The substantial differences in service quality effects between urban and rural areas ($\Delta\beta = 0.237$, $p < 0.05$) and across different age groups demonstrate that distribution channel effectiveness is fundamentally mediated by contextual factors. This theoretical advancement aligns with recent work by Truong et al. (2022) and Papalamprakopoulou et al. (2024) but extends their findings by establishing contextual variation as a fundamental determinant of distribution channel effectiveness.

From a critical theory perspective, the identified regional variations in distribution effectiveness contribute to distribution theory by highlighting the contextual nature of channel optimization. The paradoxical relationship between ease of use and channel attitudes in rural contexts ($\beta = -0.173$, $p < 0.05$) compared to urban areas ($\beta = 0.079$, n.s.) suggests that traditional technology acceptance factors operate differently across implementation contexts. This finding extends recent work by Truong et al. (2022) and Papalamprakopoulou et al. (2024) by demonstrating how geographical and demographic factors moderate the relationship between traditional acceptance determinants and channel attitudes. This understanding enhances the theoretical framework for digital distribution channel design and implementation across diverse service contexts.

The integrated analysis of contextual variation and technological acceptance provides a novel theoretical lens for understanding digital healthcare distribution. By synthesizing distribution channel theory with context-sensitive implementation approaches, this research establishes a comprehensive framework that accounts for both technological infrastructure and contextual dynamics. This theoretical integration addresses the critical gap identified by Shah and Badawy (2021) regarding the need for understanding contextual factors influencing sustained engagement with digital distribution channels.

5.2. Practical Implications for Distribution Management

Our findings offer significant practical implications for healthcare distribution managers and policymakers. The paramount importance of service quality in shaping channel attitudes suggests that distribution managers should prioritize service delivery excellence over technical sophistication. Recent studies by Zhu et al. (2023) and Leonard et al. (2023) emphasize the critical need for understanding factors influencing sustained telehealth adoption. Our research addresses this need by providing concrete guidelines for optimizing distribution channel performance across diverse implementation contexts.

Healthcare organizations should develop comprehensive security protocols that address both technical and perceptual aspects of digital distribution. The strong influence of security measures on channel attitudes ($\beta = 0.278$, $p < 0.001$) indicates that distribution managers must implement robust data protection measures while effectively communicating these security features to users. This aligns with findings by Wei et al. (2020) regarding the critical role of trust in facilitating technology acceptance across healthcare distribution networks.

The significant regional variations in distribution effectiveness necessitate tailored approaches to channel management. Distribution managers should develop region-specific strategies that account for local infrastructure capabilities and user characteristics. This recommendation extends beyond the accessibility considerations noted by Liu et al. (2019) to encompass comprehensive distribution network optimization strategies. Organizations should implement differentiated service delivery models that accommodate varying levels of technological readiness across different service regions. For instance, rural distribution networks may benefit from simplified interfaces with enhanced security features, while urban networks might emphasize service quality and advanced functionality.

The moderating effect of technological readiness ($\beta = 0.127$, $p < 0.01$) suggests that distribution managers should develop tiered support systems based on users' technological proficiency. This approach differs from the one-size-fits-all model suggested in previous implementation studies and acknowledges the diverse technological capabilities within patient populations. Healthcare organizations should invest in targeted training programs and support mechanisms that address the specific needs of different user segments across diverse implementation contexts.

The differential impact of technical support between urban ($\beta = -0.213$, $p < 0.001$) and rural areas ($\beta = 0.078$, $p < 0.05$) highlights the need for context-sensitive support strategies. Urban distribution networks may benefit from streamlined support systems that avoid overwhelming users with excessive assistance, while rural networks require more comprehensive technical support to enhance channel acceptance. This contextual variation in technical support effectiveness represents a critical consideration for healthcare organizations implementing digital distribution channels across diverse geographical regions.

5.3. Limitations and Future Research Directions

While this study provides valuable insights into digital healthcare distribution optimization, several limitations should be acknowledged, offering opportunities for future research. First, the cross-sectional nature of our data limits causal inferences regarding the temporal dynamics of distribution channel adoption. Future longitudinal studies could examine how distribution channel effectiveness evolves over time, particularly focusing on the long-term impact of contextual factors on sustained channel usage. As suggested by recent work from Williams et al. (2023) and Bond (2023), longitudinal analyses could reveal important patterns in distribution channel optimization across different implementation phases.

The geographical scope of our study, while comprehensive within its context, may limit the generalizability of findings to other distribution environments. Future research should explore digital healthcare distribution in diverse cultural and economic contexts, examining how different healthcare systems and regulatory frameworks influence distribution channel effectiveness. Studies by Bustamante et al. (2023) and Abdullah et al. (2023) highlight significant disparities in channel accessibility across different populations, suggesting the need for broader cross-cultural investigations of distribution network optimization.

Future researchers should investigate the integration of emerging technologies such as artificial intelligence and blockchain in healthcare distribution networks. As indicated by Müller et al. (2021) and Milosevic (2020), these technologies could fundamentally transform distribution channel security and efficiency. Research could explore how advanced analytics and automated decision-making systems might enhance distribution network optimization and personalization of service delivery across diverse implementation contexts.

The Socio-Technical Adaptive Channel Integration framework introduced in this study provides a theoretical foundation for understanding digital healthcare distribution. However, further theoretical development and empirical validation are needed to enhance the framework's explanatory power across different healthcare contexts. Future studies could expand the framework by incorporating additional contextual factors, exploring the role of cultural variations in channel acceptance, and examining the impact of regulatory frameworks on distribution channel effectiveness. This theoretical expansion would enhance our understanding of digital healthcare distribution dynamics while providing valuable insights for healthcare organizations implementing digital channels across diverse contexts.

Additionally, future studies should examine the role of cross-channel integration in healthcare distribution networks. While our research focused primarily on digital channels, the increasing importance of omnichannel healthcare delivery suggests the need for investigating how traditional and digital channels can be effectively integrated. This aligns with recent findings by Dhaliwal et al. (2021) regarding the expansion of hybrid care models in primary healthcare delivery.

These limitations and future directions highlight the dynamic nature of healthcare distribution research and the ongoing need for scholarly investigation in this rapidly evolving field.

6. CONCLUSION

This study advances our understanding of digital healthcare distribution optimization by introducing the Socio-Technical Adaptive Channel Integration framework. Our findings reveal that service quality ($\beta = 0.534$) and security protocols ($\beta = 0.278$) significantly influence distribution channel attitudes, with traditional usability factors playing a complementary but less prominent role. The significant contextual variations in distribution effectiveness, particularly between urban and rural areas ($\Delta\beta = 0.237$) and across different age groups, demonstrate the critical importance of contextual factors in shaping distribution channel performance.

Theoretically, this research extends traditional distribution channel models by reconceptualizing distribution channels as context-dependent socio-technical networks rather than uniform service delivery mechanisms. The strong influence of service quality and security measures on channel attitudes, combined with the significant contextual variations in distribution effectiveness, establishes a new theoretical framework for understanding digital healthcare distribution across diverse implementation contexts. The Socio-Technical Adaptive Channel Integration framework provides a comprehensive theoretical foundation for understanding how contextual factors influence distribution channel effectiveness.

From a practical perspective, these findings provide healthcare organizations with evidence-based guidelines for distribution network optimization, emphasizing the importance of service quality enhancement and security protocol implementation. The significant contextual variations in distribution effectiveness highlight the need for adaptive distribution strategies that account for regional and demographic differences in channel acceptance. As healthcare systems continue to evolve, understanding both operational factors and contextual variations becomes increasingly crucial for successful distribution channel implementation. This research provides a foundation for developing more effective, user-centered digital distribution networks while offering directions for future investigation in this rapidly advancing field.

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