BRITISH JOURNAL OF HOSPITAL MEDICINE

ARTICLE

Factors Influencing Community Health Service Utilization in Shanghai, China: A Study Based on the Andersen Behavioral Model and Smart Health Stations

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Abstract

Aim/Background Improving resource utilization efficiency during the promotion and construction process, thereby driving an overall enhancement in the utilization level of community health services (CHSs), represents a pressing practical challenge that requires urgent resolution. This study aims to investigate the factors influencing CHS utilization in Shanghai, China, with a focus on the role of smart health stations (SHS).

Methods By innovatively integrating the Andersen Behavioral Model with the Attribution Theory, we constructed a two-stage mathematical model to examine the impact of health policies and residents' perceptions on CHS utilization. A mixed-methods approach was employed, including literature review, questionnaire survey, and expert consultation.

Results The results revealed that SHS usage played a significant intermediary role between CHS utilization and satisfaction ($p < 0.05$). Age ($p < 0.001$), income ($p < 0.001$), health beliefs ($p < 0.01$), and chronic disease status ($p < 0.001$) were identified as key influencing factors. Residents' attributions towards SHS tended to be self-serving, indicating a need for enhanced publicity and trust building ($p < 0.05$).

Conclusion This study provides theoretical and practical insights implications for improving CHS utilization through the optimization of SHS. Policy recommendations are proposed to promote the integration of SHS and CHS, focusing on government-led planning, resource integration, digital transformation, and targeted development strategies.

Key words: community health service; smart health station; Andersen Behavioral Model; health service utilization; China

Submitted: 3 September 2024 Revised: 23 January 2025 Accepted: 17 February 2025

How to cite this article:
Xu G, Mi Y, Pan Z. Factors Influencing Community Health Service Utilization in Shanghai, China: A Study Based on the Andersen Behavioral Model and Smart Health Stations. Br J Hosp Med. 2025. https://doi.org/10.12968/hmed.2024.0605

Introduction

Background

With the rapid development of digital health technologies and the deepening of healthcare reforms, smart health stations (SHS) have emerged as an innovative approach to enhance the accessibility and quality of community health services (CHSs) in China. SHS, also known as health cabins or health kiosks, are community-based facilities that provide residents with self-service health monitoring, consultation, and management services through the use of intelligent devices and information systems. In Shanghai, the construction of SHS has been incorporated into the government's livelihood projects since 2019, with over 80 stations established across various districts by the end of 2020. SHS are expected to play a crucial, all-encompassing role at the community level, offering health monitoring, disease management, and medical care services, thereby improving residents' health literacy and self-management capabilities.

However, the utilization of SHS and its impact on CHS utilization, especially in the context of China's healthcare system, remain under-explored. Existing research primarily provides a glimpse into the influencing factors of CHS utilization, such as demographic characteristics, health beliefs, social support, and accessibility (Tang and Zhou, 2021). The Andersen Behavioral Model, which categorizes these factors into predisposing, enabling, and need factors, has been widely used to examine health service utilization behaviors (Andersen and Newman, 1973; Andersen, 1995). Nevertheless, few studies have investigated the role of SHS in shaping CHS utilization patterns, let alone incorporating them into the Andersen Behavioral Model. Moreover, residents' perceptions and attributions towards SHS, which may affect their willingness to use these services, have been largely overlooked in existing literature (Alrashdi, 2012; Batbaatar et al, 2015).

Objectives

To address the aforementioned research gaps, this study aims to:

(1) Assess the current status of SHS and CHS utilization in Shanghai;

(2) Identify the key factors influencing SHS and CHS utilization based on the Andersen Behavioral Model;

(3) Examine the intermediary role of SHS utilization between CHS utilization and satisfaction;

(4) Explore residents' attributions towards SHS and their impact on service utilization;

(5) Propose targeted strategies for improving SHS utilization and promoting the integration of SHS and CHS.

By investigating these proposed objectives, this study seeks to expand the application of the Andersen Behavioral Model in the context of smart health services, enrich the understanding of CHS utilization mechanisms, and provide evidence-based recommendations for optimizing community health management practices in China and beyond.

Methods

Theoretical Framework

Extension of the Andersen Behavioral Model

The expanded Andersen Behavioral Model incorporating social science and humanities factors were utilized in this study. It has been recognized that healthcare service systems across various countries or regions can significantly influence individuals' utilization of healthcare services, constituting the environmental factors for this model (Meir et al, 1993). Thus, the Andersen Behavioral Model takes into account the "environmental factors", encompassing healthcare service systems, health policies, and external environments (such as natural, economic, and political contexts), as foundational prerequisites shaping personal healthcare utilization behavior.

Personal Characteristics

The model further elaborates on individual-level influencing factors, including demographic attributes, social structures, and health beliefs, acknowledging economic, social, and cultural disparities among individuals.

Inclusion of Resident Attribution Factors

In the Andersen Behavioral Model, the requirement factor serves as the most immediate catalyst for individuals to decide on healthcare service utilization. This encompasses both individuals' subjective assessments of their illness and health status (cognitive needs) and doctors' objective measurements and professional evaluations of patients' health (evaluative needs).

Medical Behavior and Health Outcomes

During its evolution, the Andersen Behavioral Model broadens the scope of medical behavior to encompass three distinct modes of healthcare utilization: personal self-care, medical service processes, and healthcare service utilization, emphasizing the impact of medical behavior on health outcomes.

Applications of the Andersen Behavioral Model in Social Sciences, Humanities, and Resident Attribution

Social Sciences and Humanities Applications

The Andersen Behavioral Model finds application not only in analyzing healthcare utilization behavior across the general population but also in subgroups such as chronic disease patients, the elderly, and pregnant women through methodologies like path analysis and structural equation modeling. These applications illuminate disparities and patterns in healthcare utilization among diverse populations and provide a scientific rationale for targeted health policies and interventions.

Resident Attribution Application

By leveraging the Andersen Behavioral Model framework, one can delve into how personal characteristics, socio-economic status, health beliefs, and other factors influence residents' healthcare utilization behavior, revealing the attribution mechanism in healthcare utilization. This attribution analysis fosters a deeper understanding of residents' needs and barriers to accessing healthcare, providing robust support for the development of more precise and impactful health policies and interventions.

Utilization of Andersen Behavioral Model Core Characteristics in This Study

The primary function of Andersen Behavioral Model (Smith, 1984) constructed in this study lies in analysis and identification of factors influencing the utilization of SHS and CHS using the traditional four-stage Andersen Behavioral Model integrated with the propensity, facilitation, and necessity factors. The second step entails considering the utilization of SHS as a novel driving factor (intermediate factor) for CHS utilization, exploring how these factors collectively impact CHS utilization, particularly the influence on and the interaction of SHS utilization with CHS utilization, along with its sequential relationship with other factors. This sequential model offers a fresh perspective on the interplay between emerging and traditional healthcare services, facilitating a more holistic assessment of SHS's role in advancing tiered diagnosis and treatment and enhancing CHS efficiency.

This study adopted the Andersen Behavioral Model as the foundational model, integrated with innovative modifications to tailor to the research context. The Andersen Behavioral Model posits that health service utilization is determined by three categories of factors: predisposing factors (e.g., demographics, health beliefs), enabling factors (e.g., income, insurance), and need factors (e.g., perceived and evaluated health status) (Andersen and Newman, 1973; Andersen, 1995). In this study, we extended the model by including specific health policies as an enabling factor and residents' attributions towards SHS as a predisposing factor. We also constructed a two-stage model to examine the relationship between SHS utilization and CHS utilization (Bradley et al, 2002; Scheppers et al, 2006).

Study Design and Data Collection

This study employed a mixed-methods approach to analyze a sample in Shanghai, China, from 1 June to 30 September 2023. The research design included three main components: a comprehensive literature review, a cross-sectional survey, and qualitative interviews.

Initially, a comprehensive literature review was conducted to identify key indicators and influencing factors of SHS and CHS utilization (Hou et al, 2017; Zhang et al, 2021).

To comprehensively grasp the current research status and recent advancements in the utilization of CHS globally and domestically, this study adopts a systematic approach to literature retrieval. We fully exploit the extensive database resources available on our campus, encompassing international databases like Springer (https://www.springernature.com), MEDLINE (https://www.nlm.nih.gov/medline/medline_home.html), Elsevier (https://www.elsevier.com), Scopus (https://www.scopus.com), and Science (https://www.sciencemag.org), as well as domestic databases such as CNKI (https://www.cnki.net), Wanfang (http://www.wanfangdata.com), and CQVIP (http://www.cqvip.com). Advanced search strategy was conducted using both Chinese and English keywords, such as "community health services", "health services", "service utilization", "influencing factors", and "family doctor services". The scope of our literature search was confined to studies published within the last decade (2013–2023), focusing on the Chinese core journals indexed or catalogued by the "Overview of Chinese Core Journal Catalog" by the Peking University and the "Catalogue of Chinese Science and Technology Paper Statistical Source Journals" issued by the China Institute of Science and Technology Information, as well as master's and doctoral research papers. This rigorous screening process ensures the academic rigor and timeliness of the retrieved literature.

Furthermore, to broaden our research horizon, we consulted the official websites of the World Health Organization (https://www.who.int/) and the Shanghai Municipal Health Commission (https://wsjkw.sh.gov.cn/xwzx/). These channels provided a comprehensive host of relevant policies, connotations of CHS, and the current state of health service resources utilization. Notably, our research was conducted in strict adherence to national-level policy and guidance, relying on authoritative documents such as the "Notice on Carrying out the 'Quality Service Grassroots Campaign'" (Guowei Grassroots Development [2018] No. 6) and the "National Basic Public Health Service Standards (Third Edition)" (Guowei Grassroots Development [2017] No. 13), issued by the National Health Commission, as the theoretical base and framework for constructing the utilization index of CHS centers in this study. This ensures the authority and practical guidance significance of our research endeavors.

This methodology led us to multifaceted and multi-perspective literature, which not only deepened our understanding of the current research landscape globally and domestically but also laid a solid theoretical groundwork for establishing a preliminary evaluation index pool for the utilization of SHS and CHS. Harmonizing academic research with policy directives ensures both theoretical value and practical significance of this research.

For the quantitative component, a cross-sectional survey of 1827 residents was conducted using a multistage mixed sampling method. Ten community health service centers were selected from central urban, suburban, and remote suburban areas. The sample size was determined based on a single overall proportion hypothesis test, considering design effect and non-response rate. Cluster random sampling was used to select participants from neighborhood committees.

Only permanent residents living in the selected area for at least one year were included. Individuals with mental disorders, consciousness disorders, terminal illnesses, or inability to complete the survey were excluded. The questionnaire includes questions covering predisposing factors (demographics, health beliefs), enabling factors (income, insurance), need factors (perceived health status, chronic diseases), and utilization of SHS and CHS (Su and Huang, 2015; Ware et al, 1996; Xiao, 1994). Validated scales such as the Social Support Rating Scale (Xiao, 1994), Chinese Multidimensional Health Beliefs Scale (Su and Huang, 2015), and Short Form-12 (SF-12) health survey questionnaire (Ware et al, 1996) were used.

The qualitative component of this research comprised three focus group discussions with 15 participants (community residents, healthcare providers, and administrators) and 14 in-depth interviews with key informants (policymakers, community health center directors, and experts) (Andresen et al, 2018; Edward and Welch, 2011). These discussions aimed to provide deeper insights into the factors influencing SHS and CHS utilization.

This integrated approach allowed for a comprehensive examination of SHS and CHS utilization by, combining statistical analysis with in-depth qualitative insights.

Data Analysis

By utilizing statistical descriptive analysis, logistic regression modeling, structural equation modeling, mediating effect analysis, and other methodologies, this study systematically examined the influence of propensity, driving, and demand factors on the utilization of SHS and CHS, adhering to the step-by-step Andersen Behavioral Model. Special emphasis was placed on the role of SHS as intermediary variables, with weight analysis uncovering their impact mechanism on the utilization of CHS. The initial step involved analyzing factors affecting the utilization of both SHS and CHS. Subsequently, the utilization of SHS services was treated as a novel driving factor, and the combined impact of these factors on the utilization of CHS was analyzed. Through employing structural equation modeling for empirical analysis, this study delved into the promotional mechanism and the specific role of SHS service utilization in influencing residents' utilization of CHS.

Descriptive statistics, chi-square tests, and logistic regression analyses were performed to examine the relationships between various factors and service utilization outcomes (Heider et al, 2014; Kim and Lee, 2016; Spark et al, 2014). Structural equation modeling was used to test the intermediary effect of SHS utilization on the relationship between CHS utilization and satisfaction (Lo et al, 2016; Ogunsanya et al, 2016). The Consensus Experts Consultation Method was applied to determine the weights of different utilization indicators and influencing factors (Yang et al, 2021). Qualitative data from interviews were analyzed using thematic analysis techniques (Qin et al, 2022). Structural equation modeling analysis and the visualization of structural equation modeling results were conducted using SPSS 24.0 and AMOS 26.0, respectively (IBM, Armonk, NY, USA).

The Microsoft Excel 2019 software (v16.0.12026.20174, Microsoft Corporation, Redmond, WA, USA) was applied to establish a basic database, and all data retrieved from the questionnaire forms were entered into the spreadsheets by two researchers. The SPSS 24.0 was utilized to establish an analysis database for statistical description and testing. Categorical data were expressed as mode and percentage for statistical analysis, while quantitative data were subjected to normality testing prior to statistical analysis. If normality requirement is met, data expressed as mean $\pm$ standard deviation are used in statistical analysis. Quantile-quantile plot (Q-Q) and probability-probability plot (P-P) plots were used to assess whether the data followed a normal distribution. If normality requirement is not met, data presented as medians and quartiles are subjected to statistical analysis. Univariate analysis using t-test, Pearson's chi-square test or Fisher's exact probability method was performed. Multiple logistic regression analysis was used to construct the theoretical Andersen Behavioral Model. The standard single factor input for the variables in the model is 0.05, the exclusion standard output is 0.10, and the reported OR and 95% confidence interval are $p < 0.05$, indicating statistical significance of the difference. In addition, mechanisms by which SHS service utilization impacted CHS utilization were analyzed using structural equation modeling and factor weighting analysis.

Table 1. Sociodemographic characteristics of the sample (n = 1827).

Variable		n	%
Gender	Male	508	27.81
	Female	1319	72.19
Age (years)	18–25	48	2.63
	26–30	139	7.61
	31–40	578	31.64
	41–50	563	30.82
	51–60	188	10.29
	Over 60	311	17.02
Education	Junior high school and below	140	7.66
	High school/Technical secondary school	227	12.42
	Junior college	354	19.38
	Undergraduate	1010	55.28
	Postgraduate and above	96	5.25
Religious belief	No	1767	96.72
	Yes	60	3.28
Occupation	Civil or government institution	1077	58.95
	State-owned enterprise or central enterprise	124	6.79
	Private enterprise or self-employed	258	14.12
	Retired	368	20.14
Community type	Central urban area	1178	64.48
	Urban-rural interface/Non-central urban area	467	25.56
	Suburban/rural area	182	9.96
Insurance type	Urban employee insurance	1426	78.05
	Urban resident insurance	373	20.42
	Cadre medical insurance	12	0.66
	Commercial insurance or self-paying	16	0.88
Income (RMB)	<2500	213	11.66
	2501–5000	719	39.35
	5001–10,000	736	40.28
	>10,001	159	8.70

1 USD = 7.08 RMB (June 2023).

Results

Basic Demographic Information of Survey Subjects

A total of 1827 valid questionnaires were collected, with a male to female ratio of 1:2.6. The majority of respondents (62.45%, 1141 people) were aged 31–50 years. Most of the respondents had an undergraduate degree (55.28%, 1010 people), worked as civil servants or in government institutions (58.95%, 1077 people), lived in central urban areas (64.48%, 1178 people), and were covered by urban employee medical insurance (78.05%, 1426 people). The vast majority (96.72%, 1767 peo-

Table 2. Utilization level of services at community health service centers (n = 1827).

Service	Utilization	n	%
Community health services (total)	Not utilized Utilized	584 1243	31.96 68.04
Receiving general primary diagnosis and treatment services at community health service centers (stations)	Not utilized Utilized	760 1067	41.60 58.40
Receiving convenient services under family doctor contract such as health assessment, health consultation, long-term prescription for chronic disease, or extended prescription	Not utilized Utilized	905 922	49.53 50.47
Receiving public health services such as chronic disease follow-up, maternal and child follow-up, and follow-up for the impoverished population	Not utilized Utilized	1118 709	61.19 38.81
Receiving inpatient and palliative care services at community health service centers	Not utilized Utilized	1323 504	72.41 27.59
Receiving immunization and child health care services (including parents)	Not utilized Utilized	1180 647	64.59 35.41
Receiving traditional chinese medicine diagnosis and treatment services at community health service centers (stations)	Not utilized Utilized	1052 775	57.58 42.42
Receiving home visit/outreach services by family doctor team	Not utilized Utilized	1184 643	64.81 35.19
Receiving community physical examination services (including elderly physical examination, health examination, etc.)	Not utilized Utilized	1230 597	67.32 32.68
Receiving rehabilitation diagnosis and treatment services at community health service centers (stations)	Not utilized Utilized	1169 658	63.98 36.02
Receiving ophthalmological and dental diagnosis and treatment services at community health service centers (stations)	Not utilized Utilized	1191 636	65.19 34.81

Table 3. Utilization level of services at smart health station (n = 1827).

Service	Utilization	n	%
Smart health station services (total)	Not utilized Utilized	1094 733	59.88 40.12
Receiving health self-testing services at smart health stations	Not utilized Utilized	1111 716	60.81 39.19
Receiving health intervention and guidance services at smart health stations	Not utilized Utilized	1133 694	62.01 37.99

ple) had no religious beliefs. The most common income range was 5001–10,000 RMB (40.28%, 736 people) (1 USD = 7.08 RMB (June 2023)). The complete basic demographic information of survey subjects is shown in Table 1.

Table 4. Univariate analysis of predisposing factors contributing to the utilization of smart health station services.

Variable		Not utilized (n = 1094)	Utilized (n = 733)	χ^2/t	p-value
Gender	Male	303 (27.7%)	205 (28.0%)	0.016	0.899
	Female	791 (72.3%)	528 (72.0%)		
Age (years)	18–25	19 (1.7%)	29 (4.0%)	12.683	0.027
	26–30	91 (8.3%)	48 (6.5%)		
	31–40	354 (32.3%)	224 (30.6%)		
	41–50	331 (30.3%)	232 (31.7%)		
	51–60	120 (11.0%)	68 (9.3%)		
	>60	179 (16.4%)	132 (18.0%)		
Education	Junior high school and below	76 (6.9%)	64 (8.7%)	3.341	0.502
	High school/Technical secondary school	129 (11.8%)	98 (13.4%)		
	Junior college	215 (19.7%)	139 (19.0%)		
	Undergraduate	616 (56.3%)	394 (53.8%)		
	Postgraduate and above	58 (5.3%)	38 (5.2%)		
Religious belief	No	1059 (96.8%)	708 (96.6%)	0.062	0.804
	Yes	35 (3.2%)	25 (3.4%)		
Occupation	Civil or government institution	645 (59.0%)	432 (58.9%)	2.242	0.524
	State-owned enterprise or central enterprise	72 (6.6%)	52 (7.1%)		
	Private enterprise or self-employed	164 (15.0%)	94 (12.8%)		
	Retired	213 (19.5%)	155 (21.1%)		
Social support		40.80 ± 7.37	41.58 ± 8.53	–2.014	0.044
Health belief		114.09 ± 18.30	113.74 ± 21.52	0.364	0.716

Table 5. Multifactorial analysis of the predisposing factors (excluding attribution) contributing to the utilization of smart health station services.

Variable		β	SE	p-value	OR (95% CI)
Age (years)	18–25	1			
	26–30	–1.048	0.345	0.002	0.351 (0.178–0.690)
	31–40	–0.882	0.308	0.004	0.414 (0.227–0.757)
	41–50	–0.798	0.308	0.010	0.450 (0.246–0.823)
	51–60	–1.007	0.333	0.002	0.365 (0.190–0.701)
	>60	–0.722	0.317	0.023	0.486 (0.261–0.905)
Social support		0.013	0.006	0.041	1.013 (1.001–1.025)

CI, confidence interval; OR, odds ratio; SE, standard error.

Current Status of SHS and CHS Utilization

The overall utilization rate of CHS was 68.0% (1243 out of 1827 respondents). As shown in Table 2, the most frequently used CHS were basic medical services (58.4%), family doctor signing (50.5%), and traditional Chinese medicine services (42.4%). The utilization rates of community ward service (27.6%), physical examination service (32.7%), and ophthalmology and dentistry services (34.8%) were relatively low.

The utilization rate of SHS was 40.1% (733 out of 1827 respondents), which was significantly lower than that of CHS. As presented in Table 3, 39.2% of the respondents used health self-testing services, and 38.0% used health intervention guidance services in SHS.

Factors Influencing SHS and CHS Utilization

Predisposing Factors

For predisposing factors contributing to the utilization of SHS services, continuous variables were analyzed by t-test while categorical variables were analyzed by chi-square test. Table 4 shows that age and social support were significantly associated with SHS utilization ($p < 0.05$), while gender, education, occupation, religious beliefs and health beliefs were not significantly associated with CHS utilization ($p > 0.05$). The multivariate analysis shown in Table 5 further reveals that older age was associated with lower SHS utilization, while higher social support was associated with higher SHS utilization ($p < 0.05$).

Enabling Factors

For enabling factors contributing to the utilization of SHS services, categorical variables were analyzed using chi-square test. Disposable income, proportion of health management service expenditure, awareness of SHS, signing with family doctors, understanding of SHS services, and understanding of CHS services were significant predictors of SHS utilization ($p < 0.05$) (Table 6). The multivariate analysis shown in Table 7 indicates that higher disposable income, being unaware of SHS, and lack of understanding of SHS services were associated with lower SHS utilization ($p < 0.05$). In contrast, a health management service expenditure pro-

Table 6. Univariate analysis of enabling factors contributing to the utilization of smart health station services.

Variable		Not utilized (n = 1094)	Utilized (n = 733)	χ^2	p-value
Community type	Central urban area	700 (64.0%)	478 (65.2%)	0.296	0.863
	Urban-rural interface/Non-central urban area	284 (26.0%)	183 (25.0%)		
	Suburban/Rural area	110 (10.1%)	72 (9.8%)		
Insurance type	Urban employee insurance	866 (79.2%)	560 (76.4%)	4.338	0.227
	Urban resident insurance	209 (19.1%)	164 (22.4%)		
	Cadre medical insurance	7 (0.6%)	5 (0.7%)		
	Commercial insurance or self-paying	12 (1.1%)	4 (0.5%)		
Disposable income (RMB)	2500 and below	113 (10.3%)	100 (13.6%)	8.558	0.036
	2501–5000	428 (39.1%)	291 (39.7%)		
	5001–10,000	445 (40.7%)	291 (39.7%)		
	10,001 and above	108 (9.9%)	51 (7.0%)		
Health management service expenditure proportion	<10%	607 (55.5%)	346 (47.2%)	13.040	0.005
	<20%	310 (28.3%)	239 (32.6%)		
	<30%	111 (10.1%)	99 (13.5%)		
	>30%	66 (6.0%)	49 (6.7%)		
Presence of smart health station	Yes	630 (57.6%)	585 (79.8%)	104.068	<0.001
	No	72 (6.6%)	39 (5.3%)		
	Not sure	392 (35.8%)	109 (14.9%)		
Signing with a family doctor	Yes	894 (81.7%)	633 (86.4%)	9.901	0.007
	No	118 (10.8%)	48 (6.5%)		
	Not sure	82 (7.5%)	52 (7.1%)		
Being aware of smart health station services	Yes	590 (53.9%)	577 (78.7%)	117.437	<0.001
	No	97 (8.9%)	35 (4.8%)		
	Not sure	407 (37.2%)	121 (16.5%)		
Being aware of community health services	Yes	807 (73.8%)	615 (83.9%)	27.378	<0.001
	No	53 (4.8%)	28 (3.8%)		
	Not sure	234 (21.4%)	90 (12.3%)		

1 USD = 7.08 RMB (June 2023).

Table 7. Multifactorial analysis of enabling factors contributing to the utilization of smart health station services.

Variable		β	SE	p-value	OR (95% CI)
Disposable income (RMB)	2500 and below	1			
	2501–5000	–0.446	0.168	0.008	0.640 (0.460–0.890)
	5001–10,000	–0.577	0.168	0.001	0.562 (0.404–0.781)
	10,001 and above	–0.762	0.231	0.001	0.467 (0.297–0.734)
Health management service expenditure proportion	Less than 10%	1			
	Less than 20%	0.288	0.116	0.013	1.334 (1.063–1.674)
	Less than 30%	0.467	0.163	0.004	1.596 (1.160–2.196)
	More than 30%	0.145	0.209	0.489	1.156 (0.767–1.743)
Presence of smart health station	Yes	1			
	No	–0.191	0.238	0.422	0.826 (0.518–1.317)
	Not sure	–0.811	0.153	<0.001	0.444 (0.329–0.600)
Signing with a family doctor	Yes	1			
	No	–0.228	0.199	0.253	0.796 (0.539–1.177)
	Not sure	0.556	0.221	0.012	1.744 (1.131–2.689)
Being aware of smart health station services	Yes	1			
	No	–0.963	0.248	<0.001	0.382 (0.234–0.621)
	Not sure	–0.894	0.170	<0.001	0.409 (0.293–0.570)
Being aware of community health services	Yes	1			
	No	0.355	0.292	0.224	1.426 (0.804–2.526)
	Not sure	0.130	0.189	0.490	1.139 (0.787–1.648)

1 USD = 7.08 RMB (June 2023).

portion between 10% and 30% and uncertainty about signing with family doctors were associated with higher SHS utilization ($p < 0.05$).

For enabling factors contributing to the utilization of CHS, chi-square test was applied for analyzing categorical variables. For CHS utilization, community type, insurance type, disposable income, health management service expenditure, being aware of SHS, signing with family doctors, understanding of SHS services, and understanding of CHS services were significant enabling factors ($p < 0.05$) (Table 8). The multivariate analysis shown in Table 9 shows that disposable income over 10,001 RMB, and not signing or having uncertainty about signing with family doctors were associated with lower CHS utilization ($p < 0.05$), while urban resident insurance and a health management service expenditure proportion between 20% and 30% were associated with higher CHS utilization ($p < 0.05$).

Need Factors

Continuous variables were analyzed using t-test whereas categorical variables were analyzed using chi-square test. The type of chronic diseases was significantly associated with both SHS and CHS utilization (Tables 10,11) ($p < 0.01$), suggesting that chronic disease management was a key driver of service utilization. The multi-

Table 8. Univariate analysis of enabling factors contributing to the utilization of community health services.

Variable		Not utilized (n = 584)	Utilized (n = 1243)	χ^2	p-value
Community type	Central urban area	352 (60.3%)	826 (66.5%)	6.925	0.031
	Urban-rural interface/Non-central urban area	164 (28.1%)	303 (24.4%)		
	Suburban/Rural area	68 (11.6%)	114 (9.2%)		
Insurance type	Urban employee insurance	469 (80.3%)	957 (77%)	11.050	0.011
	Urban resident insurance	101 (17.3%)	272 (21.9%)		
	Cadre medical insurance	4 (0.7%)	8 (0.6%)		
	Commercial insurance or self-paying	10 (1.7%)	6 (0.5%)		
Disposable income (RMB)	2500 and below	70 (12%)	143 (11.5%)	19.464	<0.001
	2501–5000	197 (33.7%)	522 (42%)		
	5001–10,000	246 (42.1%)	490 (39.4%)		
	10,001 and above	71 (12.2%)	88 (7.1%)		
Health management service expenditure proportion	Less than 10%	332 (56.8%)	621 (50%)	9.459	0.024
	Less than 20%	160 (27.4%)	389 (31.3%)		
	Less than 30%	54 (9.2%)	156 (12.6%)		
	More than 30%	38 (6.5%)	77 (6.2%)		
Presence of smart health station	Yes	351 (60.1%)	864 (69.5%)	16.319	<0.001
	No	39 (6.7%)	72 (5.8%)		
	Not sure	194 (33.2%)	307 (24.7%)		
Signing with a family doctor	Yes	430 (73.6%)	1097 (88.3%)	66.704	<0.001
	No	94 (16.1%)	72 (5.8%)		
	Not sure	60 (10.3%)	74 (6%)		
Being aware of smart health station services	Yes	327 (56%)	840 (67.6%)	23.223	<0.001
	No	53 (9.1%)	79 (6.4%)		
	Not sure	204 (34.9%)	324 (26.1%)		
Being aware of community health services	Yes	413 (70.7%)	1009 (81.2%)	25.900	<0.001
	No	31 (5.3%)	50 (4%)		
	Not sure	140 (24%)	184 (14.8%)		

1 USD = 7.08 RMB (June 2023).

Table 9. Multifactorial analysis of enabling factors contributing to the utilization of community health services.

Variable		β	SE	p-value	OR (95% CI)
Community type	Central urban area	1			
	Urban-rural interface/Non-central urban area	–0.170	0.122	0.162	0.844 (0.665–1.071)
	Suburban/Rural area	–0.260	0.176	0.140	0.771 (0.546–1.089)
Insurance type	Urban employee insurance	1			
	Urban resident insurance	0.286	0.136	0.035	1.331 (1.020–1.738)
	Cadre medical insurance	0.251	0.636	0.693	1.285 (0.369–4.475)
	Commercial insurance or self-paying	–1.040	0.543	0.056	0.354 (0.122–1.025)
Disposable income (RMB)	2500 and below	1			
	2501–5000	0.152	0.176	0.387	1.164 (0.825–1.643)
	5001–10000	–0.212	0.174	0.223	0.809 (0.576–1.138)
	10001 and above	–0.640	0.226	0.005	0.527 (0.339–0.821)
Health management service expenditure proportion	Less than 10%	1			
	Less than 20%	0.190	0.122	0.118	1.210 (0.953–1.536)
	Less than 30%	0.412	0.179	0.021	1.510 (1.063–2.146)
	More than 30%	0.044	0.221	0.842	1.045 (0.678–1.610)
Presence of smart health station	Yes	1			
	No	0.253	0.247	0.305	1.288 (0.794–2.091)
	Not sure	–0.129	0.148	0.383	0.879 (0.658–1.174)
Signing with a family doctor	Yes	1			
	No	–1.201	0.183	<0.001	0.301 (0.210–0.431)
	Not sure	–0.478	0.210	0.023	0.62 (0.411–0.935)
Being aware of smart health station services	Yes	1			
	No	–0.275	0.235	0.241	0.759 (0.480–1.203)
	Not sure	–0.099	0.163	0.545	0.906 (0.658–1.247)
Being aware of community health services	Yes	1			
	No	0.076	0.283	0.788	1.079 (0.619–1.881)
	Not sure	–0.270	0.172	0.115	0.763 (0.545–1.068)

1 USD = 7.08 RMB (June 2023).

Table 10. Univariate analysis of need-based factors contributing to the utilization of smart health station services.

Variable		Not utilized (n = 1094)	Utilized (n = 733)	χ^2/t	p-value
Personal health level		67.62 ± 19.20	66.42 ± 18.37	1.337	0.181
Number of chronic diseases	None	647 (59.1%)	372 (50.8%)	12.622	0.002
	1–2	392 (35.8%)	314 (42.8%)		
	3 or more	55 (5.0%)	47 (6.4%)		

Table 11. Univariate analysis of need-based factors contributing to the utilization of community health services.

Variable		Not utilized (n = 584)	Utilized (n = 1243)	χ^2/t	p-value
Personal health level		70.33 ± 18.87	65.64 ± 18.70	4.978	<0.001
Number of chronic diseases	None	438 (75.0%)	581 (46.7%)	131.474	<0.001
	1–2	135 (23.1%)	571 (45.9%)		
	3 or more	11 (1.9%)	91 (7.3%)		

Table 12. Multifactorial analysis of need-based factors contributing to the utilization of community health services.

Variable		β	SE	p-value	OR (95% CI)
Personal health level		–0.006	0.003	0.046	0.990 (0.990–1.003)
Number of chronic diseases	None	1			
	1–2	1.113	0.117	<0.001	3.041 (2.422–3.835)
	3 or more	1.724	0.329	<0.001	5.612 (2.940–10.686)

variate analysis shown in Table 12 further confirms that a greater number of chronic diseases was associated with higher CHS utilization ($p < 0.001$).

Two-Stage Andersen Behavioral Model and Structural Equation Model

Univariate Analysis of Factors Influencing CHS Utilization Based on the Andersen Behavioral Model

To perform this analysis, t-test was applied to continuous variables and chi-square test to categorical variables. Univariate analysis results, as shown in Table 13, show that among the predisposing factors, age, education, occupation, and health beliefs were significantly associated with CHS utilization ($p < 0.01$). Among the enabling factors, community type, insurance type, disposable income, health management service expenditure, being aware of SHS, signing with family doctors, understanding of SHS services, and understanding of CHS services were significantly associated with CHS utilization ($p < 0.05$). Among the need-based factors,

Table 13. Univariate analysis of the utilization level of community health services based on the Andersen Behavioral Model framework.

		Not utilized (n = 584)	Utilized (n = 1243)	χ^2/t	p-value
Predisposing factors					
Gender	Male	165 (28.3%)	343 (27.6%)	0.086	0.769
	Female	419 (71.7%)	900 (72.4%)		
Age (years)	18–25	17 (2.9%)	31 (2.5%)	93.927	<0.001
	26–30	58 (9.9%)	81 (6.5%)		
	31–40	223 (38.2%)	355 (28.6%)		
	41–50	204 (34.9%)	359 (28.9%)		
	51–60	51 (8.7%)	137 (11.0%)		
	Over 60	31 (5.3%)	280 (22.5%)		
Education	Junior high school and below	20 (3.4%)	120 (9.7%)	45.620	<0.001
	High school/technical secondary school	48 (8.2%)	179 (14.4%)		
	Junior college	122 (20.9%)	232 (18.7%)		
	Undergraduate	370 (63.4%)	640 (51.5%)		
	Postgraduate and above	24 (4.1%)	72 (5.8%)		
Religious belief	No	568 (97.3%)	1199 (96.5%)	0.801	0.371
	Yes	16 (2.7%)	44 (3.5%)		
Occupation	Civil or government institution	351 (60.1%)	726 (58.4%)	99.906	<0.001
	State-owned enterprise or central enterprise	47 (8.0%)	77 (6.2%)		
	Private enterprise or self-employed	133 (22.8%)	125 (10.1%)		
	Retired	53 (9.1%)	315 (25.3%)		
Social support		41.37 ± 7.13	41.00 ± 8.18	0.987	0.324
Health belief		116.22 ± 19.42	112.88 ± 19.78	3.394	0.001
Residents' attribution to health stations and contracted services					
Establishment of health stations	Altruistic attribution	82 (14.0%)	161 (13.0%)	0.408	0.523
	Self-serving attribution	502 (86.0%)	1082 (87.0%)		

Table 13. Continued.

		Not utilized (n = 584)	Utilized (n = 1243)	χ^2/t	p-value
Self-monitoring of health indicators	Altruistic attribution Self-serving attribution	70 (12.0%) 514 (88.0%)	134 (10.8%) 1109 (89.2%)	0.583	0.445
Provision of health consultation services	Altruistic attribution Self-serving attribution	74 (12.7%) 510 (87.3%)	140 (11.3%) 1103 (88.7%)	0.762	0.383
Promotion of family doctor	Altruistic attribution Self-serving attribution	68 (11.6%) 516 (88.4%)	136 (10.9%) 1107 (89.1%)	0.198	0.657
Enabling factors					
Community type	Central urban area Urban-rural interface/Non-central urban area Suburban/Rural area	352 (60.3%) 164 (28.1%) 68 (11.6%)	826 (66.5%) 303 (24.4%) 114 (9.2%)	6.925	0.031
Insurance type	Urban employee insurance Urban resident insurance Cadre medical insurance Commercial insurance or self-paying	469 (80.3%) 101 (17.3%) 4 (0.7%) 10 (1.7%)	957 (77.0%) 272 (21.9%) 8 (0.6%) 6 (0.5%)	11.050	0.011
Disposable income (RMB)	2500 and below 2501–5000 5001–10,000 10,001 and above	70 (12.0%) 197 (33.7%) 246 (42.1%) 71 (12.2%)	143 (11.5%) 522 (42.0%) 490 (39.4%) 88 (7.1%)	19.464	<0.001
Health management service expenditure proportion	Less than 10% Less than 20% Less than 30% More than 30%	332 (56.8%) 160 (27.4%) 54 (9.2%) 38 (6.5%)	621 (50.0%) 389 (31.3%) 156 (12.6%) 77 (6.2%)	9.459	0.024
Presence of smart health station	Yes No Not sure	351 (60.1%) 39 (6.7%) 194 (33.2%)	864 (69.5%) 72 (5.8%) 307 (24.7%)	16.319	<0.001

Table 13. Continued.

		Not utilized (n = 584)	Utilized (n = 1243)	χ^2/t	p-value
Signing with a family doctor	Yes	430 (73.6%)	1097 (88.3%)	66.704	<0.001
	No	94 (16.1%)	72 (5.8%)		
	Not sure	60 (10.3%)	74 (6.0%)		
Being aware of smart health station services	Yes	327 (56.0%)	840 (67.6%)	23.223	<0.001
	No	53 (9.1%)	79 (6.4%)		
	Not sure	204 (34.9%)	324 (26.1%)		
Being aware of community health services	Yes	413 (70.7%)	1009 (81.2%)	25.900	<0.001
	No	31 (5.3%)	50 (4.0%)		
	Not sure	140 (24.0%)	184 (14.8%)		
Need factors					
Personal health level		70.33 ± 18.87	65.64 ± 18.70	4.978	<0.001
Number of chronic diseases	None	438 (75.0%)	581 (46.7%)	131.474	<0.001
	1–2	135 (23.1%)	571 (45.9%)		
	3 or more	11 (1.9%)	91 (7.3%)		

1 USD = 7.08 RMB (June 2023). The bold formatting in the table is used to distinguish the two kinds of factors.

personal health status and the type of chronic diseases were significantly associated with CHS utilization ($p < 0.001$).

Multivariate Analysis of Factors Influencing CHS Utilization Based on the Andersen Behavioral Model

Variables with statistical significance ($p < 0.05$) in the univariate analysis were included in the logistic regression model for multivariate analysis. The results in Table 14 show that age over 60 years old, working as a civil servant or in government institutions, lower health belief scores, signing with family doctors, understanding CHS services, and suffering multiple chronic diseases were associated with higher CHS utilization ($p < 0.05$).

Structural Equation Modeling of CHS Utilization Based on the Andersen Behavioral Model

The structural equation modeling results confirmed the validity of the two-stage Andersen Behavioral Model (Table 15, Fig. 1). Predisposing and enabling factors were used as independent variables, with SHS utilization being treated as an intermediate variable, CHS utilization as an intermediate outcome variable, and CHS satisfaction as an outcome variable. The results indicate that SHS utilization played an overarching intermediary role between CHS utilization and satisfaction, highlighting the critical role of SHS in influencing residents' acceptance of CHS ($p < 0.05$).

Chain Multiple Mediating Effect Analysis

The chain multiple mediating effect analysis revealed the complex relationships among predisposing factors, enabling factors, need factors, SHS utilization, CHS utilization, and service satisfaction (Babitsch et al, 2012; Evashwick et al, 1984; Kislov et al, 2019; Kukafka et al, 1999; Mitchell et al, 2010). Key findings include the following:

(1) Predisposing factors directly influenced service satisfaction and indirectly influenced it through CHS utilization, while the indirect influence through enabling factors was not significant (Table 16).

(2) Need factors and CHS utilization could not significantly mediate the influence of predisposing factors on service satisfaction (Table 17).

(3) Enabling factors influenced service satisfaction through multiple pathways, including need factors and CHS utilization (Table 18).

(4) SHS utilization was a significant mediator between predisposing factors, enabling factors, and service satisfaction (Tables 19,20).

(5) Need factors directly influenced service satisfaction, but SHS utilization and CHS utilization could not significantly mediate this effect (Table 21).

Table 14. Multifactorial analysis of the utilization level of community health services based on the Andersen Behavioral Model framework.

Variable		β	SE	*p*-value	OR (95% CI)
Age (years)	18–25	1			
	26–30	–0.172	0.465	0.711	0.842 (0.339–2.093)
	31–40	–0.249	0.429	0.562	0.780 (0.336–1.807)
	41–50	–0.262	0.435	0.547	0.770 (0.329–1.804)
	51–60	0.609	0.480	0.204	1.838 (0.718–4.704)
	Over 60	1.964	0.584	0.001	7.126 (2.269–22.375)
Education	Junior high school and below	1			
	High school/Technical secondary school	–0.292	0.364	0.422	0.747 (0.366–1.524)
	Junior college	–0.233	0.373	0.533	0.793 (0.382–1.646)
	Undergraduate	–0.194	0.376	0.607	0.824 (0.394–1.723)
	Postgraduate and above	0.773	0.469	0.100	2.167 (0.863–5.438)
Occupation	Retired	1			
	Civil or government institution	0.811	0.363	0.026	2.249 (1.104–4.584)
	State-owned enterprise or central enterprise	0.505	0.417	0.225	1.657 (0.732–3.751)
	Private enterprise or self-employed	0.097	0.372	0.795	1.102 (0.532–2.283)
Health belief		–0.013	0.004	0.001	0.987 (0.980–0.995)
Health management service expenditure proportion	Less than 10%	1			
	Less than 20%	–0.050	0.147	0.733	0.951 (0.713–1.269)
	Less than 30%	0.019	0.219	0.932	1.019 (0.663–1.566)
	More than 30%	–0.376	0.275	0.171	0.686 (0.400–1.177)
Community type	Central urban area	1			
	Urban-rural interface/Non-central urban area	–0.199	0.149	0.181	0.820 (0.613–1.097)
	Suburban/Rural area	–0.220	0.215	0.307	0.803 (0.527–1.223)
Insurance type	Urban employee insurance	1			
	Urban resident insurance	0.049	0.172	0.775	1.050 (0.750–1.472)
	Cadre medical insurance	–0.523	0.855	0.541	0.593 (0.111–3.171)
	Commercial insurance or self-paying	–0.896	0.680	0.187	0.408 (0.108–1.546)

Table 14. Continued.

Variable		β	SE	p-value	OR (95% CI)
Disposable income (RMB)	2500 and below	1			
	2501–5000	0.324	0.215	0.133	1.382 (0.906–2.108)
	5001–10,000	0.149	0.216	0.489	1.161 (0.760–1.772)
	10,001 and above	–0.303	0.283	0.284	0.738 (0.424–1.286)
Presence of smart health station	Yes	1			
	No	0.360	0.296	0.224	1.433 (0.803–2.557)
	Not sure	0.352	0.175	0.044	1.422 (1.010–2.003)
Signing with a family doctor	Yes	1			
	No	–1.116	0.231	<0.001	0.328 (0.208–0.515)
	Not sure	–0.837	0.274	0.002	0.433 (0.253–0.741)
Being aware of smart health station services	Yes	1			
	No	0.024	0.276	0.931	1.024 (0.596–1.759)
	Not sure	0.043	0.195	0.824	1.044 (0.713–1.529)
Being aware of community health services	Yes	1			
	No	–0.462	0.333	0.165	0.630 (0.328–1.210)
	Not sure	–0.436	0.211	0.039	0.646 (0.427–0.978)
Personal health level		–0.003	0.004	0.428	0.997 (0.990–1.004)
Number of chronic diseases	None	1			
	1–2	0.860	0.149	<0.001	2.363 (1.766–3.163)
	3 or more	1.177	0.386	0.002	3.245 (1.522–6.919)

1 USD = 7.08 RMB (June 2023).

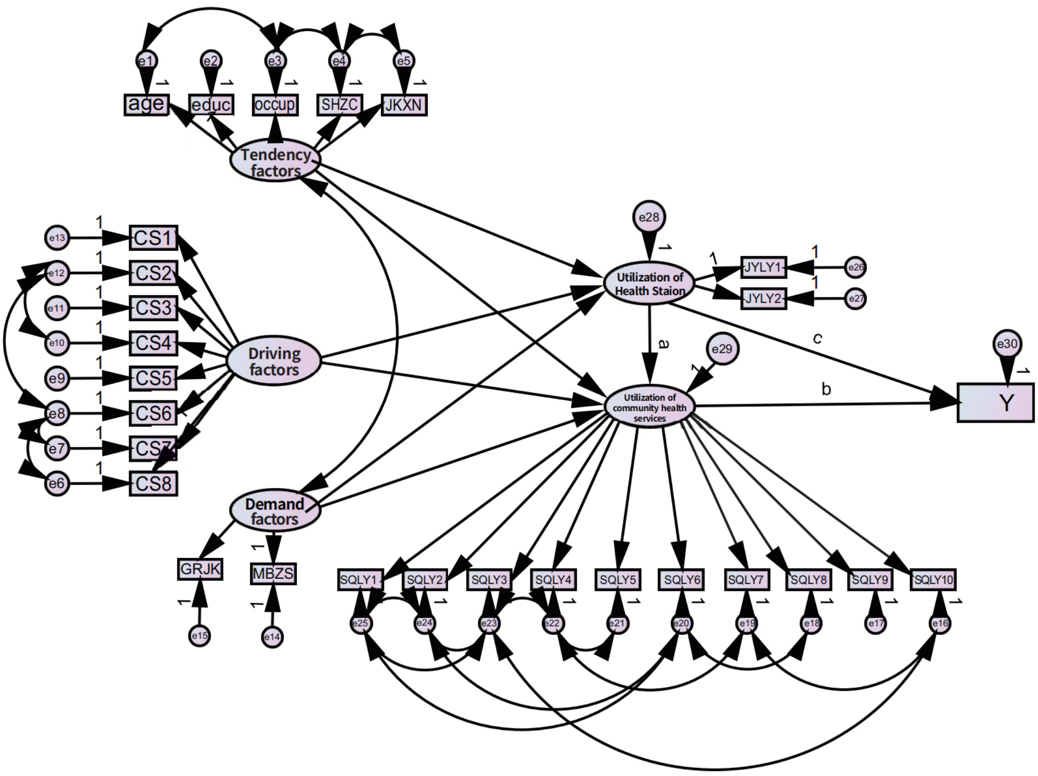

Fig. 1. Structural equation model of community health service utilization based on the Andersen Behavioral Model. This image was created using AMOS 26.0 (IBM, Armonk, NY, USA). In AMOS, the number 1 usually represents a path coefficient of 1. Specifically, when building a model, if you point a latent variable to an explicit variable, the path coefficient is assigned a value of 1, indicating a complete correlation between the latent and explicit variables. "a, b, c" represent different road force coefficients. CS 1-8 represents the eight enabling factors in Table 13. Demand factors represents needing factors in Table 13. GRJK represents personal health level. MBZS represents number of chronic diseases. SQLY 1-10 represents utilization of community health services,10 factors in Table 2. JYLY represents the utilization of health station services, which include acceptance of health self-testing services and acceptance of health intervention guidance services. SHZC represents health belief. JKXN represents social support. e1-30 represents each observation corresponding to a specific residual term.

Table 15. Hypothesis testing of path relationships in the utilization of community health services based on the Andersen Behavioral Model.

Path			Standardized coefficient	SE	CR	*p*-value
Utilization of health stations	<—	Predisposing factors	–0.014	0.028	–0.566	0.571
Utilization of health stations	<—	Enabling factors	0.335	0.067	12.798	<0.001
Utilization of health stations	<—	Need factors	–0.029	0.016	–1.420	0.156
Utilization of community services	<—	Predisposing factors	0.069	0.018	3.964	<0.001
Utilization of community services	<—	Enabling factors	–0.017	0.041	–0.963	0.336
Utilization of community services	<—	Need factors	–0.025	0.011	–1.546	0.122
Utilization of community services	<—	Utilization of health stations	0.782	0.017	41.148	<0.001
Satisfaction with community services	<—	Utilization of community services	0.085	0.038	2.193	0.028
Satisfaction with community services	<—	Utilization of health stations	0.068	0.034	1.783	0.075

”<—” is the data exported from AMOS software, representing the relationship between the left and right factors. CR, critical ratio; SE, standard error.

Table 16. Chain mediating effect analysis of predisposing factors, enabling factors, community health service utilization, and service satisfaction.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Predisposing factors – Enabling factors – Service satisfaction	0.001	0.001	–0.001	0.002	0.561
Predisposing factors – Community health service utilization – Service satisfaction	0.001	0.000	0.000	0.002	0.005
Predisposing factors – Enabling factors – Community health service utilization – Service satisfaction	–0.001	0.000	–0.002	–0.001	0.001
Total indirect effect	0.000	0.001	–0.002	0.002	0.634
Direct effect	0.023	0.003	0.018	0.029	0.001

Table 17. Chain mediating effect analysis of predisposing factors, need factors, community health service utilization, and service satisfaction.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Predisposing factors – Need factors – Service satisfaction	0.000	0.001	–0.003	0.001	0.383
Predisposing factors – Community health service utilization – Service satisfaction	0.000	0.000	–0.001	0.001	0.726
Predisposing factors – Need factors – Community health service utilization – Service satisfaction	0.000	0.000	0.000	0.000	0.002
Total indirect effect	–0.001	0.001	–0.003	0.001	0.428
Direct effect	–0.305	0.114	–0.531	–0.101	0.004

Residents' Attributions Towards SHS

The big majority of residents in our sample perceived that the purpose of SHS establishment, health monitoring, health consultation, and family doctor signing are grounded in self-serving, rather than altruistic motives (Table 22) (Peterson et al, 1982). For instance, 86.7% of respondents attributed the establishment of SHS to the government's need to complete tasks rather than for the benefit of residents' health (Thom et al, 2004). The mediating effect analysis further revealed that residents' attributions played a mediating role in the influence of predisposing and need factors on SHS and CHS utilization (Tables 23,24,25,26,27,28).

Weight Analysis of Influencing Factors

As shown in Table 29, occupation (4.812%), health management service expenditure (14.409%), and chronic disease status (16.505%) were identified as the

Table 18. Chain mediating effect analysis of enabling factors, need factors, community health service utilization, and service satisfaction.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Enabling factors – Need factors – Service satisfaction	–0.052	0.020	–0.102	–0.023	<0.001
Enabling factors – Community health service utilization – Service satisfaction	0.092	0.017	0.060	0.127	0.001
Enabling factors – Need factors – Community health service utilization – Service satisfaction	–0.009	0.004	–0.019	–0.004	<0.001
Total indirect effect	0.031	0.029	–0.032	0.083	0.333
Direct effect	–0.242	0.066	–0.374	–0.119	0.001

Table 19. Chain mediating effect analysis of predisposing factors, smart health station utilization, community health service utilization, and service satisfaction.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Predisposing factors – Smart health station utilization – Service satisfaction	–0.001	0.000	–0.002	0.000	0.016
Predisposing factors – Community health service utilization – Service satisfaction	0.000	0.000	0.000	0.001	0.438
Predisposing factors – Smart health station utilization – Community health service utilization – Service satisfaction	0.000	0.000	–0.001	0.000	0.344
Total indirect effect	–0.001	0.001	–0.002	0.000	0.114
Direct effect	0.022	0.003	0.016	0.028	0.001

Table 20. Chain mediating effect analysis of enabling factors, smart health station utilization, community health service utilization, and service satisfaction.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Enabling factors – Smart health station utilization – Service satisfaction	0.093	0.031	0.033	0.158	0.002
Enabling factors – Community health service utilization – Service satisfaction	–0.002	0.003	–0.012	0.003	0.441
Enabling factors – Smart health station utilization – Community health service utilization – Service satisfaction	0.045	0.023	0.001	0.092	0.049
Total indirect effect	0.136	0.022	0.095	0.180	0.001
Direct effect	–0.347	0.063	–0.471	–0.224	0.001

Table 21. Chain mediating effect analysis of need factors, smart health station utilization, community health service utilization, and service satisfaction.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Need factors – Smart health station utilization – Service satisfaction	0.005	0.011	–0.013	0.034	0.467
Need factors – Community health service utilization – Service satisfaction	–0.019	0.019	–0.062	0.016	0.229
Need factors – Smart health station utilization – Community health service utilization – Service satisfaction	0.002	0.006	–0.004	0.027	0.351
Total indirect effect	–0.013	0.023	–0.059	0.036	0.622
Direct effect	–0.566	0.113	–0.809	–0.362	0.002

Table 22. Attribution scores for health stations and contracted services (*n* = 1827).

Item	Min	Max	Mean (M)	Standard deviation (SD)	Altruistic attribution, *n* (%)	Self-serving attribution, *n* (%)
Purpose of establishing health stations	1	8	6.540	1.750	243 (13.300)	1584 (86.700)
Purpose of self-monitoring health indicators	1	8	6.650	1.670	204 (11.200)	1623 (88.800)
Purpose of providing health consultation services at health stations	1	8	6.640	1.660	214 (11.700)	1613 (88.300)
Purpose of promoting family doctor contract services	1	8	6.690	1.640	204 (11.200)	1623 (88.800)

Table 23. Mediating effect of residents' attribution in the predisposing factors contributing to the utilization of smart health station services.

Path	Effect value	SE	Bias-corrected 95% CI		*p*-value
			Lower	Upper	
Indirect effect	0.002	0.001	0.001	0.003	0.040
Direct effect	–0.001	0.001	–0.004	0.002	0.467
Total effect	0.001	0.001	–0.001	0.003	0.636

most important factors influencing CHS utilization (Hall and Dornan, 1990; Hui and Tse, 2008; Xie et al, 2019). The weights of health self-testing (16.064%) and health intervention guidance (16.599%) in SHS utilization were also relatively high (Dagger et al, 2007; Yip and Hsiao, 2014).

Table 24. Mediating effect of residents' attribution in the pathway from predisposing factors to the utilization of community health services.

Path	Effect value	SE	Bias-corrected 95% CI		p-value
			Lower	Upper	
Indirect effect	0.003	0.001	0.001	0.005	0.001
Direct effect	–0.006	0.001	–0.008	–0.003	0.001
Total effect	–0.003	0.001	–0.004	–0.001	0.003

Table 25. Mediating effect of residents' attribution in the pathway from enabling factors to the utilization of smart health station services.

Path	Effect value	SE	Bias-corrected 95% CI		p-value
			Lower	Upper	
Indirect effect	0.023	0.010	0.005	0.046	0.01
Direct effect	–0.267	0.034	–0.335	–0.201	0.001
Total effect	–0.244	0.033	–0.308	–0.180	0.001

Table 26. Mediating effect of residents' attribution in the pathway from enabling factors to the utilization of community health services.

Path	Effect value	SE	Bias-corrected 95% CI		p-value
			Lower	Upper	
Indirect effect	0.015	0.009	–0.002	0.034	0.076
Direct effect	–0.151	0.025	–0.200	–0.106	0.001
Total effect	–0.136	0.022	–0.178	–0.092	0.001

Table 27. Mediating effect of residents' attribution in the pathway from need factors to the utilization of smart health station services.

Path	Effect value	SE	Bias-corrected 95% CI		p-value
			Lower	Upper	
Indirect effect	–0.027	0.012	–0.051	–0.005	0.013
Direct effect	0.066	0.046	–0.026	0.147	0.194
Total effect	0.039	0.045	–0.057	0.115	0.556

Table 28. Mediating effect of residents' attribution in the pathway of need factors contributing to the utilization of community health services.

Path	Effect value	SE	Bias-corrected 95% CI		p-value
			Lower	Upper	
Indirect effect	–0.046	0.015	–0.087	–0.023	$<$0.001
Direct effect	0.351	0.066	0.218	0.472	$<$0.001
Total effect	0.304	0.061	0.165	0.403	0.001

Table 29. Weight of various influencing factors.

Item		Information entropy value	Information utility value (d)	Weight (%)
Predisposing factors	Age	0.986	0.014	1.870
	Occupation	0.963	0.037	4.812
	Education level	0.982	0.018	2.291
	Social support	0.995	0.005	0.700
	Health belief	0.996	0.004	0.529
Enabling factors	Community type	0.981	0.019	2.461
	Insurance type	0.997	0.003	0.378
	Disposable income	0.973	0.027	3.437
	Health management service expenditure proportion	0.888	0.112	14.409
	Presence of smart health station	0.956	0.044	5.716
	Signing with a family doctor	0.988	0.012	1.557
	Being aware of smart health station services	0.953	0.047	6.114
	Being aware of community health services	0.973	0.027	3.491
Need factors	Personal health	0.976	0.024	3.066
	Total number of chronic diseases	0.872	0.128	16.505
Utilization of smart health stations	Receiving health self-testing services	0.875	0.125	16.064
	Receiving health intervention guidance services	0.871	0.129	16.599

Qualitative Findings

The qualitative component of the study comprised three focus group discussions with 15 participants and 14 in-depth interviews. Participants included community residents ($n = 5$), healthcare providers ($n = 5$), community administrators ($n = 5$), policymakers ($n = 2$), community health center directors ($n = 2$), and healthcare experts ($n = 1$). The age range of participants was 38–70 years, with an average of 12 years of experience in their respective fields. This diverse group of stakeholders provided comprehensive insights into the utilization of SHS and CHS, which bring several key themes to the surface:

(1) Limited awareness and utilization of SHS. Despite widespread deployment, awareness and utilization of SHS remained at low levels. A participant noted, "Smart health stations were quite intensely advertised three years ago...but after the pandemic, the publicity has diminished."

(2) Functionality and equipment issues. Participants reported that SHS equipment was often outdated or malfunctioning. A healthcare provider stated, "The detection equipment in the health station is now often sluggish, not very smooth to use."

(3) Integration with CHS. The integration between SHS and CHS was perceived as insufficient. A community health center director commented, "To truly help with promoting hierarchical diagnosis and treatment, we still need to fully realize the interconnection and sharing of electronic health records, electronic medical records, and public health information with higher-level hospitals."

(4) Perception of SHS purpose. Many residents viewed SHS as government projects rather than health initiatives. One resident mentioned, "I hope the government departments can make this role clear at the station. For example, specialists from higher-level hospitals could come down to the community station for guidance and consultation."

(5) Suggestions for improvement. Participants proposed several improvements, including:

(i) Enhanced publicity and education about SHS services;

(ii) Regular updates and maintenance of equipment;

(iii) Better integration of SHS data with CHS and hospital systems;

(iv) Expansion of SHS functions to include more medical services.

(6) Role in hierarchical medical system. Stakeholders emphasized the potential of SHS in promoting the hierarchical medical system. A policy researcher suggested, "Only when we truly realize the mechanism linkage and information interconnection with higher-level hospitals can we really help to promote hierarchical diagnosis and treatment."

These findings highlight the challenges and opportunities in optimizing the use of SHS to enhance community health services and promote a more efficient healthcare system.

Discussion

This study provides a comprehensive analysis of the factors influencing the utilization of SHS and CHS in Shanghai, China, using an innovative extension of the Andersen Behavioral Model. Our findings reveal several key insights that have important implications for both theory and practice in the field of CHS and smart healthcare solutions.

Key Findings and Their Significance

Our results indicate that the utilization rate of SHS (40.1%) is significantly lower than that of CHS (68.0%). This discrepancy suggests that despite the potential benefits of SHS, there are still barriers to their widespread adoption and use. The lower utilization of SHS may be attributed to factors such as lack of awareness, limited functionality, and insufficient integration with existing CHS.

Interestingly, our study shows that 88.8% of residents attributed the establishment of SHS to government task completion rather than genuine health concerns. This perception bias could significantly impact the utilization of these services and highlight the need for improved communication and public engagement strategies.

Theoretical Contributions

This study extends the Andersen Behavioral Model by incorporating SHS utilization as a mediating factor of predisposing, enabling, and need factors with CHS utilization (Babitsch et al, 2012; Evashwick et al, 1984). Our "two-stage Andersen Behavioral Model" provides a novel framework for understanding the complex relationships between traditional and innovative health services (Kislov et al, 2019; Kukafka et al, 1999). This extension allows for a more nuanced understanding of how emerging technologies like SHS can influence traditional health service utilization patterns.

Moreover, our inclusion of residents' attributions as a predisposing factor offers new insights into the psychological aspects of health service utilization, particularly for novel services like SHS (Healy, 2017; Mitchell et al, 2010).

Practical Implications

The findings of this study have important implications for improving the utilization and effectiveness of SHS and CHS in China. First, the government should strengthen its leading role in planning and investing in SHS construction, with an emphasis on optimizing resource allocation, upgrading information systems, and enhancing service quality (Shanghai Municipal People's Government Office, 2023; Xu, 2023). Second, targeted publicity strategies should be developed to raise residents' awareness and trust in SHS, leveraging both traditional and new media channels (Chao et al, 1987; Wang, 1984). Third, the integration of SHS and CHS should be promoted through strengthened information sharing, business collaboration, and service coordination mechanisms (Chen et al, 1998; Wang, 1998). Fourth, the functionality and service content of SHS should be expanded to meet the diverse health needs of residents, with a focus on chronic disease management, health education, and telemedicine services (Zhang, 1998). Fifth, a differentiated development strategy should be adopted to cater to the specific needs of different regions and populations, such as the elderly, migrant workers, and rural residents (Hou et al, 2017; Zhang et al, 2021).

Limitations and Future Directions

This study had several limitations that should be acknowledged. First, the cross-sectional design limited the ability to make causal inferences, and future longitudinal studies are needed to examine the dynamic relationships between various factors and service utilization outcomes (Lu et al, 2018). Second, the sample was limited to Shanghai; therefore, the generalizability of our findings to other regions in China may be limited (Jiang et al, 2009). Third, some important variables, such as community environment and family structure, were not included in the model, and future research should explore a wider range of influencing factors (Johansson et al, 2002). Fourth, the study lacked a cost-benefit analysis of SHS, and future studies should incorporate economic evaluation methods to assess the long-term sustainability and cost-effectiveness of SHS (Gu et al, 2018).

Methodological Contributions

Using structural equation modeling to test the mediating role of SHS utilization represents a methodological advancement in this field. This approach allowed us to simultaneously examine multiple pathways of influence, providing a more comprehensive understanding of the factors affecting health service utilization.

Unexpected Findings

Interestingly, our study reveals that higher income and education levels were associated with lower utilization of both SHS and CHS. This result is contrary to our initial hypothesis and suggests that socioeconomic factors may play a complex role in health service utilization in urban China. This finding opens up new avenues for research and highlights the need for nuanced strategies to promote health service utilization across different socioeconomic groups.

This study contributes significantly to our understanding of the factors influencing the utilization of SHS and CHS in urban China. By extending the Andersen Behavioral Model and providing empirical evidence on the role of SHS, our research offers valuable insights for improving CHS delivery and advancing the integration of innovative technologies in healthcare. The findings underscore the need for targeted interventions, improved public communication, and continued research to fully realize the potential of SHS in enhancing community health.

Conclusion

This research provides critical insights into the complex dynamics of SHS and CHS utilization in urban China. By extending the Andersen Behavioral Model and empirically demonstrating the mediating role of SHS, our study offers a novel framework for understanding and improving health service delivery in the digital age. As the global healthcare systems face the dual challenges of aging populations and increasing chronic disease burdens, the findings from this study can inform evidence-based strategies to enhance the integration, accessibility, and effectiveness of community health services. Ultimately, this research contributes to the ongoing efforts to create more responsive, efficient, and equitable healthcare systems that can better address the diverse health needs of urban populations. Future research and policy initiatives should build upon these insights to fully harness the potential of smart health technologies in improving public health outcomes.

Key Points

- Utilization of SHS correlates positively with service satisfaction but needs improvement due to limited functionality and recognition.
- Enhanced functions, innovative models, intense publicity, and collaborative efforts are essential for improving SHS and CHS.
- This study extends the Andersen Behavioral Model by incorporating smart health components, revealing pathways for optimizing service provision and hierarchical diagnosis in SHS and CHS.

Availability of Data and Materials

All data included in this study are available from the corresponding author upon reasonable request.

Author Contributions

GJX conceived and designed the study and wrote the manuscript. YKM and ZGP performed the research and analyzed the data. All authors read and approved the final manuscript. All authors contributed to revising the manuscript critically for important intellectual content. All authors agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Ethics Approval and Consent to Participate

This study was reviewed and approved by the Ethics Committee of Zhongshan Hospital of Fudan University (Ethics approval number: B2021-301R), and conducted in compliance with the Declaration of Helsinki. All participants provided written informed consent.

Acknowledgement

Not applicable.

Funding

This research received no external funding.

Conflict of Interest

The authors declare no conflict of interest.

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