Analysis of Smart Home use based on the Degree of Health-related Risk Variation: A Cross - Sectional National Survey in China

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Abstract

Background

Digital health has become a heated topic today and smart homes have received much attention as an important area of digital health. However, most of the existing studies have focused on discussing the impact of smart homes on people or the attitudes of older people towards smart homes. Only few studies have focused on relationship between health-related risks and use of smart homes.

Aims

To investigate the association between health-related risks and the use of smart homes, provide new recommendations to promote the implementation of digital health strategies and achieve health for all.

Methods

We used data from 11,031 participants aged 18 and above. The population was clustered based on five health-related risk factors: perceived social support, family health, health literacy, media use, and chronic diseases self-behavioral management. A total of 23 smart homes were categorized into three sub-categories: entertainment smart home, functional smart home, and health smart home. We analyzed demographic characteristics and utilization rate of smart home across different cluster.

Results

The participants were clustered into three groups: low risk, meddle risk, and high risk. The utilization rate of smart home was the most popular in the low risk group (total smart home: 86.97%; entertainment smart home: 61.07%, functional smart home: 77.42%, and health smart home: 75.33%; $p < 0.001$). For entertainment smart home, smart TV had the highest utilization rate (low risk: 45.73%; middle risk: 43.52%, high risk: 33.38%, $p<0.001$). For functional smart home, smart washing machine (low risk: 37.66%, middle risk: 35.11%, high risk: 26.49%; $p<0.001$) and smart air conditioner (low risk: 35.95%, middle risk: 29.13%, high risk: 24.61%) were higher than other of this category. For health smart home, sports bracelet has the highest utilization rate (low risk: 37.29%, middle risk: 24.49%, high risk: 22.83%).

Conclusion

Health-related risks are an important factor affecting the use of smart homes. Joint efforts of government and product manufacturers are needed to broaden the smart home market and promote the implementation of digital health strategies.

Introduction

Along with accelerated industrialization, urbanization, and population aging, China's disease spectrum continues to change. The death rate from chronic non-communicable diseases is in the proportion to 88% of all deaths. The resulting disease burden accounts for over 70% of the total disease burden. China government developed a "Healthy China" strategy in 2017 to improve the health literacy of residents, prevent diseases, and improve the quality of life of residents [1]. The Internet of Things has experienced rapid growth in the past decade, covering many fields, critical digital health. Following the development trend of technology, the World Health Organization has proposed a global digital health strategy for 2020-2025, advocating the promotion of digital health and the application of digital health to achieve the goal of universal health[2]. To help drive the development of health in China, the government is also using

Internet technology. It has been continuously focusing on the innovative home sector since 2008, promulgating policy documents to support the development of smart homes[3].

Constantly developing smart homes are an important role in digital health and can effectively alleviate many health problems. From an age perspective, stress and fatigue from school or work endanger young people's physical and mental health. Studies have shown that work stress is a significant risk factor for colorectal, lung, and oesophageal cancers[4]. Treatments to reduce stress and exhaustion in concert with other therapies can make adolescent depression treatment more effective[5]. Service robotic massage systems with human behavioral sensing can effectively relieve users of physical fatigue, leading to physical and mental relaxation and a higher quality of life [6]. Smart homes can also effectively mitigate the impact of aging. For older adults with deteriorating physical functions, reduced mobility become a significant problem in their lives. Homes intelligently set up can automatically adapt to their behavior and reduce inconvenience, such as intelligent adaptive toilets [7]. In addition, visual impairment also seriously affects the health of the elderly, such as falls, loneliness, and depression, and intelligent lighting devices can dynamically adjust the light to alleviate this problem effectively [8]. Empty nesters live alone all year round and suffer from social isolation and loneliness, seriously affecting their health and quality of life [9]. Smart homes connected to the Internet can establish a connection between the elderly and the outside community, and smart homes with entertainment properties can also alleviate the loneliness of the elderly living alone [10]. From the perspective of special populations, smart speakers can help people with disabilities who have communication difficulties enhance their understanding of speech and improve their communication [11]. Remote support services can help enhance the sense of security provided by people with intellectual and related developmental disabilities [12]. From a more macro perspective, smart homes can effectively relieve pressure on the healthcare system. By connecting to the Internet, smart homes can monitor and deliver disease and health information to healthcare institutions in real time, benefiting both users and healthcare institutions [13].

The report "China Internet Development 2021" released by the Internet Society of China shows that China's Internet penetration rate has reached 70.4%, the internet of things market size reached 1.7 trillion yuan, the artificial intelligence market size rose to 303.1 billion yuan, and the market size of online medical and health services climbed to 196.1 billion yuan [14], which in general means that China has a good Internet foundation to carry out digital health. However, research shows that the development and popularity of smart homes in China are policy-driven rather than demand-driven [3]. There is still space to improve the market scale. To expand the smart home market, improve people's quality of life and promote the implementation of the health China strategy, it is necessary to deeply study the real needs of consumers and promote the structural reform from the supply side from the demand side.

Much attention has been paid to research on smart homes in recent years. However, most of them have been considered from the perspectives of their effects and impacts on people [15, 16] and people's attitudes towards smart homes [17, 18]. In contrast to previous studies, our study clustered populations according to health-related risk factors and analyzed the characteristics of different groups and their use of smart homes. Frija-Masson J[15] investigated whether smart scales are more accurate in weight and body composition than dual X-ray absorptiometry (DEXA) that is the gold standard, and showed that smart scales are not a substitute for DEXA. New smart robots, walkers, can proactively approach users in complex indoor environments and avoid obstacles to improve mobility safety[16]. Sajay Arthanat reveals the extent of smart home technology adoption among seniors, finding varying rates of adoption of specific types of devices with carbon monoxide alarms reaching 81.5% of respondents and water leak detectors and automatic oven shut-offs ranking in the top two categories of potential usage among the 13 products surveyed at 41.8% and 38% respectively, with these types of safety products. These safety products are more popular with the older age group. At the same time, voice-activated assistants and motion-activated cameras were not used by 63.5% and 67% of respondents, respectively, with lower usage and potential usage of these innovative and trendy products[17].

Jachan DE compared older people's satisfaction with smart homes with traditional mobility support tools and value for money. Overall, users rated all installed smart homes higher in terms of satisfaction. In terms of value for money, smart homes are of higher quality but also more expensive. The authors suggest that products can be modularized, thus reducing smart home product prices[18].

Different groups of people have various needs for smart homes, and expanding the smart home market requires understanding the needs of the audience on different sides of the product. The development of products cannot be separated from the support of technology and policies. In the context of the continuous development of the Internet and the much attention paid to the digital health strategy, understanding the differences in smart home needs of people with different health-related risks is conducive to smart homes producing products that meet consumer needs and promoting the development of this market, which can also, in turn, promote the effective implementation of the digital health strategy.

The present study

The role of health-related risks in the link between smart home use has not been explored in previous studies, despite the profound impact of health-related risks on the smart home use. The aim of this study is to examine the role of health-related risk in linking smart home use in China. Based on the above literature review, the following hypotheses are proposed.

Hypothesis 1

The health-related risk is negatively associated with smart home use. The lower the health-related risk is, the better the smart homes are used.

Hypothesis 2

Different health-related risk groups will prioritize different types of smart homes.

Method

Data and Procedure

The data used in this study is conducted in 23 provinces, 5 autonomous regions, and 4 municipalities directly under the central government from July to September 2021. The survey is a multi-stage sampling, using the random number table method to select 2-6 cities from each noncapital prefecture-level administrative region of each province and an autonomous region, a total of 120 cities; based on the data results of "the seventh national census in 2021", quota sampling (quota attributes are gender, age, and urban-rural distribution) was conducted for 120 urban residents, so that the gender, age and urban-rural distribution of the samples basically conform to the demographic characteristics. Finally, 11031 valid questionnaires were obtained that have high quality and accurate national representation and comply with the ethical review rules (JNUKY-2021-018).

Variables

Characteristic Variable

The characteristic variable in this study included respondents' socio-economic background (age, gender, income, Hukou, residence, education, public insurance, location recently, chronic disease, Disability, work status and Politics), family characteristics (Marriage, family type, number of children, household) and lifestyle (drinking status). See Supplementary Table S1 for details of definitions and classifications.

Smart Home Use

This paper investigates the Smart Home Use (SHU) of people for 23 kinds of smart homes, and divides them into three categories according to the functions of smart homes: entertainment SHU (consists of Smart TV, VR glasses, body sensing car, smart speaker), function assistance SHU (consists of a smart robot, smart lighting, smart washing machine, smart switch, smart door lock, smart toilet, smart mosquito repellent, electric curtain, smart air conditioner, smart clothes hanger, smart monitoring) and health SHU (consists of sports bracelet, temperature and humidity sensor, smart socket, danger button, smoke transducer, body fat scale, air purifier, smart medicine cabinet). At the same time, the utilization rate of smart homes and the composition ratio of people are analyzed.

Health-related Risk

We identified five factors that influence health-related risk based on previous studies: perceived social support [19], family health [20], health literacy [21], media use [22], and chronic disease self-behavioral management [23]. These five aspects were negatively associated with health-related risk, and we classified health-related risks according to the distribution characteristics of these five aspects.

Perceived social support was measured using The Perceived Social Support Scale (PSSS) based on the Zimet Perceived Social Support Scale. A 12-item scale divided into three dimensions: family support, friend support, and other supports, as shown in Table S2 in the attached table. "strongly disagree", "slightly disagree", "neutral", "slightly agree", "agree", "Strongly agree" seven options, these seven options are assigned a score of 1-7 (Strongly disagree = 1). The higher the score, the higher the perceived social support. The alpha coefficients for family support, friend support, other supports and the full scale were 0.87, 0.85, 0.91 and 0.88 for the sample of 275 cases (139 males and 136 females) respectively, with retest reliability of 0.85, 0.75, 0.72 and 0.85 [24].

Family health was measured using the Family Health Scale-Short Form (FHS-SF) based on the AliceAnn Crandall [25] (Supplementary Table S3). For each item, subjects rated "strongly disagree", "somewhat disagree", "neither agree nor disagree", "somewhat agree " and "strongly agree", with the three dimensions (7 items) other than "family health resources" being assigned a value of 1-5 in order ("strongly disagree" = 1), while the three items for "family health resources" were assigned the opposite value ("strongly agree"=1). Cronbach's alpha for the 10-item scale was 0.80 and Cronbach's alpha for the FHS-SF was 0.84.

Health literacy was measured using the Short-Form Health Literacy Instrument (HLS-SF12) developed by Tuyen V Duong [26]. The scale has 12 items covering the three health domains of health care, disease prevention, and a health promotion, as detailed in Table S6 in the Supplementary Material. “very difficult”, “difficult”, " easy", and "very easy" for each item, in order of assignment from 1 to 4 ("very difficult" = 1). The higher the score is, the higher the health literacy is. This scale has high reliability with a Cronbach's alpha of 0.85.

In order to find out how the participants use the media, we developed our own media use scale with seven items. The scale has five options: "never use", "occasionally use", "sometimes use", "often use" and "almost every day" that are assigned a value of 0-4 in order (never use =0), see Table S4 in the Supplementary Material.

Chronic disease self-behavioral management was measured using the Chronic Disease Self-management Study Measure (CDSMS) developed by Lorig[27, 28]. The scale is divided into two sub scales: self - management behavior and self-management effectiveness. The self-management behavior scale consists of 15 items including exercise, cognitive symptom management practices, and communication with a doctor. The five items were rated on a scale of 0-4 (not done=0), with higher scores resulting in higher status. See Table S5 in the Supplementary Material for details. The Cronbach coefficient for the CDSMS was 0.72-0.75.

Statistical Analysis

For segmentation, non-hierarchical K-means cluster analysis was conducted based on 5 health-related risk-related factors: family health, health literacy, chronic self-behavior management, perceived social support, and media use. Suppose a factor has a relatively large cluster center value. In that case, it can be characterized as a cluster that is positively affected by the factor. Then we conducted a t-test to explore the differences in the health-related risk-related factors, according to the clustering.

Firstly, we made a descriptive analysis of the demographic characteristics and the characteristics of each Characteristic Variable in the three clusters. The number distribution of each variable in the three clusters, the composition ratio distribution of each variable classification in the same cluster, and the proportional distribution of the same variable classification in the three clusters is counted. Chi-square verification was performed by comparing these data. Thirdly, we also make a descriptive analysis on the overall use of smart homes based on demographic characteristics. The smart home is divided into three categories, plus the overall unused category, and the number of users, the composition ratio, and the utilization rate of the following variables in these four categories are counted. Then, perform chi-square verification. Fourth, we made a descriptive analysis of the needs of the three groups for the specific 23 smart homes under the three categories. We counted the number and the composition ratio of the three groups. Then, perform chi-square verification. Fifthly, according to the above analysis, we mainly focus on the differences in the demand for smart homes among the three variables of residence, gender, and age, and then make a descriptive analysis. The number and the composition ratio of 23 types of smart homes used by people of three age groups with urban and rural residence, male and female gender are counted. Then, perform chi-square verification.

Results

Segmentation Based on Health-related risk

As the clustering was more balanced in each group when clustered into three groups and there were significant differences in health-related risk characteristics among the groups, the clustering can be judged that is convincing when clustered into three groups. Table 1 showed the results of the clustering defined into three groups. The analysis shown that there was a significant difference among three clusters in Chronic self-behavior management, Health literacy, Media use, Perceive social support and Family health ($p< 0.05$).

Table 1
Results of cluster analysis for health-related risk.

	Cluster 1	Cluster 2	Cluster 3	p-value
	Low Risk	Middle Risk	High Risk	
n	2679	4589	3763	
Chronic disease self-behavioral management	18.82 ± 5.30	10.45 ± 2.93	13.18 ± 5.08	<0.001
HLS	40.99 ± 5.38	36.94 ± 4.94	33.36 ± 5.69	<0.001
Media Use	17.19 ± 4.37	10.50 ± 3.65	11.12 ± 4.47	<0.001
PSSS	68.42±10.54	65.46 ± 9.07	47.99 ± 9.33	<0.001
FLS	40.96 ± 5.94	41.44 ± 4.71	31.68 ± 4.06	<0.001
FLS_ social and emotional health processes	13.26 ± 1.82	13.12 ± 1.65	9.41 ± 2.04	<0.001
FLS_ healthy lifestyle	8.88 ± 1.25	8.83 ± 1.13	6.36 ± 1.43	<0.001
FLS_ health resources	10.32 ± 3.96	11.25 ± 2.99	9.65 ± 2.00	<0.001
FLS_ external social supports	8.50 ± 1.37	8.23 ± 1.30	6.26 ± 1.35	<0.001
HLS: Health Literacy Scale; PSSS: Perceived Social Support Scale; FLS: Family Health Score				

The clusters were defined and named based on the level of health-related risks and characteristics. cluster 1 ‘low risk’ is a group that the mean values of each variable were each higher than their overall respective mean values. they take the lowest health-related risk. cluster 2 ‘middle risk’ is a group whose mean values are above average except for media use and chronic self-behavior management. their health-related risks are moderate but still require control. cluster’3 ‘high risk’ is the highest health-related risk group that means values lower than average. the difference among the factors for each group can be seen in figure 1.

Descriptive statistics and correlations

Table 2 shows the demographic and covariant characteristics of each cluster. There was a significant difference in some Characteristic Variables among the three groups. The proportion of females in Cluster1, Cluster2, and Cluster 3 was higher. Among Cluster1, Cluster2, and Cluster 3, the proportion of young and middle-aged people aged 19 ~ 45 was higher, and the proportion of people aged over 91 was lower. The Middle Income Group of Cluster 1 with income from 3001 to 7500 and the High Income Group of above 7501 were higher than the Middle Income Group of Cluster 2 and Cluster 3 with income from 3001 to 7500. Cluster 1, Cluster 2, and Cluster 3 have a higher proportion of the urban population, and the difference is more obvious in Cluster 1. The other parties in Cluster 1, Cluster 2, and Cluster 3 had higher percentages, and the disparity was even greater in Cluster2. The proportion of postgraduates and doctorates in Cluster1, Cluster2, and Cluster 3 was higher than that in middle school and Lower Education, and the disparity in Cluster 1 was more obvious. The proportion of in-services in Cluster1, Cluster2, and Cluster 3 was higher than that of retired. Cluster 1, Cluster 2, and Cluster 3 had a higher proportion of Nuclear family types and a lower proportion of single-parent families. The proportion of the urban population in Cluster 1, Cluster2, and Cluster 3 was higher. The proportion of married and unmarried people was higher in Cluster 1 and Cluster3, and the proportion of married people was higher in Cluster 2. The proportion of childless people in Cluster 1, Cluster2, and Cluster 3 was higher, and the difference was even greater in Cluster 1. A higher percentage of cluster 1, Cluster 2 and Cluster 3 had one or two people living with them. The proportion of the population using public health insurance is higher in Cluster 1, Cluster 2 and Cluster 3.

There were no chronic diseases in Cluster 1, Cluster2, and Cluster 3, but a high percentage of people with disabilities. Among Cluster 1, Cluster 2 and Cluster 3, the proportion of people who had recently consumed alcohol was higher.

Table 2
Demographic characteristics of each cluster [n (%)].

	Cluster 1	Cluster 1	Cluster 1	P-value
	Low risk	**Low risk**	**Low risk**	
Gender				<0.001
Man	1330 (49.6%)	1846 (40.2%)	1857 (49.3%)	
Woman	1349 (50.4%)	2743 (59.8%)	1906 (50.7%)	
Age				<0.001
~18	280 (10.5%)	433 (9.4%)	352 (9.4%)	
19~45	1766 (65.9%)	2532 (55.2%)	2303 (61.2%)	
46~59	502 (18.7%)	1025 (22.3%)	691 (18.4%)	
60~75	110 (4.1%)	445 (9.7%)	320 (8.5%)	
76~90	17 (0.6%)	150 (3.3%)	93 (2.5%)	
91~	4 (0.1%)	4 (0.1%)	4 (0.1%)	
Income				<0.001
~3000	532 (19.9%)	1380 (30.1%)	1334 (35.5%)	
3001~7500	1299 (48.5%)	2294 (50.0%)	1732 (46.0%)	
7501~	848 (31.7%)	915 (19.9%)	697 (18.5%)	
Hukou				<0.001
Urban	1787 (66.7%)	2567 (55.9%)	2006 (53.3%)	
Rural	892 (33.3%)	2022 (44.1%)	1757 (46.7%)	
Politics				<0.001
CPC	749 (28.0%)	798 (17.4%)	574 (15.3%)	
Communist youth league	862 (32.2%)	1138 (24.8%)	1056 (28.1%)	
Other parties	965 (36.0%)	2433 (53.0%)	1918 (51.0%)	
Masses	103 (3.8%)	220 (4.8%)	215 (5.7%)	
Education				<0.001
Below secondary school	26 (1.0%)	163 (3.6%)	189 (5.0%)	
Secondary Education	272 (10.2%)	1139 (24.8%)	777 (20.6%)	
College and Bachelor	424 (15.8%)	847 (18.5%)	707 (18.8%)	
Master and PhD	1658 (61.9%)	2201 (48.0%)	1891 (50.3%)	
Below secondary school	299 (11.2%)	239 (5.2%)	199 (5.3%)	
Work status				<0.001

	Cluster 1	Cluster 1	Cluster 1	P-value
	Low risk	Low risk	Low risk	
Working	1297 (48.4%)	1953 (42.6%)	1387 (36.9%)	
Retired	161 (6.0%)	438 (9.5%)	285 (7.6%)	
Student	933 (34.8%)	1217 (26.5%)	1164 (30.9%)	
No fixed occupation	288 (10.8%)	981 (21.4%)	927 (24.6%)	
Family type				<0.001
Nuclear family	1662 (62.0%)	2847 (62.0%)	2038 (54.2%)	
Conjugal family	429 (16.0%)	625 (13.6%)	709 (18.8%)	
Backbone family	251 (9.4%)	635 (13.8%)	459 (12.2%)	
Single-parent family	75 (2.8%)	168 (3.7%)	175 (4.7%)	
Other	262 (9.8%)	314 (6.8%)	382 (10.2%)	
Location recently				0.075
Eastern region	1427 (53.3%)	2306 (50.3%)	1877 (49.9%)	
Central region	658 (24.6%)	1196 (26.1%)	998 (26.5%)	
Western region	593 (22.1%)	1087 (23.7%)	886 (23.6%)	
Residence				<0.001
Urban	2134 (79.7%)	3271 (71.3%)	2603 (69.2%)	
Rural	545 (20.3%)	1318 (28.7%)	1160 (30.8%)	
Marriage				<0.001
Unmarried	1205 (45.0%)	1582 (34.5%)	1576 (41.9%)	
Married	1421 (53.0%)	2803 (61.1%)	2002 (53.2%)	
Divorce	43 (1.6%)	66 (1.4%)	98 (2.6%)	
Widowed	10 (0.4%)	138 (3.0%)	87 (2.3%)	
Children				<0.001
No	1415 (52.8%)	1819 (39.6%)	1828 (48.6%)	
One	772 (28.8%)	1350 (29.4%)	937 (24.9%)	
Two	418 (15.6%)	1064 (23.2%)	752 (20.0%)	
Three or more	74 (2.8%)	356 (7.8%)	246 (6.5%)	
Household				<0.001
No	267 (10.0%)	301 (6.6%)	495 (13.2%)	
One	810 (30.3%)	1479 (32.3%)	1327 (35.3%)	
Two	791 (29.6%)	1389 (30.3%)	963 (25.6%)	

	Cluster 1	Cluster 1	Cluster 1	P-value
	Low risk	Low risk	Low risk	
Three	440 (16.4%)	739 (16.1%)	507 (13.5%)	
Four	150 (5.6%)	323 (7.0%)	214 (5.7%)	
Five or more	217 (8.1%)	355 (7.7%)	254 (6.8%)	
Public insurance				<0.001
No	833 (31.1%)	1325 (28.9%)	779 (20.7%)	
Yes	1846(68.9%)	3264(71.1%)	2984(79.3%)	
Chronic disease				<0.001
No	2352 (87.8%)	3595 (78.3%)	3037 (80.7%)	
One	242 (9.0%)	661 (14.4%)	479 (12.7%)	
Two or more	85(3.2%)	333(7.3%)	247(6.6%)	
Disability				0.001
No	2603 (97.2%)	4464 (97.3%)	3617 (96.1%)	
Yes	76 (2.8%)	125 (2.7%)	146 (3.9%)	
Drinking status				<0.001
Yes, within 30 days	1491 (55.7%)	2842 (61.9%)	2245 (59.7%)	
Yes, before 30 days	342 (12.8%)	510 (11.1%)	456 (12.1%)	
No	846 (31.6%)	1237 (27.0%)	1062 (28.2%)	

Table3 describes the differences in the demographics and Characteristic Variables for smart home usage. The gender factor in the overall use has the remarkable difference, displays for the female overall use rate to be higher than the male. There were significant differences in age factors. The overall rate of using entertainment smart home was higher among 19-45-year-olds, and the rate of using smart home for functional and health was higher among 91-year-olds. The income factor has the remarkable difference, manifests for the income above 7500 high income crowd each kind of smart home use ratio to be high. There are significant differences in household factors, and the proportion of various kinds of smart home in rural household is high. There are significant differences in the political landscape, with a higher proportion of CPC smart homes being used. The educational factor has the remarkable difference, displays for the master degree above crowd to use each kind of intelligent home the proportion to be big. There were significant differences in the working environment, with a higher proportion of in-services using various types of smart home. There were significant differences in household type factors, with people with Nuclear family type using a higher proportion of different types of smart home. There is a significant difference between recreation and health in the factors of recent residence, which shows that the proportion of recreation is higher in the western region and health is higher in the Eastern Region. There are significant differences in the factors of residence, indicating that the proportion of urban population using various kinds of smart home will be higher. There were significant differences in factors related to marital status, which indicated that unmarried people had a higher overall utilization rate and a higher proportion of healthy smart homes, while divorced people used a higher proportion of functional smart homes. There was a significant difference in the number of children, as demonstrated by the higher overall utilization rate of one child and the higher utilization rate of recreational smart homes, and the higher proportion of functional and health analogs among the childless population. There are significant differences in the factors of public insurance, as a result of the high usage rate of various smart homes among the insured population. There were significant differences in the factors of chronic diseases, and the proportion of using various smart home without chronic diseases was higher. There was a significant difference in the factors of drinking, which showed that the proportion of using health smart homes was higher among the people who drank before 30 days. See Table S7 in the Supplementary Material for more details on demographic differences in overall smart home use. The analysis of demographic differences in users is detailed in Table S7 in Supplementary Material.

Table 3
Demographic differences in utilization rate of smart home

	Total smart home		Entertainment smart home		Functional smart home		Health smart home	
	Utilization rate	P-value	Utilization rate	P-value	Utilization rate	P-value	Utilization rate	P-value
Gender		<0.001		0.303		0.011		0.089
Man	78.96%		52.43%		65.25%		59.55%	
Woman	81.74%		51.45%		67.56%		61.14%	
Age		<0.001		<0.001		<0.001		<0.001
~18	82.07%		53.80%		64.69%		61.50%	
19~45	83.00%		54.13%		69.19%		64.78%	
46~59	79.44%		51.04%		65.83%		57.66%	
60~75	67.54%		40.46%		54.63%		41.37%	
76~90	61.92%		34.23%		50.38%		31.54%	
91~	83.33%		33.33%		91.67%		83.33%	
Income		<0.001		<0.001		<0.001		<0.001
~3000	72.03%		46.52%		56.75%		48.27%	
3001~7500	82.85%		52.13%		68.19%		62.10%	
7501~	86.46%		58.50%		75.73%		72.76%	
Register Residence		<0.001		<0.001		<0.001		<0.001
Urban	66.07%		42.77%		55.36%		52.49%	
Rural	83.19%		76.08%		96.03%		81.41%	
Politics		<0.001		<0.001		<0.001		<0.001
CPC	83.97%		55.59%		72.14%		69.45%	
Communist youth league	82.62%		52.52%		66.92%		64.66%	
Other parties	77.82%		49.66%		63.54%		54.61%	
Masses	80.67%		55.95%		71.19%		57.99%	
Education		<0.001		<0.001		<0.001		<0.001
Illiteracy	59.79%		36.24%		47.88%		30.95%	
Below secondary school	72.12%		48.03%		58.32%		45.29%	
Secondary Education	80.94%		52.22%		66.23%		58.70%	

	Total smart home		Entertainment smart home		Functional smart home		Health smart home	
	Utilization rate	P-value	Utilization rate	P-value	Utilization rate	P-value	Utilization rate	P-value
College and Bachelor	84.12%		53.11%		69.76%		66.43%	
Master and PhD	86.16%		61.06%		75.71%		78.02%	
Work status		<0.001		<0.001		<0.001		<0.001
In-service	84.49%		55.34%		71.71%		67.03%	
Retired	73.64%		44.12%		60.18%		49.55%	
Student	81.38%		51.81%		64.36%		62.40%	
No fixed occupation	73.36%		47.91%		61.29%		47.81%	
Family type		<0.001		<0.001		0.004		<0.001
Nuclear family	82.86%		53.75%		67.33%		62.78%	
Conjugal family	79.24%		51.79%		67.90%		61.26%	
Backbone family	74.87%		46.10%		63.64%		52.86%	
Single-parent family	75.36%		46.89%		61.24%		54.07%	
Other	76.51%		49.79%		64.61%		56.05%	
Location recently		0.810		0.002		0.620		<0.001
Eastern region	80.48%		50.45%		66.84%		61.93%	
Central region	80.79%		52.49%		66.48%		61.50%	
Western region	80.09%		54.48%		65.74%		55.85%	
Residence		<0.001		<0.001		<0.001		<0.001
Urban	82.79%		54.05%		69.21%		65.21%	
Rural	74.33%		46.21%		59.35%		47.70%	
Marriage		<0.001		<0.001		<0.001		<0.001
Unmarried	81.71%		53.24%		65.67%		63.37%	
Married	80.34%		51.56%		67.49%		59.33%	
Divorce	78.26%		49.28%		71.01%		57.97%	
Widowed	62.98%		38.30%		51.91%		36.17%	
Children		<0.001		<0.001		<0.001		<0.001
No	82.00%		53.08%		66.77%		64.34%	
One	82.77%		51.98%		68.03%		64.11%	

	Total smart home		Entertainment smart home		Functional smart home		Health smart home	
	Utilization rate	P-value	Utilization rate	P-value	Utilization rate	P-value	Utilization rate	P-value
Two	78.16%		51.34%		67.10%		53.54%	
Three or more	66.27%		44.53%		55.62%		36.98%	
Household		0.088		0.007		0.016		0.013
No	81.75%		51.36%		69.24%		62.84%	
One	79.09%		49.64%		66.43%		58.35%	
Two	81.01%		52.85%		65.70%		62.17%	
Three	81.73%		53.08%		67.50%		60.44%	
Four	81.80%		56.62%		69.00%		61.57%	
Five or more	79.06%		52.42%		62.23%		58.72%	
Public insurance		<0.001		0.004		<0.001		<0.001
No	78.46%		49.46%		62.82%		55.40%	
Yes	82.51%		54.30%		70.13%		65.35%	
Chronic disease		<0.001		<0.001		<0.001		<0.001
No	81.81%		52.77%		67.65%		62.21%	
One	75.33%		47.83%		60.71%		53.11%	
Two or more	73.08%		48.57%		63.01%		51.28%	
Disability		0.003		0.321		0.112		0.038
No	80.67%		51.98%		66.63%		60.59%	
Yes	74.35%		49.28%		62.54%		55.04%	
Drinking status		0.503		0.066		0.939		<0.001
Within 30 days	80.13%		50.99%		66.37%		58.82%	
Before 30 days	81.35%		53.06%		66.67%		62.39%	
No	74.44%		49.11%		61.43%		57.95%	

Table 4 showed that there were significant differences among the three groups in the needs of 23 smart homes in three categories. Among them, the low risk group had higher demand for smart homes, especially functional homes, with a utilization rate of 77.42%. It was much higher than that in the middle risk groups and high risk groups. Except that the demand for entertainment smart homes in the medium-risk groups was higher than that in the high risk group, the demand for functional and health smart home was lower than that in the high risk group. For the entertainment class, smart TV had the highest utilization rate, while VR glasses and body sensing cars had a lower utilization rate. For the functional class, the utilization rates of smart washing machines and smart air conditioners were high, while the utilization rates of electric current, smart clothes changers, smart mosquito reply, and smart robots were low. For healthsmart home, sports brace, body fat scale, and air purifier were used more frequently, while temperature and humidity sensor, danger button, smoke transmitter, and smart medicine cabinet were used less frequently.

Table 4
The utilization rate of smart home for each cluster [n (%)].

	Cluster 1	Cluster 2	Cluster 3	P-value
	Low risk	**Middle risk**	**High risk**	
n	2679	4589	3763	
Total smart home	2484 (92.72%)	3749 (81.70%)	3083 (81.93%)	<0.001
Entertainment smart home	1636 (61.07%)	2364 (51.51%)	1725 (45.84%)	<0.001
Smart TV	1225 (45.73%)	1997 (43.52%)	1256 (33.38%)	<0.001
VR glasses	258 (9.63%)	125 (2.72%)	252 (6.70%)	<0.001
Body sensing car	220 (8.21%)	93 (2.03%)	201 (5.34%)	<0.001
Smart speaker	681 (25.42%)	706 (15.38%)	558 (14.83%)	<0.001
Functional smart home	2074 (77.42%)	2857 (62.26%)	2405 (63.91%)	<0.001
Smart robot	333 (12.43%)	241 (5.25%)	308 (8.18%)	<0.001
Smart lighting	571 (21.31%)	544 (11.85%)	537 (14.27%)	<0.001
Smart washing machine	1009 (37.66%)	1611 (35.11%)	997 (26.49%)	<0.001
Smart switch	545 (20.34%)	521 (11.35%)	529 (14.06%)	<0.001
Smart door lock	570 (21.28%)	551 (12.01%)	530 (14.08%)	<0.001
Smart toilet	443 (16.54%)	469 (10.22%)	379 (10.07%)	<0.001
Smart mosquito repellent	338 (12.62%)	239 (5.21%)	322 (8.56%)	<0.001
Electric curtain	312 (11.65%)	162 (3.53%)	292 (7.76%)	<0.001
Smart air conditioner	963 (35.95%)	1337 (29.13%)	926 (24.61%)	<0.001
Smart clothes hanger	343 (12.80%)	293 (6.38%)	331 (8.80%)	<0.001
Smart monitoring	417 (15.57%)	400 (8.72%)	416 (11.06%)	<0.001
Health smart home	2018 (75.33%)	2531 (55.15%)	2115 (56.21%)	<0.001
Sports bracelet	999 (37.29%)	1124 (24.49%)	859 (22.83%)	<0.001
Temperature and humidity sensor	272 (10.15%)	170 (3.70%)	261 (6.94%)	<0.001
Smart socket	454 (16.95%)	392 (8.54%)	455 (12.09%)	<0.001
Danger button	245 (9.15%)	131 (2.85%)	262 (6.96%)	<0.001
Smoke transducer	261 (9.74%)	231 (5.03%)	262 (6.96%)	<0.001
Body fat scale	994 (37.10%)	1291 (28.13%)	853 (22.67%)	<0.001
Air purifier	719 (26.84%)	646 (14.08%)	520 (13.82%)	<0.001
Smart medicine cabinet	225 (8.40%)	104 (2.27%)	222 (5.90%)	<0.001

Subgroup analysis

According to Table 5, there were significant differences in the demand for smart homes between urban and rural populations. The urban population accounts for more than 70%, while the rural population accounts for less than 30%. This difference was caused by the differences in urban and rural economy, urban and rural education, the actual use place of smart home, and the practicability of the smart home.

Table 5
Residence, gender, and age Subgroup analysis of smart home utilization rate.

Categories/definition	Residence(%)		P-value	Gender(%)		P-value	Age(%)			P-value
	Urban	Rural		Male	Female		45~59	60~75	76~	
Entertainment smart home										
Smart speaker	78%	22%	<0.001	54%	46%	0.073	75%	20%	5%	<0.001
VR glasses	79%	21%	<0.001	61%	39%	0.013	76%	20%	4%	<0.001
Body sensing car	74%	26%	<0.001	61%	39%	0.024	58%	30%	12%	<0.001
Smart TV	72%	28%	<0.001	53%	47%	0.016	71%	23%	6%	<0.001
Functional smart home										
Smart robot	80%	20%	<0.001	55%	45%	0.120	72%	24%	3%	<0.001
Smart air conditioner	73%	27%	<0.001	50%	50%	0.844	72%	23%	5%	<0.001
Smart lighting	71%	29%	<0.001	49%	61%	0.779	70%	22%	8%	<0.001
Smart washing machine	73%	27%	<0.001	49%	61%	0.477	73%	21%	5%	<0.001
Smart switch	71%	29%	<0.001	50%	50%	0.961	69%	23%	9%	<0.001
Smart door lock	82%	18%	<0.001	50%	50%	0.882	78%	18%	5%	<0.001
Smart toilet	85%	15%	<0.001	49%	51%	0.748	71%	23%	6%	<0.001
Smart mosquito repellent	75%	25%	<0.001	51%	29%	0.730	70%	27%	3%	<0.001
Smart clothes hanger	80%	20%	<0.001	43%	57%	0.021	70%	25%	5%	<0.001
Electric curtain	75%	25%	<0.001	55%	45%	0.120	66%	26%	8%	<0.001
Smart monitoring	66%	34%	<0.001	51%	49%	0.621	63%	29%	9%	<0.001
Healthsmart home										
Smart bracelet	80%	20%	<0.001	55%	45%	0.018	78%	17%	6%	<0.001
Body fat scale	78%	22%	<0.001	49%	51%	0.438	75%	20%	5%	<0.001
Smart medicine cabinet	80%	20%	<0.001	61%	39%	0.018	66%	29%	6%	<0.001
Smart socket	70%	30%	<0.001	56%	44%	0.036	74%	22%	5%	<0.001
Temperature and humidity sensor	79%	21%	<0.001	59%	41%	0.017	70%	28%	2%	<0.001
Danger button	73%	27%	<0.001	52%	48%	0.580	59%	30%	11%	<0.001
Smoke transducer	83%	17%	<0.001	53%	47%	0.346	63%	30%	7%	<0.001
Air purifier	85%	15%	<0.001	50%	50%	0.860	71%	25%	4%	<0.001

There were significant differences in the demand for smart homes among people of different ages. The middle-aged (45 ~ 49 years old) account for more than 50%, while the elderly (76 ~ years old) were generally less than 10%. This difference was caused by educational level, cognitive ability, physical action, and economic status

There were gender differences in the needs of VR glasses, body-sensing cars, smart TV, smart brace, smart medicine cabinet, smart socket, temperature, and humidity sensors, and the demand of men was higher than that of women. This difference was caused by physiological differences, family structure, and income differences. At the same time, gender differences also had differences in the demand for smart clothes changers, which shows that the demand of women was higher than that of men. The reason for this difference is that women pursue fashion and appearance more than men do. And women's clothing is more expensive than men's, so women will pay attention to the protection and proper custody of clothing.

Discussion

In the context of the COVID-19 pandemic, the importance and convenience of digital health are becoming more and more prominent[29, 30], with telemedicine enabling people to have medical consultations at home and avoid infections, and many countries and regions are actively promoting the development of digital health [31, 32]. Identifying the needs of different groups of people for smart homes is important to promote the implementation of digital health strategies, and we conducted a cluster analysis of the population based on health-related risks, divided into three groups: the low risk group, the medium-risk group, and the high risk group, and confirmed the differences in the needs of different groups of people for smart homes through research and analysis.

The usage rate of smart homes for the low health-related risk group was 86.97%, the usage rate for the medium health-related risk group was 79.23% and the usage rate for the high health-related risk group was 77.36%, the lower the health-related risk the better the usage of the smart home. The low health-related risk group had higher health literacy and chronic disease self-behavior management had a stronger health mindset, were better able to self-manage their diseases [33, 34], and were more likely to use smart homes for health management. In addition to this, the population of the low health-related risks group had the best media use among those, with greater information exposure, and more likely to learn about smart home-related information. In addition to these factors, sociodemographic characteristics also had an impact on smart home use in the three groups

The age distribution of the low risk group was younger than the other two groups, with younger people using smart homes better than older people, and Alhuwail D's study also indicated that younger people used smart devices more than older people [35]. Our analysis suggests that age affects smart home use in four main ways. Firstly, consumer perceptions are different; while older people show positive attitudes during the experience of the entertainment smart home - VR glasses - they do not have a strong desire to buy them, believing that smart homes are unnecessary in their lives, while younger people associate the experience more with the content being fun [36]. Secondly, the prevalence of chronic diseases is higher among the elderly [37–39], and studies have shown that three-quarters of the elderly in China suffer from at least one chronic disease [40], and health a smart homes can help them with daily check-ups of diseases and daily behavior management [41–43]. The China Quality of Life Development Report for the Elderly (2019) shows that about 29.6% of the elderly in China have not attended school, 41.5% have a primary school education, and 25.8% have middle and high school education. It can be seen that the literacy level of older people in China is relatively low [44], and the low level of education limits the use of smart products by older people. Finally, due to the deterioration of physical functions, the elderly have difficulty in understanding the operation of smart homes and are worried about not being able to use them independently without help [45, 46].

The low risk group has the highest proportion of high-income people, and income is one of the influencing factors for smart home usage. Smart home products have higher technical requirements for research and development, require a higher level of R&D talents, and have high manufacturing costs. Small companies also find it difficult to enter this industry due to technical and financial problems, making it difficult to achieve scale effects, which leads to the problem of high prices of smart home products, and many users also indicated during the survey that purchase cost is one of the main considerations [47].

The low risk group had a larger urban population, and place of residence was also a significant influencing factor on smart home use, with urban use better than rural. According to the survey, 84.2% of urban students in the Washington State school district reported being able to use reliable broadband to watch instructional videos, while only 67.5% of rural areas agreed [48]. In China, the Internet gap between urban and rural areas is gradually decreasing, but there is still a 24.1% difference in penetration rates [49]. Smart homes are built on the internet, rural Internet infrastructure is weaker than urban areas, and the digital divide is a barrier to the spread of digital health in rural areas [50, 51], which is one of the reasons for the low usage of smart homes in rural areas. In addition to this, there are differences in access to health information between rural and urban residents, with rural residents having less access to health related information from sources such as specialists, magazines and less frequent use of search engines than urban residents [52], which may contribute to rural residents not knowing enough about digital health and smart homes.

Although there are many differences in the demand for smart homes among different health-related risk groups, they also show similarities: men have a significantly higher purchase rate for VR glasses, body cars, smart bracelets, smart pillboxes, smart sockets, and temperature and humidity sensors than women, but women have a significantly higher usage rate for smart drying racks than men. This is mainly determined by lifestyle, income, and subjective willingness. Currently, men generally have higher incomes than the income of women [53, 54], which determines that men have stronger purchasing power for higher-priced smart homes. Secondly, men and women have different household lifestyles; women take on more household chores [55, 56] and maybe more interested in smart drying racks related to household chores, while men have more leisure time at home and purchase more entertainment products. In addition, research has shown significant differences in the technology acceptance between men and women, with men showing a stronger intention to use technology [57, 58], while women are more interested in fashion products during consumption [59] and maybe more interested in daily protection of clothing closely related to fashion.

Looking at the three broad smart home categories, smart TVs have the highest usage rate in the category of entertainment, with VR glasses and body sense cars having lower usage rates. This is related to the high frequency of use and usefulness of TVs as traditional homes [60], while VR glasses and body cars may show lower usage because our sample includes middle aged and elderly people, who are limited by their age and physical mobility [61] to use such exercise products. In the category of functional, smart washing machines and smart air conditioners were used more frequently, while electric curtains, smart hangers, smart mosquito repellents and smart robots were used less frequently. This is related to the influence of the early use of washing machines and air conditioners that are widely used and highly practical, while electric curtains, smart drying racks and mosquito extinguishers are less practical and cost-effective, and smart robots are narrowly used, expensive and technically immature, with most of the experiencers expressing a neutral attitude[62].In the health category, the usage rate of sports bracelets, body fat scales and air purifiers were high, while the usage rate of temperature and humidity sensors, hazard buttons, smoke sensors and smart medicine cabinets was low. This is related to the development of supporting facilities such as the Internet, the popularity of sports bracelets, body fat scales and air purifiers, and their low prices. The rest of the products are not as popular, cost-effective and practical, and have fewer manufacturers. We could not find any information about these products on the official websites of the larger Chinese smart home manufacturers, Xiaomi and Huawei.

Implementing a digital health strategy requires a concerted effort by product manufacturers and the government. As older people consume products with greater consideration for ease of use and practicality, manufacturers should pay more attention to the older market and simplify the steps and the interface design of their products. Studies have shown that user involvement in the product design can effectively improve the quality, relevance and prevalence of work [63, 64], and companies can recruit volunteers to participate in the design process as appropriate to the actual situation. Health products are of importance for aging [42], but the current smart home market has a small range of such products, so manufacturers need to implement the concept of digital health and increase the development, production and promotion of such products. Because of the poor usage of smart homes among the elderly, low-income groups, rural residents and women, manufacturers should pay more attention to the positive and negative factors influencing their purchases and broaden the market for their products.

The high production costs of companies lead to the high pricing of products, which is one of the major obstacles to people using smart homes. The government can enhance policy guidance to attract investors and capital into the smart home market and reduce the production pressure on enterprises. In addition, the government should also encourage enterprises to invest in technology research and development to break through existing technical difficulties, thereby reducing the difficulty of product production and achieving lower product prices. Secondly, because there is also no unified industry-standard specification for smart homes in China [3], while different companies have different product compatibility [65], leading to the problem that elderly users feel more difficult to use in the process. The relevant authorities should formulate industry standards to address this issue and solve the problem of different product compatibility. Finally, the government also needs to pay attention to strengthening the construction of residents' health knowledge system, raising their health awareness, reducing their health-related risks, improving their ability and awareness of using technology for health management, and fully implementing digital health strategies to improve the quality of their healthy lives and achieve health for all.

Our study clustered the five influencing factors of health-related risk: family health, perceived social support, health literacy, chronic disease behavior management and media exposure into three groups: the low risk group, the medium-risk group, and the high risk group, which contributed to a new way of segmentation. In addition to this, the relationship between health-related risk and smart home use has never been looked at in previous studies, but our study demonstrates that smart home use differs between health-related risk groups, with the low health-related risk groups showing better overall smart home use, and confirms that people currently prefer functional smart home products and that low health-related risk groups are also concerned about health products. This suggests that our research hypothesis that different levels of health-related risk influence smart home use are valid. These findings provide important new insights that have implications for the development of the smart home industry and the implementation of digital health strategies.

However, due to limitations in research experience and resources, our study also has certain limitations. Our survey was conducted through respondents retrospectively completing a questionnaire, which may be subject to recall bias. Secondly, our study was a cross-sectional survey and was unable to demonstrate a causal relationship between health-related risks and smart home use, which could be explored in future studies through longitudinal research. Finally, we analyzed health-related risk through five dimensions: family health, perceived social support, health literacy, chronic disease behavior management, and media exposure, possibly ignoring the effect of other variables on health-related risk.

Abbreviations

HLS: Health Literacy Scale

PSSS: Perceived Social Support Scale

FLS: Family Health Score

Self-management: chronic disease self-behavioral management

DEXA：X-ray absorptiometry

SHU：Smart Home Use

CDSMS：Chronic Disease Self-management Study Measure

FHS-SF：Family Health Scale-Short Form

HLS-SF12：Short-Form Health Literacy Instrument

Declarations

Competing interests

The authors have no conflicts of interest to declare.

Availability of data and materials

The datasets supporting the conclusions of this article are included within the article and its additional files. All raw data can be obtained by sending an email to the corresponding author.

Authors’ Contributions

HFY, WYB, YJ, LSW, and CJY participated in the conception and design of the study. WYB, DYQ, ZLP, CJX, and SXY completed the data collection. YJ, LLH, WFJ, KYF, and YSPJTES completed the collation of the data. YJ, CKE, and XJY completed the data analysis and wrote the first draft of the manuscript. CJY, HFY, and LSW contributed to supervising the data analysis and writing the manuscript. All authors contributed to the revision of the article and approved the final draft submitted.

Ethics approval and consent to participate

This study was reviewed by the Ethics Committee of Jinan University and written informed consent was required from all participants. The ethical approval number is JNUKY-2021-018. The study was conducted in accordance with the Declaration of Helsinki of the World Medical Association.

Consent for publication

Not applicable.

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Figures

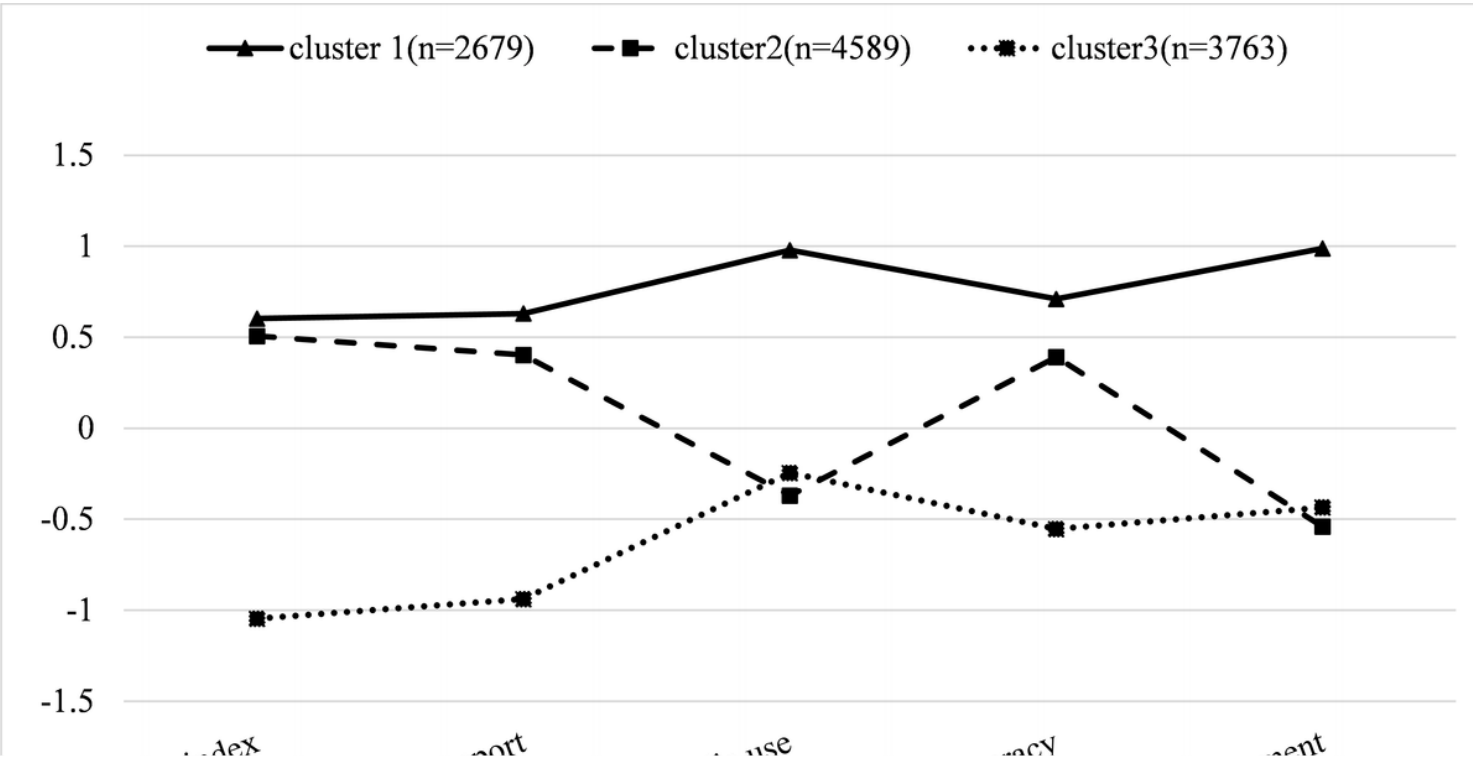

Figure 1

Clusters for health-related risk factors.

Note: The definition of the classes: class 1, low risk; class 2, middle risk; class 3, high risk.

Self-management: chronic disease self-behavioral management.

Supplementary Files

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- SupplementaryMaterials.docx
- database.xlsx