早稲田大学審査学位論文

博士（人間科学）

Roles of Wearable Devices and Traditional Chinese Medicine in Health Management of the Elderly

高齢者の健康管理におけるウェアラブルデバイスと中国伝統医学の役割

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Chapter 1 Background and purpose

1.1 Background

In 2015, there were an estimated 901 million people aged 60 or older and accounting for 12% of the global population [1]. As the general life expectancy continues to increase, the health condition and disease composition of the elderly has also changed, particularly in developing countries [2]. Taking the incidence of hypertension as an example, more than 75% of newly hypertensive patients in the next 10 years will appear in developing countries and most of them are the elderly [3]. These new issues require novel health responses for taking care of the elderly. It is crucial that we pay attention to the health management of the elderly.

The needs of healthy elderly have also changed. The elderly now pay more attention to their own health by participating in health activities and increasing communication with doctors. A survey showed that the demand for health knowledge and needs of health management by the elderly increased yearly [4]. Another study showed that doctor communication is critical during the diagnosis and treatment processes, and the elderly are willing to maintain a good relationship with their doctors to improve convenience of diagnosis [5]. These situations show that it is necessary to find a good way to meet demands of the elderly.

In response to the needs of the elderly, the Chinese government has proposed the use of "information communication technology" and "traditional Chinese medicine" to contribute to health management [6, 7].

1.1.1 Wearable devices in health management

Wearable devices are a new type of tools that play an important role in health management of the elderly [8]. Wearable devices can be combined with the Internet of Things (IoT) to provide comprehensive health management services to the elderly [9]. At present, smart watches, smartphones, and smart clothing are mainstream products embedded with wearable technologies that can execute health management functions [10]. Wearable devices are primarily used in medical institutions to monitor real-time health data and record patient symptoms [11]. Wearable devices are also equipped with the Global Positioning System (GPS) to monitoring the elderly when they are outdoors [12]. However, the current applications for wearable devices among the elderly are relatively few.

Wearable devices have been used to monitor heart disease. Pevnick et al. showed that the use of wearable devices during daily activity prescribed for patients at risk for heart disease [13]. Bravata et al. found that simply wearing pedometers increased daily activity, and lowered body mass index (BMI) and blood pressure. Pedometers help patients manage their blood pressure and prevent their hypertension from worsening [14]. Wearable devices are also used in the treatment of Parkinson's disease. One study showed that wearable devices can monitor patients' physical movements and alert them when experiencing tremors [15]. Wearable devices are used to monitor healthy quality of life among patients with type 2 diabetes by recording sleep patterns and tracking movements [16].

As life expectancy continues to increase, the elderly are becoming more concerned about their health. Studies have shown that wearable devices can be used to collect physiological and motor data to enable patients' condition monitoring, and record the patients' posture and manage rehabilitative behaviors [17]. A combination of wearable devices and the Internet of Things can protect the security of the elderly, reduce their risk of falls, and assist them with improving their quality of life [18].

Health-monitoring devices are used to prevent injuries and facilitate early detection of illnesses or disorders and to implement appropriate interventions [19]. Wearable devices can be used to record a wide range of physiological indicators (e.g., temperature, heart rate, oxygen saturation) or bioelectronics [20].By using wearable devices, the elderly can instantly read their health data, including blood pressure, heart rate, and step count [21].

1.1.2 Traditional Chinese medicine in health management

Traditional Chinese medicine (TCM) has a history of thousands of years. It is formed by summarizing the precious experience of understanding life, maintaining health, and fighting diseases accumulated in daily life, production and medical practice. It not only has systematic theories, but also has abundant preventative and therapeutic methods for disease [72].

Traditional Chinese medicine (TCM) has been recognized as a complementary and alternative medicine in most countries in the world. Traditional medical theories have confirmed that a person is a whole organic unit, and the pulse is one of the body's physiological reactions [142]. A TCM doctor can understand the pathological changes in one's internal organs by conducting a pulse diagnosis. TCM doctors use fingers to feel the pulse by perception of radial space [22].

With the continuous development of informatization, ICT interventions have been implemented across various fields. Instruments such as "pulse diagnosis instruments" record pulse data and classify diagnosis results [89]. Pulse palpation is a convenience diagnostic tool in TCM. However, the mastery of pulse diagnosis requires long-term experience, and remains subjective up to a certain degree even in an advanced stage of practice [23]. Considerable research efforts have been made to objectively measure radial pulse and consequently automate oriental pulse diagnosis using technological aids [24].

An important step in ensuring the objectivity of the pulse diagnosis is standardization. One study has recommended the unification of devices that are used for pulse image acquisition, and similar standardizations are recommended for pulse pattern analysis [25]. On the other hand, the properties of pulse are influenced by physiological and demographic factors such as gender, age, body weight [143]. Although pulse diagnosis instruments are rapidly developing, the penetration rate is not high enough. These instruments are primarily used in the affiliated hospitals of universities [26].

1.2 Literature review

1.2.1 Methods

This study used the Web of Science, PubMed, Institute of Electrical and Electronics Engineers (IEEE), CiNii (Japan), and China Knowledge Network Full Text Database (CNKI) databases, with guideline of collect, organize, and analysis of information in a systematic manner [27]. The Chinese keywords were as follow: “老年人”(meaning elderly)、“可穿戴设备”(meaning wearable device)、“中国传统医学”(meaning Traditional Chinese Medicine)、“健康”(meaning health). The English keywords were as follow: “elderly”, “wearable device”, “Traditional Chinese Medicine”, “health”. The Japanese keywords were as follow: “高齢者”(meaning elderly)、“ウェアラブルデバイス”(meaning wearable device)、“中国伝統医学”(meaning Traditional Chinese Medicine)、

“健康”(meaning health).

Studies were focused on the role of wearable devices and TCM in health management of the elderly, and summarized the eligibility criteria (Table 1-1).

Table 1-1. Eligibility criteria

Inclusion criteria	Exclusion criteria
(1) Documents published from January 1, 1998 to December 31, 2017. (2) Subjects were the elderly (Age ＞ 60 years old). (3) Research variables included use of wearable devices and use of TCM. (4) Published in Chinese, English, or Japanese.	(1) Repeated publication. (2) Original text did not provide relevant evidence and could not be obtained from the author.

According to the Agency for Healthcare Research and Quality (AHRQ), the quality evaluation criteria for observational research include 10 items, with “yes”, “no”, and “unclear” as the answer options [28]. The literature was evaluated from data sources, study design, participants, variables, data, sample size, quantitative variables, and statistical methods.

The literatures were extracted: (1) general information: title of the article, the name of the author, and the date of publication; (2) research characteristics: sample size, general situation, use of wearable devices, use of TCM; (3) outcome indicators: impact of wearable devices or TCM.

Health management is divided into three stages: health monitoring, health analysis, and health promotion [29]. This study analyzed the extracted literatures based on the three stages of health management to explore the role of wearable devices and TCM.

“Health monitoring” was defined as the record of health indicators in the elderly that used wearable devices. Further, “health analysis” was defined as the analysis of data collected by wearable devices [29]. “Health promotion” was defined in the first International Health Promotion

Conference (Ottawa, Canada, 1985), as follows: "the process that enables people to strengthen their health control and improve their health" [30]. In this study, "health promotion" refers to the use of wearable devices and TCM to promote the health of the elderly.

1.2.2 Results

The initial search identified 10,737 studies reviewed. After removal of duplicate publications, 5,369 records were obtained. Following initial screening by reviewer to exclude clearly irrelevant papers, 517 titles and abstracts were selected and subsequently screened independently. Further, 115 articles were identified for full text review. From these, 34 were selected for inclusion. A flow diagram summarized the systematic search and study selection process was given in Figure 1-1.

Table 1-2 presents extracted studies pertaining to the health information record from wearable device for the elderly through the application of various sensors. Table 1-3 presents studies with data collected by wearable devices to analysis the health condition of the elderly. Table 1-4 presents findings of studies extracted regarding health promotion.

All the included articles scored higher than 6 points on the scale. Participants were over 60 years of age, and questionnaires and interviews showed high reliability and validity. The principles of wearable devices in the study were clear. Most of the study variables were well defined, the sample size was sufficient, and the statistical methods were appropriately used (Table 1-5).

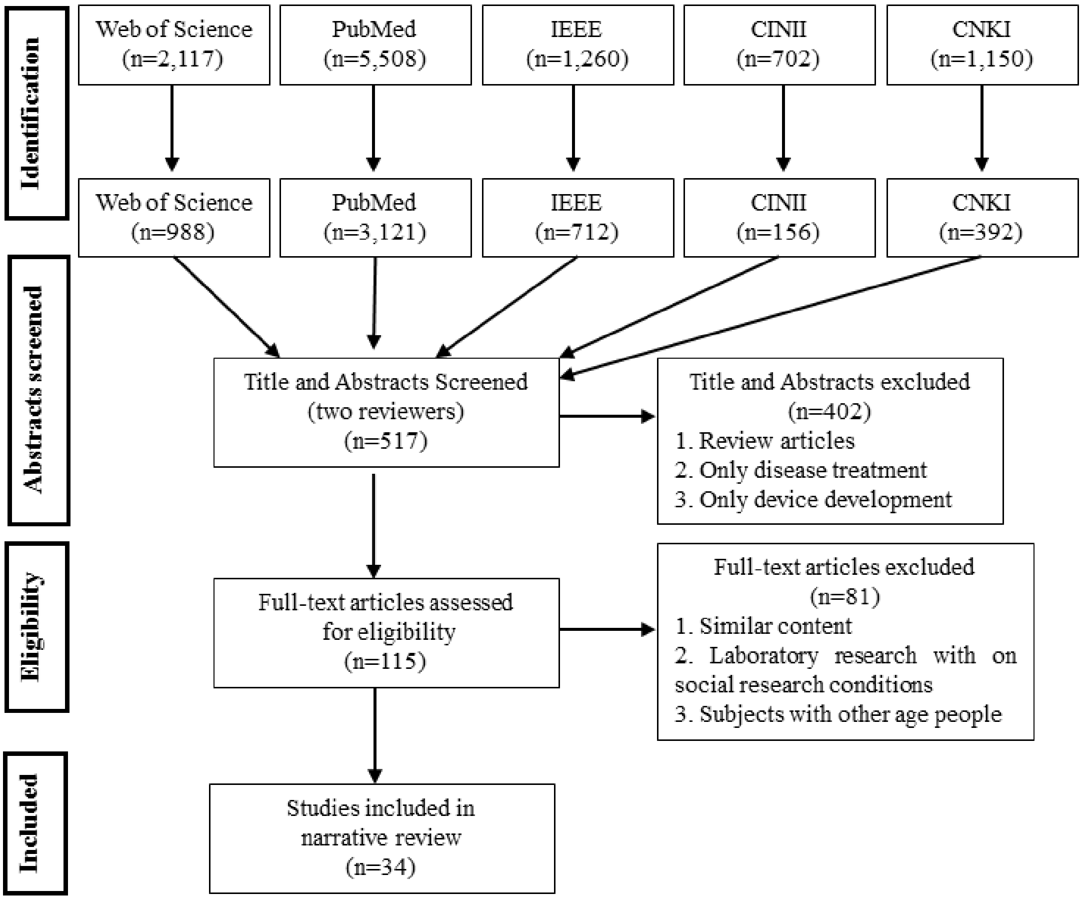

Figure 1-1. Flowchart for previous studies for a systematic review

1.2.2.1 Health monitoring

Cross-sectional and longitudinal study designs were used in health monitoring. Wearable devices monitored the indicators such as position, energy consumption and stress to facilitate more accurate understanding of the participants' condition [33, 36, 40]. One study found that using wearable devices could monitoring the physical performance and physical activity [38]. For the elderly with diseases such as stroke, the behavioral monitoring functions of wearable devices were used to improve gait performance [35, 39]. Other studies also found that the use of wearable devices was associated with the quality of life in the elderly. The wearable device used to measure behaviors such as face-to-face interactions, body posture and activity, and thereby assessed the social attributes and quality of life [31, 32, 34, 37]. In this study, unlike the previous studies focus on the accuracy of wearable devices, the use of wearable devices was related more to the health and social attributes of the elderly.

1.2.2.2 Health analysis

In addition to cross-sectional and longitudinal studies, randomized controlled pilot trial study designs were used effectively to analyze the changes in health by using wearable devices [45]. One study investigated potential attitudinal barriers to home healthcare adoption by use wearable devices [49]. Another major function of wearable devices was to calculate the risk of falls in the elderly by analyzing the walking posture [47, 48, 50]. Several studies analyzed the balancing ability of the elderly. These studies also proposed the recommended walking mode for the elderly [46, 51]. Another implementation modality was to combine wearable devices with other smart hardware. Wearable devices were interfaced with smart medicine boxes which analyzed the use of drugs in real-time, and aimed to prevent misuse use of drugs [42]. Some studies explore the acceptability of the elderly by using wearable devices and found the elderly were mostly accepting of wearable device in health analysis [41, 44].

TCM instruments such as pulse diagnosis instruments and tongue diagnosis instruments analyzed the TCM quantitative data. Among them, the use of machine learning methods was reported to improve the accuracy of TCM instruments [43, 52, 53, 54].

1.2.2.3 Health promotion

Health promotion is a follow-up stage of health monitoring and health analysis. The health effects of wearable devices are mainly in terms of behavior and health indicators improvement. Wearable devices reduced high risk of chronic diseases for the elderly, and corrected any risky elements in walking style such as improving the stability of the trunk during walking [55, 60, 61]. Wearable devices and TCM have been reported to improve the sleep quality, blood circulation irregularities and quality of life [56, 58, 59, 63]. The role of wearable devices and TCM in rehabilitation and stroke were particularly evident among the elderly [62, 64]. Most of elderly participants took Chinese herbal decoction for health promotion [57].

Based on a summary of the 34 included articles, this study formulated a recommended pattern of health management for seniors at all stages (Figure 1-2).

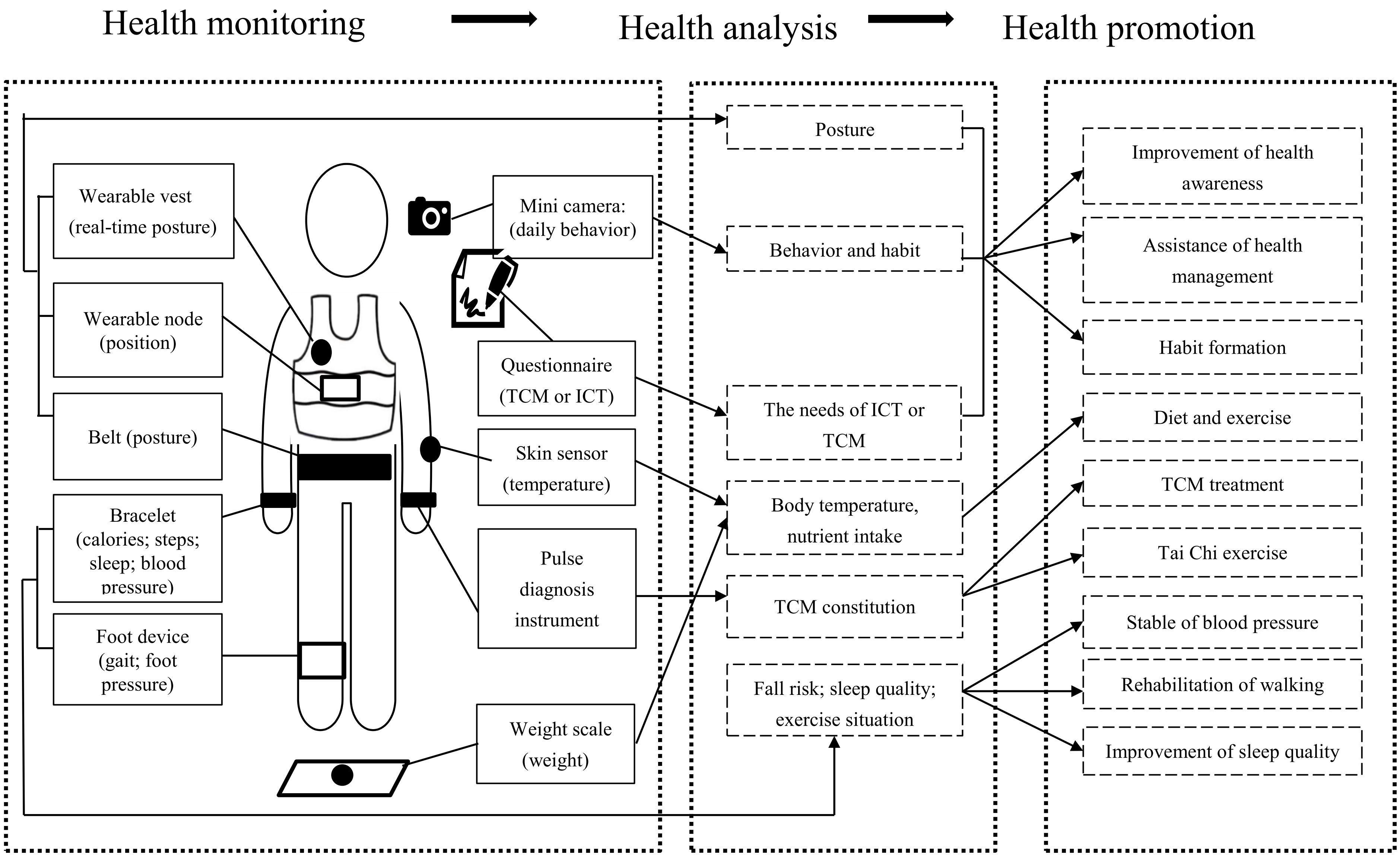

Figure 1-2. Summary of previous studies

Table 1-2. Summary of 10 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices in the health monitoring of the elderly

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Kouhei Masumoto et al., (2017)[31]	To quantitatively measure and visualize face-to-face interactions among the elderly in an exercise program.	27	73	Longitudinal study	*t*-test; Network analysis	Factors affecting interaction: 1. Time of interaction. 2. Inhabitants acceptance. 3. Agreeableness.	Wearable devices' data would be useful for carrying out efficient interventions.
Wenyen Lin et al., (2016)[32]	To test the usability of novel wearable devices in the lives of the elderly.	50	78	Longitudinal study	Path analysis	The development of wearable instrumented vests for posture monitoring could help the elderly realize their posture and activity conditions.	Although the elderly are anxious about some newly developed wearable technologies, they look forward to wearing this instrumented posture monitoring vest in the future.
Tigest Tamrae et al., (2012)[33]	To assess the utility of wearable devices to prevent falls among the elderly.	12	79	Longitudinal study	Contrast sensitivity test	Standing up from a reclined position was used to understanding the difference between fall and non-fall event.	This study provides more data for the machine-learning algorithm to identify true/false positives.
Yingling LR et al., (2017)[34]	To explore the user characteristics for wearable technology among community-based population.	99	60	Longitudinal study	Fisher's exact tests; Logistic regression analysis	Lower socioeconomic individuals may be more likely than higher SES participants to interact with the hub-based m-Health.	M-Health systems with a wearable device and data collection hub may feasibly target PA in resource-limited communities.
Sarah A. Moore et al., (2017)[35]	To determine the feasibility, validity, and reliability of stroke gaits application based on wearable devices.	25	63	Cross sectional	Shapiro-Wilk test; Spearman's rank correlation	1. Wearable devices accurately reflect the step count. 2. The reliability of the wearable device is good.	The AX3 wearable system promises to be a feasible and reliable tool to measure gait characteristics after stroke.

Abbreviations: ANOVA, analysis of variance; GEMS, Gait-enhancing Mechatronic System; BMI, body mass index; PA, physical activity; TEE, total energy expenditure; PP, physical performance; HSD, honestly significant difference.

Table 1-2. Summary of 10 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices in the health monitoring of the elderly (Continued)

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Jane Murphy et al., (2017)[36]	To estimate the relationship between daily energy expenditure and patterns of activity by using wearable devices.	20	78	Longitudinal study	*t*-test; Multiple stepwise linear regression	After taking BMI and sleep duration into consideration, TEE no longer correlated with energy intake.	Wearable devices have the potential to offer real-time monitoring to provide appropriate nutrition management.
Gemma Wilson et al., (2016)[37]	To explore the acceptance, experience, and usability of a wearable camera.	18	66	Qualitative study	Semi-structured interviews; Thematic analysis	Camera is useful for record behavior.	The experience of wearable cameras varies greatly, and affects the rate of usage by the elderly.
Van Lummel RC et al., (2015)[38]	To explore the relationships among PP and PA measures.	49	82	Cross sectional study	Spearman's rank correlations; Factor analysis	1. Strength of the association between PP and PA is depend on the activity type 2. Monitoring capabilities of wearable device is sustainable.	PP and PA represent associated separate domains of physical functions for the elderly.
Su-Hyun Lee et al., (2017)[39]	To verify a robotic exoskeleton device aimed to improve gait performance and quality of life.	30	74	Longitudinal study with computer assisted	ANOVA; Tukey's HSD test	Foot pressure distribution is increase by using GEMS.	Wearable device such like GEMS may present an alternative way of restoring age-related changes in gait.
Basel Kikhia et al., (2016)[40]	To measure the stress level in the elderly with dementia by using a wristband sensors.	6	75	Longitudinal study	Comparison of negative and positive	Wearable devices can be used to detect pressure conditions at different levels of thresholds.	Wearable devices can provide clinicians with pressure-aware information for older patients.

Abbreviations: ANOVA, analysis of variance; GEMS, Gait-enhancing Mechatronic System; BMI, body mass index; PA, physical activity; TEE, total energy expenditure; PP, physical performance; HSD, honestly significant difference.

Table 1-3. Summary of 14 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices and traditional Chinese medicine in the health analysis of the elderly

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Yu-Min Fang et al., (2016)[41]	To explore the acceptability of the elderly by using wearable devices.	24	65	Cross sectional study	*t*-test; Multiple stepwise linear regression	Personal attributes and requirement for medical care affect the psychological perception and attitudes.	Wrist was the most favorable location to attach a wearable device.
Blaine Reeder et al., (2013)[42]	To explore the role of wearable devices in drug management.	96	80	Longitudinal study	Multiple stepwise linear regression	Nearly all participants perceived the medication dispensing device is easy to use.	The wearable device can alert the patient in drug management.
Aini Fu et al., (2014)[43]	To find the needs of TCM and influencing factors of community health services.	612	68	Cross sectional study	Descriptive analysis	1. The elderly's satisfaction with TCM is 64.6%. 2. The most dissatisfied is few number of TCM doctors.	There is a need to increase the satisfaction of TCM and increase the number of TCM doctors.
Arjun Puri et al., (2017)[44]	To assess acceptance and usage of wearable activity trackers.	20	64	Cross sectional study	Wilcoxon signed rank test; Multivariable regression analysis	1. Smartphones designed as facilitators of wearable activity trackers. 2. Privacy is less of a concern for wearable activity trackers.	Wearable activity trackers were uniquely considered more personal than other types of technologies.
Elizabeth J Lyons et al., (2017)[45]	To determine the feasibility, acceptability, and effect on physical activity of wearable devices.	40	61	Randomized controlled pilot trial	ANCOVA; Box-Cox transformations	Physical activity and sedentary behavior intervention using wearable device was found to be feasible and acceptable in the elderly.	Wearable devices analyze the energy for increasing physical activity and decreasing sedentary behavior.

Abbreviations: ANCOVA, analysis of covariance; SVM, support vector machine; SVM-REF, support vector machine recursive feature; CHD, Coronary heart disease.

Table 1-3. Summary of 14 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices and traditional Chinese medicine in the health analysis of the elderly (Continued)

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Michael Schwenk et al., (2015)[46]	To examine the ability of wearable devices, sensor-based, in-home assessment of gait.	125	79	Cross sectional study	Chi-square test; ANCOVA; Logistic regression	Gait speed, hip sway, and steps/day were the most sensitive parameters for identification of pre-frailty.	Present findings highlight the potential of wearable sensor technology for in-home assessment of frailty condition.
Fang Wang et al., (2013)[47]	To exploit a webcam-based system for in-home gait assessment of the elderly.	8	87	Longitudinal study	Gait Analysis Methodology	Using wearable devices to evaluate gait can improve the health of the elderly.	The using of wearable devices provides support for gait assessment in the home.
Michael Marschollek et al., (2011)[48]	To assess the risk of falling in the elderly by using wearable devices.	50	65	Longitudinal study	Simple logistic regression	A fall model built with a wearable device can be applied to the elderly.	Sensor-based objective measurements of motion parameters in patients can used to assess individual fall risk.
Neil Charness et al., (2017)[49]	To explore supportive home health care technology for the elderly.	35	75	Cross sectional study	Multiple regression	The elderly had stable ratings for comfort while wearing wearable device to collect data.	The elderly are willing to use comfortable wearable devices.
George Demiris et al., (2016)[50]	To explore the availability of wearable devices.	8	86	Longitudinal study	Interview; Descriptive study	While participants enjoyed wearable devices, they were unhappy with the volume of false alarms and obtrusiveness.	Wearable devices need to have high accuracy which suitable for the elderly.
Dylan Drover et al., (2017)[51]	To developing algorithms-based faller classification method.	76	74	Longitudinal study	Machine learning	The risk of the elderly walking when turning is higher than going straight.	The fall detection device has different algorithms in different walking situations.

Abbreviations: ANCOVA, analysis of covariance; SVM, support vector machine; SVM-REF, support vector machine recursive feature; CHD, Coronary heart disease.

Table 1-3. Summary of 14 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices and traditional Chinese medicine in the health analysis of the elderly (Continued)

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Fufeng Li et al., (2012)[52]	To provide an automatic and quantitative approach for the diagnosis of TCM based on the lip images.	257	65	Cross sectional study	Machine learning	SVM-REF achieves the best classification accuracy in feature selection.	Automatic and quantitative diagnosis system of TCM is effective to distinguish four lip image classes.
Rui Guo et al., (2015)[53]	To distinguishing between patients with the coronary heart disease and normal people by using TCM pulse diagnosis.	50	65	Cross sectional study	Machine learning	There were significant differences in the pulse energy between the CHD group and normal group.	TCM pulse classification could be appropriately used to analyze pulses of patients with CHD.
Jianfeng Zhang et al., (2016)[54]	To develop a diagnostic method of diabetes based on standardized tongue image using SVM.	296	60	Cross sectional study	Machine learning	The accuracy rate of cross validation was grown from 72% to 83.06% by using SVM.	TCM tongue diagnosis can be discriminated by machine learning.

Abbreviations: ANCOVA, analysis of covariance; SVM, support vector machine; SVM-REF, support vector machine recursive feature; CHD, Coronary heart disease.

Table 1-4. Summary of 10 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices and traditional Chinese medicine in health promotion among the elderly

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Laura Sookhai et al., (2015) [55]	To analyze the health behavior of the elderly using activity trackers.	17	70	Longitudinal study	Descriptive analysis	The elderly health awareness with the use of activity trackers is increased.	Activity tracker makes it easy for the elderly to understand their behavior.
Ryang-Hee Kim et al., (2012)[56]	To evaluate the effectiveness of SHGS for hypertensive treatment.	12	65	Longitudinal study	*t*-test; Wilcoxon signed rank test	All patients' blood pressure dropped to the normal range after wearing SHGS.	SHGS decreases blood pressure, improves irregular blood circulation, and can be an effective device for the elderly.
Liu Zhongdi et al., (2017)[57]	To investigate understood and used TCM of the elderly.	3,410	61	Cross sectional study	Chi-square test	1. 80.7% of residents believed TCM was effective in disease treatment. 2. 85.7% of residents taken TCM patent drug.	TCM is highly trusted in the elderly.
Haiying Kong et al ., (2011)[58]	To explore how TCM is used as a tool of construction in elderly life.	20	64	Cross sectional study	Grounded theory	TCM allows elderly to: 1. Reaffirm cultural identity. 2. Fulfill social roles.	TCM has social significance for the elderly in addition to clinical significance.
Timothy Kwok et al., (2013)[59]	To investigate the effectiveness of acupuncture on sleep quality of elderly with dementia.	19	88	Longitudinal study	Wilcoxon signed rank tests	Subjects gained significantly more resting time and total sleep time in treatment period than control period.	TCM therapy combined with wearable devices can improve the sleep quality in the elderly.
Hwang-Jae Lee et al., (2017)[60]	To investigate the effectiveness of a newly developed wearable hip assist robot.	30	74	Longitudinal study	ANOVA	Participants demonstrated improved gait function, decreased muscle effort, and reduced metabolic cost.	Wearable hip assist robot has the potential to improve stabilization of the trunk during walking in the elderly.

Abbreviations: SHGS, Smart Healthcare Glove System; ANOVA, analysis of variance; GEE, generalized estimating equation; TCM, traditional Chinese medicine; ICT, information and communications technology; QOL, quality of life.

Table 1-4. Summary of 10 studies published worldwide from January 1, 1998 to December 31, 2017 in Chinese, English, or Japanese, which evaluated the role of wearable devices and traditional Chinese medicine in health promotion among the elderly (Continued)

Citation	Study purpose	Samples	Average age	Study design	Analytic methods	Finding	Conclusion
Liangfeng Pan et al., (2016)[61]	To explore the intervention effect of wearable devices on groups at high risk with chronic non-communicable diseases.	400	67	Longitudinal study	Chi-square test	The number of health indicators, diet and exercise improvement in chronically ill patients have increased.	Wearable devices can reduce high risk of chronic diseases through correct behaviors.
Nancye M. Peel et al., (2016)[62]	To test whether activity levels can be increased by the provision of monitored activity data to patients.	255	81	Randomized controlled trial	Chi-square test; GEE regression model	Subjects in the intervention group had significantly higher walking time than control group.	Objective monitoring of activity levels by using wearable devices could provide clinicians with information.
Helena A Figueira et al., (2010)[63]	To establish the possible impact of TCM techniques on the QOL of the elderly.	36	70	Randomized controlled trial	*t*-test; Mann–Whitney U test	Positive effect was observed in QOL scores for those using TCM, as compared to the general population.	TCM might raise QOL of the elderly.
Chien-Chang Liao et al.,(2012)[64]	To investigates how TCM is used in stroke patients.	359	65	Cross sectional study	Chi-square test; Multivariate logistic regression	1. The utilization rate of TCM was higher in stroke patients than in the general population. 2. Women were more likely to use TCM.	Patients with history of stroke have higher TCM utilization rate than people without history of stroke.

Abbreviations: SHGS, Smart Healthcare Glove System; ANOVA, analysis of variance; GEE, generalized estimating equation; TCM, traditional Chinese medicine; ICT, information and communications technology; QOL, quality of life.

Table 1-5. Methodological quality assessment of included studies

		Evaluation entry										
Stage	Author	①	②	③	④	⑤	⑥	⑦	⑧	⑨	⑩	Total
Health monitor -ing	Kouhei Masumoto(2017)[31]	Y	Y	Y	N/A	Y	Y	Y	Y	Y	Y	9
	Wen-yen Lin (2016)[32]	Y	N/A	Y	N/A	Y	Y	Y	N	Y	Y	7
	Tigest Tamrae (2012)[33]	Y	Y	N	N/A	Y	Y	Y	N	Y	Y	7
	Leah R Yingling, BS (2017)[34]	Y	Y	N	N/A	Y	Y	Y	N	N	Y	6
	Sarah A. Moore (2017)[35]	Y	Y	Y	N/A	Y	Y	Y	N	Y	Y	8
	Jane Murphy (2017)[36]	Y	Y	Y	N/A	Y	Y	Y	Y	Y	Y	9
	Gemma Wilson (2016)[37]	Y	Y	N	N/A	Y	N	Y	N	Y	Y	6
	Rob C. van Lummel (2015)[38]	Y	Y	N	N/A	Y	Y	Y	N	Y	Y	7
	Su-hyun Lee (2017)[39]	Y	Y	Y	N/A	Y	Y	Y	Y	Y	Y	9
	Basel Kikhia (2016)[40]	Y	Y	Y	N/A	Y	Y	N	N	Y	Y	7
Health analysis	Yu-min Fang (2016)[41]	Y	Y	Y	N/A	Y	Y	Y	N	Y	Y	8
	Blaine Reeder (2013)[42]	Y	Y	Y	N/A	Y	N	Y	Y	N	Y	7
	Aini Fu (2014)[43]	Y	Y	N	N/A	Y	N	Y	Y	N	Y	6
	Arjun Puri (2017)[44]	Y	Y	Y	N/A	Y	Y	Y	Y	Y	Y	9
	Elizabeth J Lyons (2017) [45]	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	10
	Michael Schwenk (2015)[46]	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	9
	Fang Wang (2013) [47]	Y	Y	N	N/A	Y	Y	Y	Y	Y	Y	8
	Michael Marschollek (2011)[48]	Y	Y	N	N/A	Y	N	Y	Y	Y	Y	7
	Neil Charness (2017)[49]	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	9
	George Demiris (2016) [50]	Y	Y	N	N/A	Y	Y	Y	Y	Y	Y	8
	Dylan Drover (2017)[51]	Y	Y	N	N/A	Y	N	Y	Y	Y	Y	7
	Fufeng Li (2012)[52]	Y	Y	N	N/A	Y	N	N	Y	Y	Y	6
	Rui Guo (2015)[53]	Y	Y	N	N/A	Y	N	N	Y	Y	Y	6
	Jianfeng Zhang (2016)[54]	Y	Y	N	N/A	Y	N	Y	Y	Y	Y	7
Health promoti -on	Laura Sookhai (2015)[55]	Y	Y	N	Y	Y	N	Y	Y	Y	N	7
	Ryang-Hee Kim (2012)[56]	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	10
	Zhongdi Liu(2017) [57]	Y	Y	Y	N/A	Y	Y	Y	Y	Y	Y	9
	Haiying Kong (2011)[58]	Y	Y	Y	N/A	Y	N	Y	Y	Y	Y	8
	Timothy Kwok (2013)[59]	Y	Y	Y	N/A	Y	Y	Y	Y	Y	Y	9
	Hwang-Jae Lee (2017)[60]	Y	Y	Y	Y	N	N	N	Y	Y	Y	7
	Liangfeng Pan (2016)[61]	Y	Y	Y	N/A	Y	N	Y	Y	Y	Y	8
	Nancye M. Peel (2016)[62]	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	10
	Helena A Figueira (2010)[63]	Y	Y	Y	N/A	Y	N	N	Y	Y	Y	7
	Chien-chang Liao (2012)[64]	Y	Y	N	N/A	Y	N	Y	Y	Y	Y	7

Evaluation item Note: (Y: indicates yes, N: indicates no or not mentioned; N/A: not clear)

①Is the source clear? ②Are the inclusion and exclusion criteria for exposed and non-exposed groups listed or referenced to previous publications? ③ Is the patient evaluation time period mentioned? ④It is a source of field investigation? ⑤Subjective factors of the evaluator does not mask other aspects of the research object? ⑥ Has any assessment for quality assurance been performed? ⑦ Are the reasons for excluding patients from the analysis explained? ⑧ Is the evaluation and control confounding factors described? ⑨ If possible, data processing and analysis been explained? ⑩ Have patient response rate and data collection integrity aspects been summarized?

1.2.3 Discussion

This study summarizes the role of wearable devices and TCM in the health management of the elderly. Since wearable devices integrate various sensors, the objective data recorded by the sensors is more accurate than the subjective feelings, which allows the elderly to have a better understanding of their health [49]. The continuous monitoring of data by wearable devices can more fully reflect the health condition [38]. Wearable device function as a reminder of risk factors for falls that allow the elderly to better control their behavior when they walking [46,51]. Regarding social aspects, wearable devices have a recording function that can sense the unconscious behavior of the elderly [31, 37]. However, it is also found that some limitations of wearable devices have been reported. Wearable devices are now still relatively expensive for the elderly [144]. Wearable devices are not yet popular in health management [145].

TCM plays an important role in the health management of the elderly. TCM is characterized by its low price and convenient diagnosis [65]. TCM has a significant effect in the treatment of chronic diseases, and TCM treatment methods are very popular among the elderly [146]. With the development of ICT, quantitative analysis of pulse is become possible [66]. It is reported that pulse diagnosis, tongue diagnosis, and other treatment methods can recorded through wearable devices, and analyzed by machine learning algorithms to understand health condition [54,67]. TCM is also used as a complementary medical that used in the world [68]. However, TCM also has some limitations. The diagnosis based on experience and documented in ancient books [69]. TCM doctors often rely on abstract descriptions in their interpretation [70]. The association between pulse and health indicators is not clear [71, 72].

1.3 Purpose and organization of this study

The purpose of this study is to analyze the roles of wearable device and traditional Chinese medicine in health management of the elderly.

Chapter 1 begins with the introduction and literature review. With the continuous development of ICT in recent years, it is possible to use wearable devices and TCM to assist the elderly to management their health. However, there are some problems that remain unsolved: (1) the indeterminate of pulse diagnosis instruments for healthy adults [53]; (2) associations between pulse and health indicators are unclear [72]; and (3) there remains a lack of studies on TCM doctors' evaluations of wearable devices and pulse diagnosis instruments.

Chapter 2 presents an analysis of changes in health indicators of the elderly using wearable devices. 18 elderly were selected as subjects, and wearable devices were used to collect their health data, which included step count, sleep quality, blood pressure, and heart rate. The duration of the study lasted for 4 months. This study measured temporal changes in health indicators and analyzed the causes of changes in the health condition of the elderly. Additionally, another study examined the role of wearable devices in observable changes in social capital.

Chapter 3 includes three studies. Chapter 3-1 presents the results of two analytical methods that pertain to the diagnostic accuracy of pulse diagnosis instruments. Pulse diagnosis instruments and a TCM doctor diagnose the pulse, and medical statistics and machine learning methods are used to calculate the diagnostic accuracy. The results showed that the accuracy was different for single pulse and composite pulse. In Chapter 3-2, pulse and health indicators were obtained from 8 elderly using wearable devices and pulse diagnosis instruments. Subsequently, the associations of pulse and health indicators were analyzed. Chapter 3-3 predicted changes of step count by using wearable devices. The time series method was used to predict the health indicators changes of the elderly.

Chapter 4 presents TCM doctors' evaluations of wearable devices and pulse diagnosis instruments. Through semi-structured interviews with 10 TCM doctors, it is possible to understand their evaluations of wearable devices and pulse diagnosis instruments.

Chapter 5 summarizes the contents that have been presented in Chapters 1–4. Additionally, this chapter explicates the innovativeness and effectiveness of this study. Finally, after comprehensive review, the significance to the field of human sciences is explicated (Figure 1-3).

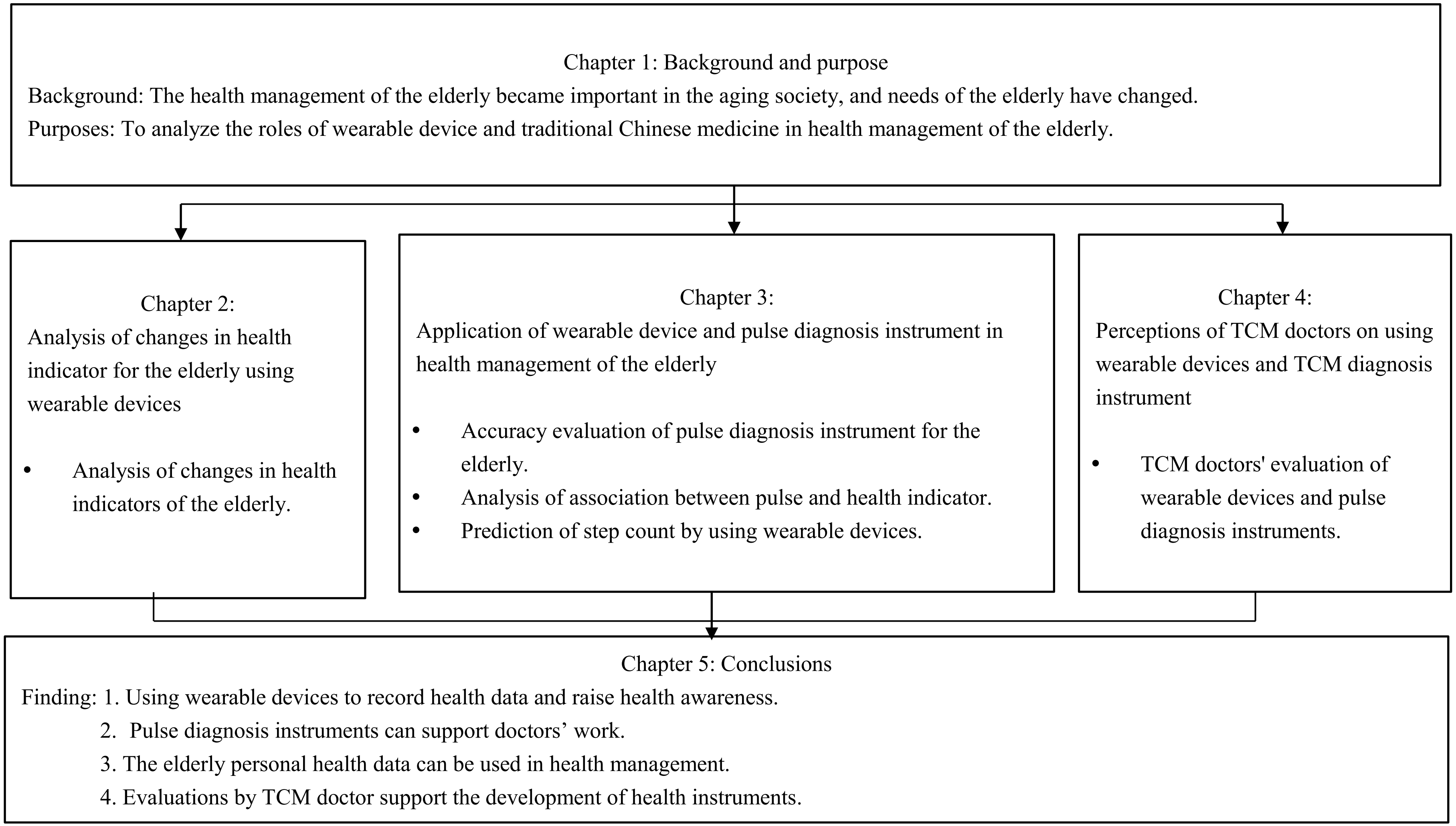

Figure 1-3. Organization of the thesis

Chapter 2 Analysis of changes in health indicator for the elderly using wearable devices

2.1 Introduction

Wearable devices are being increasingly used in recent years. Based on the use of wearable devices, garments with embedded sensors can detect motion and location [73]. The detection of chronic diseases is also an important scenario for wearable devices. In order to manage patients with epilepsy, risk of falls, heart disease, breathing problems, or other chronic diseases, wearable devices were used to track their health data and communicate with their doctors [74]. Through the tandem connection between wearable devices and IoT, an effective closed loop is formed, which provides full-time health services to the elderly [42]. With the convergence of wearable devices, various instruments of healthcare and medicine have been developed to improve the service efficiency and promote the health of the elderly.

The purpose of this study is analysis of changes in health indicators of the elderly using wearable devices.

2.2 Subjects and methods

2.2.1 Subjects

20 elderly were selected from February 1st to May 31st 2017, in Hangzhou and Jiaxing, Zhejiang Province, China. The sample included 9 men and 11 women, aged 58 to 68 years (average age 63.44 ± 3.55 years). The inclusion criteria were: (1) male age ≥ 60 years, female age ≥ 55 years; (2) have clear consciousness and normal communication; (3) voluntary participation in the study and provide signed informed consent. The exclusion criteria were the presence of: (1) cognitive

dysfunction; (2) severe complications; (3) previous history of mental illness or taking antipsychotic drugs; (4) severe liver and kidney dysfunction or heart disease. Based on the sample size proposed method, PASS software (Power Analysis and Sample Size) was used for calculation. The minimum sample size is 14 people. The sample calculation formula is (2-1):

$$M = 2[\,1 + (K-1)_p]\frac{\sigma^2(Z_{1-\frac{\alpha}{2}}+Z_{1-\beta})^2}{K\delta^2} \tag{2-1}$$

This study was approved by the Waseda University Ethics Committee (ID: 2017-224).

2.2.2 Data collection method

In this study, bracelets produced by 37 Degree Technology were used to record health data (Figure 2-1). The specifications of the bracelet are: main dimension: 42.8*17.3*9.8 mm; weight: 24 g; full length: 238 mm; waterproof level: IP67+; communication: Bluetooth low energy; and system requirement: Android 4.3+ or IOS 7+. The bracelet can detect heart and lung function (blood pressure, heart rates, and respiratory rates), record the step count and sleep quality. The implementation method included: (1) communicated one-to-one with the elderly, and taught the elderly how to wear the bracelet and use the application (37 Degree Technology); (2) the elderly send their health data to the researchers every day, at 20:00; (3) used the application data export function and send weekly data to the researchers every week.

Figure 2-1. Smart health bracelet (June 15, 2017, photograph by author)

2.2.3 Research quality control

All researcher involved in the field investigation underwent rigorous training and assessment. During the investigation, data on the elderly were recorded accurately. The notes were maintained in the research office. The results of the daily investigations were audited, such that abnormality in data could be verified. As two bracelets were found to be defective during the research process, the final analysis included 18 individuals.

2.2.4 Statistical methods

SPSS20.0 software was used for the statistical analysis. The data were expressed as "$\chi \pm s$." The experiment time was divided into 4 months, using one-way analysis of variance (ANOVA), based on the confirmation of the homogeneity of variance, judging the changes in the step count, blood pressure, sleep quality and heart rate during the period when the wearable devices were used. The mean blood pressure was calculated as: Mean blood pressure = Diastolic blood pressure + (Systolic blood pressure - Diastolic blood pressure) / 3.

2.3 Results

2.3.1 General descriptive statistics

In terms of the general characteristics of the subjects, there were 11 women and 7 men who met the inclusion criteria and their specific health indicators are shown in Table 2-1. The average step count for 15 of the subjects was more than 8,000, and achieved the National healthy exercise walking steps standard [75]. In terms of the sleep quality, 6 of the subjects were more than 90 points, while the remaining 12 people had scored in the 80-90 range. As for the blood pressure, 3 elderly' daily average systolic blood pressure higher than 130 mmHg, and diastolic blood pressure values higher than 89 mmHg. The heart rate of all the subjects was 60-100 times/min, and was in line with the health standard [75]. All the subjects had a respiratory rate in the 12-24 breaths/minute range; this was also in line with the health standard [75].

Table 2-1. General situation of the respondents

No.	Steps	Sleep quality (score)	SBP (mmHg)	DBP (mmHg)	Heart rate (bpm)	Respiratory rate (breaths/min)
1	9,648.6±2935.7	86.3±7.2	115.6±15.0	80.7±11.2	69.8±8.3	17.5±3.2
2	12,696.1±3671.1	91.1±3.8	135.4±10.2	93.4±7.6	76.2±6.9	17.7±4.0
3	6,373.3±3064.7	90.2±3.7	131.8±12.5	89.9±9.7	81.5±10.6	17.7±3.9
4	8,360.8±2881.5	89.8±3.3	122.0±9.0	85.2±8.6	77.5±11.4	17.7±3.4
5	10,227.2±2866.8	90.5±4.0	121.4±12.0	86.2±10.1	77.2±10.1	19.7±4.1
6	9,425.8±2399.1	81.5±8.1	127.5±8.7	88.3±8.9	83.8±7.8	18.7±3.2
7	7,965.2±2394.5	91.6±2.4	117.4±11.5	81.2±8.7	78.5±9.6	18.3±2.9
8	11,898.0±2832.6	94.1±3.8	122.7±11.5	84.1±10.3	78.4±10.0	16.7±3.4
9	12,115.3±3426.7	85.6±5.7	115.2±14.5	77.0±10.8	79.5±9.6	18.0±3.5
10	5,538.0±2095.2	85.5±5.8	124.9±10.8	86.1±10.3	78.9±12.0	18.7±3.2
11	9,539.3±3419.1	89.8±6.4	118.3±12.5	84.6±11.0	72.9±9.7	19.1±4.1
12	15,010.4±3939.8	86.6±5.1	118.3±12.9	79.6±8.5	74.0±11.9	17.6±4.0
13	14,157.2±3043.6	90.7±4.4	118.1±8.6	79.4±8.8	73.7±8.9	18.2±4.2
14	8,960.7±3331.4	82.3±7.4	124.1±9.1	84.3±7.8	70.5±11.5	19.1±3.9
15	10,021.6±1574.5	83.4±7.7	112.2±11.9	73.5±10.2	76.6±10.3	18.5±3.8
16	8,262.2±2194.8	86.6±4.0	125.1±9.5	78.8±6.9	75.5±8.6	16.7±2.6
17	7,710.4±2193.9	87.8±4.4	133.1±8.9	89.8±8.9	76.1±4.5	15.8±2.6
18	8,943.8±2010.3	87.0±4.8	126.4±8.3	83.0±7.8	85.5±5.7	16.6±2.3

SBP: Systolic blood pressure; DBP: Diastolic blood pressure

2.3.2 Changes of the health condition

The time period was divided into 4 months, and changes of the step count, sleep quality, blood pressure, and heart rate were analyzed. After the one-way ANOVA was performed, the step count, mean blood pressure and heart rate were found to be significantly changed; no significant changes were observed in terms of sleep quality. The monthly average step count steadily increased in 4 months. The average step count in the 3 months following the 1st month was higher than in the 1st month (Figure 2-2). In terms of blood pressure, the mean blood pressure of the elderly was found to be gradually stabilized, and showed a downward trend (Figure 2-3). In terms of heart rate, the elderly generally maintained in normal range (Figure 2-4). Finally, Jonckheere-Terpstra trend test was used to analysis the trend of step count and blood pressure. The results showed that the trend of step count was increased and the trend of blood pressure was stable.

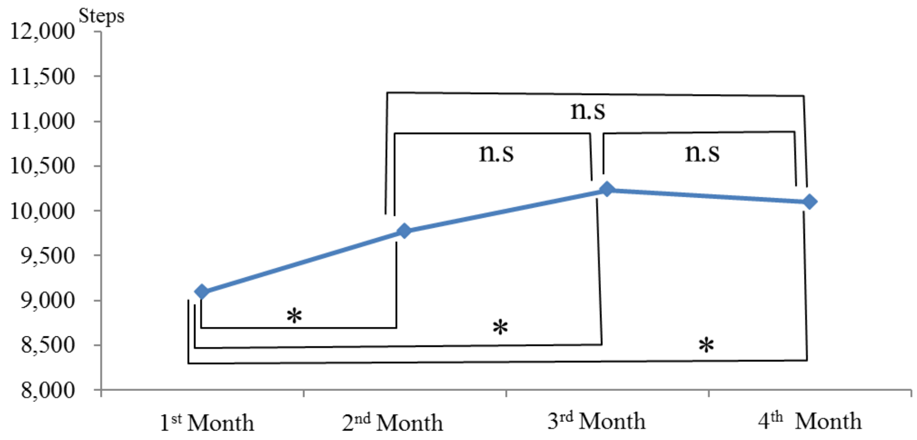

Figure 2-2. Changes of step count (One-way ANOVA)

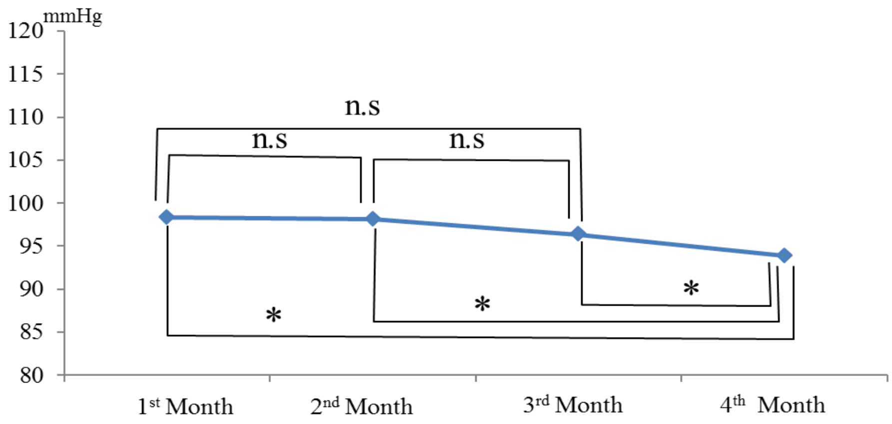

Figure 2-3. Changes of blood pressure (One-way ANOVA)

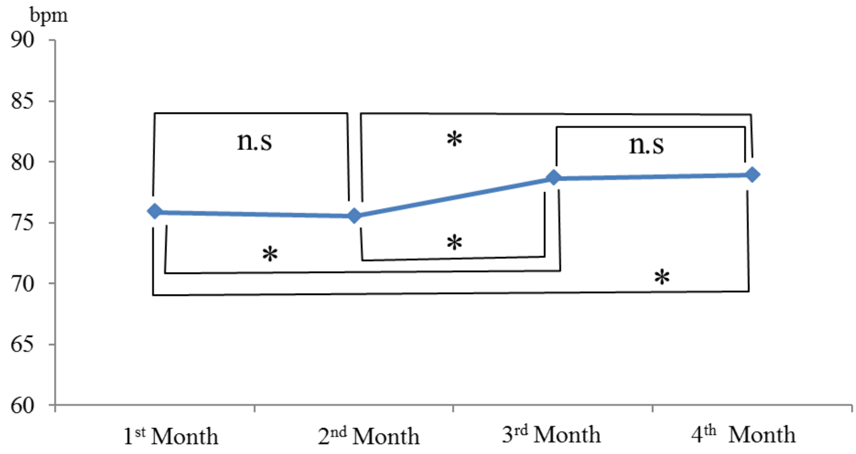

Figure 2-4 Changes of heart rate (One-way ANOVA)

2.4 Discussion

This study showed that wearable devices can continuously record the health indicators of the elderly through 4 months. This indicated that wearable devices can be used as a tool for long-term health management of the elderly.

First, the use of wearable devices aids the elderly in visualizing their health data. Table 2-1 showed that subjects were healthy; they had exercise habits, and their sleep quality was generally higher. According to the health standard pertaining to heart rate and respiratory rate (heart rate: 60 to 100 beats / min; respiratory rate: 12 to 24 breaths / min) [75], the values were within the normal range. Through the display of mobile application, the elderly can have a clear understanding of their health. Visualization helps the elderly understand health information more clearly [76]. A study shows that visualization of health indicators for the elderly helps them to focus on their health [77].

Second, the use of the wearable devices made the elderly pay close attention to their health. The health condition was found different across various periods. The average step count in the 3 months following the first month was higher than that taken in the first month. There are 2 reasons for this result: (1) with the onset of warming weather conditions, the demand for the elderly in outdoor exercises was increased [78]; (2) after the initial phase of adapting to use, the elderly approval of wearable devices made them willing to using them [45]. A study has showed that habitual walking can safely and effectively contribute to the blood pressure lowering [79]. ANOVA showed that the step count, blood pressure and heart rate were significantly different as the months changed. The use of wearable devices can help the elderly record continuous step count [80]. The health awareness of the elderly is improved after using wearable devices, and the elderly are willing to improve their health through exercise.

It is thought that the use of wearable devices contributed to the extension of the social capital, predominantly in the following areas:

(1) After using wearable devices, the elderly are willing to share their health data with family and friends. A study has shown that the elderly are willing to inform their families about their health information through used ICTs [81].

(2) The elderly are willing to increase health knowledge. A study has shown that the elderly are concerned with health knowledge [82].

(3) The elderly will tell their family or friends to monitor their daily activities. A study has shown that elderly who are able to obtain supervision are more aware of their health goals and can refine daily exercise schedules [83].

Chapter 3 Application of wearable device and pulse diagnosis instrument in health management of the elderly

3.1 Accuracy evaluation of pulse diagnosis instrument for the elderly

3.1.1 Introduction

TCM doctors perform pulse diagnosis to examine pathological changes in internal organs by using three fingers to touch three special positions on a patient's body to determine the radial artery pulse [147] (Figure 3-1). All these diagnostic methods require considerable skills and knowledge from experienced TCM doctors, and it takes beginners many years to understand the complicated relationships between symptoms and different diseases [84]. Among the four diagnoses methods, pulse diagnosis is the most recognized. A study indicated that pulse diagnosis is most used, about 44%, among the four diagnostic methods [85].

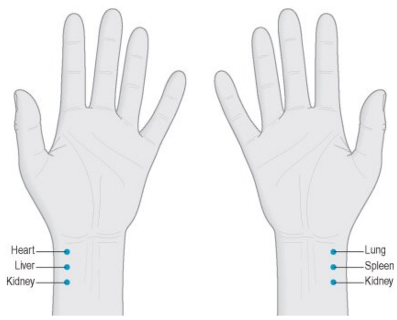

Figure 3-1. Pulse diagnosis location map

Machine learning has evolved from the study of pattern recognition and computational learning, which constantly improves its algorithms by using big data. Machine learning has now been applied in medical fields [86].

In the TCM field, many diagnosis devices have been developed to help TCM doctors with diagnosis. Luo et al. did a study using a Bi-Sensing Pulse Diagnosis Instrument (BSPDI), and proposed a novel plain pulse wave (PPW) to classify string like pulses based on an array of pulse signals, mimicking TCM doctors' finger-reading skill [87]. Zhang et al. used flexible sensors to capture radial artery pressure pulse waves and utilized high frequency B mode ultrasound scanning technology to synchronously obtain information on radial extensions and axial movement [88]. Modern TCM instruments based on combination of software and hardware have become an aid for TCM doctors.

In the field of medicine and information science, there are different methods for judging the accuracy of pulse diagnosis. In the field of medicine, Hu et al. evaluated the consistency of SM-1A TCM pulse diagnosis instrument for comparing the pulse veins, polypulmonary veins, tough veins, and turbulent veins of 120 patients with heart disease. They found that the consistency of TCM doctor diagnoses and pulse diagnosis instrument was 81.7% [89]. The results obtained using the pulse diagnosis instrument provide references for the TCM doctor to perform a diagnosis.

The purpose of this study is to clear the accuracy of the pulse TCM diagnosis instrument.

3.1.2 Subjects and methods

3.1.2.1 Subjects

10 elderly in Hangzhou, Zhejiang Province, China, were selected between March 15th and June 15th 2018. The samples included 5 men and 5 women, aged 65 to 76 years (average age 70.0±3.9

years). The elderly used the pulse diagnosis instrument to record pulse data and received a TCM doctor diagnosis. “Power Analysis and Sample Size” was used to determine a minimum sample size of 6 people. Eventually, 10 people were selected to participate in the study. The sample calculation formula was (3-1):

$$M = [\,1 + (K-1)_p]\,\frac{\sigma^2(Z_{1-\frac{\alpha}{2}}+Z_{1-\beta})^2}{K\delta^2} \qquad (3\text{-}1)$$

This study was approved by the Waseda University Ethics Committee (ID: 2017-224).

3.1.2.2 Data collection

A TCM pulse diagnosis instrument was used to record pulse data every week. The pulse is a TCM term that refers to the pulse's speed, strength, and depth [91]. A DS01-C Information Collection System of Pulse Condition Diagnosis (Shanghai FDA Food and Drug Administration No.20152270429) was used for data collection for pulse condition diagnosis and to record pulse characteristics in different periods (Figure 3-2). Four pulses (“HUA pulse”, “XIAN pulse”, “SE pulse”, “HUAN pulse”) were selected as representative pulses from the 28 pulses. Because the four pulses are easy to diagnosed and belong to common pulses in the elderly [90].These four pulses are considered by the “Mai Jin Book” to reflect the health of the elderly. The “HUA pulse” means slippery pulse. It is described as smooth flowing, “like pearls rolling in a dish”. The “XIAN pulse” means “taut pulse”. It feels straight, long and tense, “like pressing a tight string of a musical instrument”. The “SE pulse” means choppy pulse, which is described as “slow, relaxed, stagnant, difficult, and fine, which may stop and loose a beat but then recover”. The “HUAN pulse” means moderate pulse, as it is level and harmonious, and relaxed and forceful [91].

Figure 3-2. DS01-C Information Collection System of Pulse Condition Diagnosis (http://www.daosh.com/product/detail.aspx?id=3) (accessed June 15, 2018)

A TCM doctor performed diagnose for the subjects every week. He graduated from Zhejiang Chinese Medical University and had 15 years of diagnostic experience. He used the “Mai Jin Book” as a gold standard to diagnosis and recorded his diagnosis results. In this study, “accuracy” is equivalent to “consistency.” In order to ensure the results of the pulse diagnosis instrument do not affect the TCM doctor’s diagnosis, the TCM doctor made the diagnosis first, and then, the pulse diagnosis instrument was used. In order to ensure that the pulse was not affected by external factors, the subjects were required to take 15 minutes of rest before pulse diagnosis.

3.1.2.3 Research quality control

All researchers involved in the field investigation underwent rigorous training and assessment. During the investigation, data on the elderly were recorded accurately and the notes were maintained in the research office. The results of the investigations were audited so that abnormities in the data could be verified. The final statistical analysis included 8 individuals because two subjects quit halfway during the process.

3.1.2.4 Statistical methods

Python 3.7 and SPSS20.0 software were used for statistical analysis. In terms of the medical statistics, the precision values (3-2), Youden index (3-3), and Kappa statistics (3-4-1,2,3) were used to evaluate the consistency between the results of the pulse diagnosis instrument and the TCM doctor's diagnosis.

The formulas and the variables (Table 3-1) for calculating these are as follows:

$$Precision\ value = (a + d)/(a + b + c + d) \times 100\% \tag{3-2}$$

$$\textit{Youden index} = \{a/(a + c) \times 100\% + d/(b + d) \times 100\% - 1\} \tag{3-3}$$

$$\textit{Kappa statistic}:\ k = (P_0 - P_e) \div (1 - P_e) \tag{3-4-1}$$

$$P_0 = (a + b)/(a + b + c + d) \tag{3-4-2}$$

$$P_e = \frac{(a+c)\times(a+b)+(b+d)\times(c+d)}{(a+b+c+d)^2} \tag{3-4-3}$$

Table 3-1. The variables

	+	-	Total
+	*a*	*b*	*a*+*b*
-	*c*	*d*	*c*+*d*
Total	*a*+*c*	*b*+*d*	*a*+*b*+*c*+*d*

The closer the Youden index is to 1, the higher the accuracy. The consistency evaluation of Kappa statistic [92] is shown in Table 3-2.

Table 3-2. Consistency evaluation of Kappa statistic

Kappa statistic	Consistency evaluation
0.0-0.2	Slight
0.2-0.4	Fair
0.4-0.6	Moderate
0.6-0.8	Substantial
0.8-1.0	Almost perfect

The k-nearest neighbor (k-NN) algorithm was used for evaluating the accuracy of the pulse diagnosis instrument [93]. The k-NN algorithm is a type of lazy learning, which is regarded as the simplest machine-learning algorithm. It stores the characteristic (or attributes/variables) vectors and their corresponding labels. In this study, each pulse was detected as a binary (negative, positive) and was suitable for use with the k-NN method.

The pulse diagnostic data were labeled as follows: [negative (-) pulse = 0] and [positive (+) pulse = 1]. There were 8 characteristics, negative HUA pulse (HUA-), positive HUA pulse (HUA+), negative XIAN pulse (XIAN-), positive XIAN pulse (XIAN+), negative SE pulse (SE-), positive SE pulse (SE+), negative HUAN pulse (HUAN-), and positive HUAN pulse (HUAN+). The classifications were completely non-compliant (diagnostic results were mismatched), and fully met (diagnostic results completely matched) which were labeled as 1, 2, respectively.

The data were normalized using Equation (3-5),

$$X = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{3-5}$$

and the Euclidean distance was used to calculate the distances between objects using Equation (3-6),

$$\mathrm{d}(x, y) = \sqrt{\sum_{k=1}^{n} (x_k - y_k)^2} \tag{3-6}$$

which were then sorted from the smallest to largest values. According to previous studies, 75% and 25% of the data were used as training sample and test sample, respectively, and the correct rate was calculated by comparison with the label using Equation (3-7).

$$Accuracy = 1 - \frac{errorCount}{validCount} \tag{3-7}$$

3.1.3 Results

3.1.3.1 Pulse diagnosis results

The results of pulse diagnosis by the TCM doctor and the results obtained using the pulse diagnosis instrument is shown in Table 3-3. Among the four pulses, the detection rate for the TCM doctor is higher than that for the pulse diagnosis instrument. The detection rates of the XIAN pulse and HUAN pulse are higher than those of the HUA pulse and SE pulse.

Table 3-3. Results of pulse diagnosis

	HUA pulse	XIAN pulse	SE pulse	HUAN pulse
TCM doctor	48 (46.2%)	67 (64.4%)	20 (19.2%)	65 (62.5%)
Pulse diagnosis instrument	37 (35.6%)	59 (56.7%)	16 (15.4%)	49 (47.1%)

3.1.3.2 Diagnostic accuracy evaluation by medical statistics and machine learning methods

The results of pulse diagnosis are shown in Table 3-5.

According to equations (3-2), (3-3), (3-4-1,2,3), the precision value, Youden index and Kappa statistic were calculated (Table 3-4). The diagnostic precision of pulse is between 79% and 94%. Compared with other pulses, the Youden index of the HUA pulse is lower. Youden index of the other pulses exceeds 0.7, which proves that the pulse diagnosis instrument can correctly judge the pulse. The Kappa statistic of all the pulses is higher than 0.4, indicating that the consistency evaluation of the pulse is in accordance with Moderate. SE pulse's Kappa statistic is 0.71. This shows that consistency evaluation of the SE pulse is substantial.

Table 3-4. Pulse indicators

Pulse	Precision value	Youden index	Kappa statistic
HUA	79.8%	0.58	0.51
XIAN	84.6%	0.71	0.52
SE	94.2%	0.74	0.71
HUAN	82.6%	0.71	0.49

Table 3-5. Comparison between the diagnosis results

HUA pulse		TCM Doctor diagnosis		Total
		+	-	
Pulse diagnosis instrument	+	32	5	37
	-	16	51	67
Total		48	56	104
XIAN pulse		TCM Doctor diagnosis		Total
		+	-	
Pulse diagnosis instrument	+	55	4	59
	-	12	33	45
Total		67	37	104
SE pulse		TCM Doctor diagnosis		Total
		+	-	
Pulse diagnosis instrument	+	15	1	16
	-	5	83	88
Total		20	84	104
HUAN pulse		TCM Doctor diagnosis		Total
		+	-	
Pulse diagnosis instrument	+	48	1	49
	-	17	38	55
Total		65	39	104

+: positive, -: negative

The *k*-NN method is used to judge the accuracy of the pulse diagnosis instrument for various pulse measurements. The algorithm involves 5 steps.

It can be seen that the recognition rates vary under different characteristics (Table 3-6). The recognition rate was 57% when 8 characteristics s were selected for recognition. The average accuracy was 62%.

Table 3-6. Diagnostic accuracy evaluation of pulse diagnosis instrument

Characteristic	Accuracy
1	0.73
2	0.80
3	0.69
4	0.63
5	0.61
6	0.59
7	0.57
8	0.57

Algorithm：

Input: Unclassified sample *x,* training samples $X=\{x_1,\ldots,x_n\}$ with the corresponding class labels

$Y=\{y_1,\ldots,y_n\}$ *and the number of nearest neighbors, k.*

Output: predict result and performance metrics

Step 1. Do normalize *X*

Step 2. Use the Euclidean distance to obtain the *k* nearest neighbors of sample *x,* $\{x_1,\ldots,x_n\}$ and

their classes labels $Y=\{y_1,\ldots,y_n\}$

Step 3. Sort the calculated distances in ascending order based on distance values,

$$y = \frac{1}{K}\sum_{i=1}^{x} y_1$$

Step 4. Get top *k* rows from the sorted array and get the most frequent class of these rows.

$$y = \sum_{i=1}^{k} W(x_0, x_i) y_1, k_0 = (x_0, x_i)_{ed}$$

Step 5. Estimate the accuracy of test data

3.1.4 Discussion

3.1.4.1 Accuracy analysis of pulse diagnosis instrument

With the emphasis on TCM, the modernization of TCM continues to occur [94]. TCM places an emphasis comprehensive categorization and interpretation of tongue and pulse patterns, and characteristic categorization of diseases and drugs. These could be important sources for developing and validating innovative mindsets, methods, tools, and strategies that could complement biology-based diagnosis [95]. However, as the number of TCM doctors continues to decrease, it has become difficult for people to obtain TCM treatment [96]. Hence, the pulse diagnosis instrument can be used to relieve the burden on TCM doctors and provide a diagnosis reference for them. Therefore, the accuracy of the pulse diagnosis instrument is very important.

(1) Medical statistics

From the perspective of medical statistics, the diagnostic accuracy of the pulse diagnosis instrument for the HUA pulse, XIAN pulse, and HUAN pulse is similar to the results in previous studies [97]. Among them, the Youden index values of the XIAN pulse, SE pulse, and HUAN pulse are greater than 0.7. The Youden index has frequently been utilized in biomedical diagnosis, as it is directly related to the sensitivity and specificity, and it provides an optimal cut-point that maximizes the overall classification effectiveness for diagnosis [98]. In this study, the Youden index is greater than 0.7, which proves that the diagnostic accuracy of the pulse diagnosis instrument for the XIAN pulse, SE pulse, and HUAN pulse is high. However, the Youden index of the HUA pulse is lower, indicating that the diagnostic accuracy of the pulse diagnosis instrument for the HUA pulse is poor.

The Kappa statistic is a commonly used measure of the inter-rater agreement. It is used to quantify the degree of agreement beyond chance when two raters simultaneously score the same subjects on a nominal or ordinal scale. The inter-observer reliability is measured by comparing the observed proportion of agreement, Po, with the proportion of agreement expected by chance, Pe, and scaling the difference so that a value of 1 indicates perfect agreement while 0 indicates no agreement beyond that expected by chance [99]. The Kappa statistics of the HUA pulse, XIAN pulse, and HUAN pulse are all ~ 0.5, which indicates that there are moderate consistencies. However, the Kappa statistic of the SE pulse is 0.71, which shows that the consistency is substantial. A study showed that the SE pulse is the pulse of atrial fibrillation [100]. The elderly have weaker heart functions and are prone to abnormal conditions. This may be the reason for the high accuracy obtained using the pulse diagnosis instrument [132]. The pulse diagnosis instrument has different accuracy for different pulse types. In addition, compared with the TCM doctor's diagnosis, the accuracy of the instrument has yet to be improved.

(2) Machine learning method

In this study, after used *k*-NN method, the average accuracy of the pulse diagnosis instrument was 62%. Compared with previous studies, the accuracy is within the normal range. This algorithm can be used to evaluate the diagnostic accuracy of the pulse diagnosis instrument. In addition, for modeling using the *k*-NN algorithm, the best classification recognition rate was obtained using the proposed characteristic extraction method instead of linear discriminant analysis and principle component analysis [101]. This study draws on this approach and this classification is recognized by TCM doctors and can aid in better diagnosis.

In the risk assessment of cardiovascular disease, the *k*-NN method, the decision tree method and the random forest method all reflect the overall performance of machine learning [102]. Since the classification of the pulse diagnosis instrument is based on the theory of TCM, the characteristic of TCM is "yin and yang", so the classification of pulse image is also based on "yin and yang". The *k*-NN method is applicable to the two categorical variables, and it is suitable for the pulse classification of TCM diagnosis.

3.1.4.2 Compare with other machine learning method

In the field of machine learning, the random forest method is used to evaluate the accuracy of pulse diagnosis instrument. Random forest is composed of numerous decision trees, which are formed using a stochastic method. Thus, it is also called a random decision tree. Trees in a random forest do not correlate. After test data are used as input in a random forest to classify each decision tree, the category with the highest classification results in all decision trees is selected as the final result [103].

A study used Hilbert-Huang transform (HHT) and random forest classification methods to provide objective and quantitative parameters of TCM pulse conditions. This method is used to distinguish different pulses in patients with coronary heart disease (CHD) and normal people. The energy and the sample entropy characteristics were extracted by applying the HHT to TCM pulse by treating these pulse signals as time series. The study used pulse characteristics as input data to build a classification model. Finally, the study found that the identifiable rate of pulse in patients with coronary heart disease was 76.35% [53]. Another study showed that integrating clinical indexes into four-diagnostic information contributes to the TCM syndrome diagnosis of chronic

Hepatitis B [104].Compared with the *k*-NN method; the random forest research method has higher specificity for pulse detection in disease.

3.1.4.3 Application of different analytical methods

The use of different methods to determine the diagnostic accuracy revealed significant differences. The medical statistics provide the diagnostic accuracy of a single pulse, while the machine-learning method provides a more comprehensive accuracy. However, with the machine-learning method, the diagnostic accuracy of the pulse diagnosis instrument was not high enough, but as a comprehensive diagnosis, it can reflect the consistency of the pulse between pulse diagnosis instrument and TCM doctors. The *k*-NN classifier can confirm whether the results of the pulse diagnosis instrument match the TCM doctor's diagnosis. A study showed that doctors are willing to use ICT products as work assistants to ensure high accuracy [105]. In the case of several patients, the pulse diagnosis instrument can use historical pulses to diagnose patients in advance, classify the elderly according to the pulse, reducing the TCM doctor's workload, and shorten the time of treatment.

In summary, from the perspective of medical statistics, the diagnostic consistency of SE pulse is acceptable. Pulse abnormalities can provide references for TCM doctors. From the perspective of machine learning, the discriminating function of the pulse diagnosis instrument can provide pulse information for elderly patients in the absence of doctors.

3.2 Analysis of association between pulse and health indicators

3.2.1 Introduction

Pulse diagnosis is an important diagnostic method in TCM. Recently, some characteristics used to describe pulse images are interpretable as parameters obtained by pulse waveform analysis such as the pulse wave velocity and augmentation index [106]. With the continuous development of information technology, the combination of TCM diagnosis has become an important topic [107]. Through the development of TCM technology, various conditions such as pulse diagnosis have been classified to support TCM doctors in assist diagnosis and treatment [108]. However, in TCM treatment, acquiring an accurate pulse can only be performed by experienced TCM doctors [109]. Therefore, the use of wearable devices and pulse diagnosis instruments to record health indicators can contribute to health data quantification.

The purpose of this study is to clear the association of pulse and health indicators.

3.2.2 Subjects and methods

3.2.2.1 Subjects

10 elderly in Hangzhou, Zhejiang Province, China, were selected between March 15th and June 15th 2018. The sample included 5 men and 5 women, aged 65 to 76 years (average age 70.0 ± 3.9 years). Subjects were healthy elderly people who attend physical examination every year, and whose electronic health records (EHR) infer that they do not have chronic diseases.

This study was approved by the Waseda University Ethics Committee (ID: 2017-224).

3.2.2.2 Data collection methods

The health bracelet utilized is presented in Figure 3-3. This EHP health bracelet (model name: EHP-A86) was produced in Shenzhen, China. The specifications of the bracelet were: main dimension, 57×20×13.9 mm; weight, 24 g; senor, acceleration sensor, dynamic optical sensor; and system requirement, Android 4.3+ or IOS 7+. The bracelet can detect health data (blood pressure and heart rate) and record the step count and sleep quality. The specific implementation method consisted of: (1) communicating one-on-one with elderly subjects, teaching them how to wear the bracelet and use the application; (2) using the application data export function, and send weekly data to the researchers every week.

Figure 3-3. Wearable device (June 15, 2018, photograph by author)

The wearable device measured the step count, sleep quality, blood pressure and heart rate. The wearable device has a three-axis accelerometer that captures the data of the three dimensions in real time, and finally converts the data into step count by the algorithm. The bracelets recorded the elderly blood pressure and heart rate hourly. The blood pressure and heart rate were automatically averaged daily. The step count was counted from 0:00 to 20:00 daily. The built-in body motion recorder of the wearable device measured the sleep quality according to the amplitude and frequency of wrist movement during sleep [110]. Sleep quality score interval is 0–100. Wearable device estimated the blood pressure by collecting the pulse waveform, the rising slope of the pulse wave, and the band time by a photoelectric sensor. Green light-emitting diode (LED) light of the wearable device was matched with a photodiode to illuminate the subcutaneous blood vessels of the wrist. Through the principle of blood reflecting red light and absorbing green light, wearable devices measure blood flow and calculate the heart rate [111].

The TCM pulse diagnosis instrument was used to record pulse data weekly. Pulse is a TCM term that refers to pulse position, strength, and rhythm [91]. The DS01-C Information Collection System of Pulse Condition Diagnosis (Shanghai Food and Drug Administration No. 20152270429) was used to record pulse (Figure 3-4). This system was applied to collect pulse condition diagnosis data, it recorded or saved the pulse characteristic in different periods. Pulse parameters are presented in Table 3-7, Figure 3-6, and Figure 3-7.

The standard pulse acquisition procedure is as follows: (1) the assistant senses the pulse position and marks it; (2) the assistant wears the pulse position fixer; (3) the assistant installs the pressure sensor; (4) the sensor follows the “floating, medium, sinking” method of compression pulse measurement and pulse diagnosis data is preserved in the software (Figure 3-5).

Figure 3-4. DS01-C Information Collection System of Pulse Condition Diagnosis (http://www.daosh.com/product/detail.aspx?id=3) (accessed June 15, 2018)

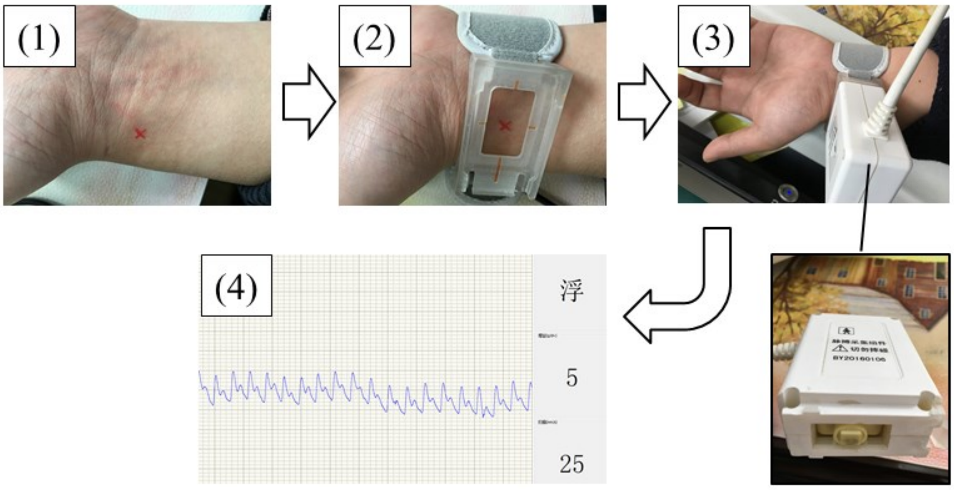

Figure 3-5. The standard pulse acquisition procedure (June 15, 2018, photograph by author)

Table 3-7. Explanation of the pulse diagram

Pulse wave (time)	Physiological explanation	Pulse amplitude	Physiological explanation
t1 (Starting point to the main peak point)	Rapid ejaculation of the left ventricle	h1 (Main amplitude)	Aorta compliance and strength
t2 (Starting point to the main wave gorge)	Heartbeat state	h2 (Main wave gorge amplitude)	Reflecting arterial elasticity
t3 (Starting point to re-pulse front wave)	Heartbeat state	h3 (Pre-pulse amplitude)	Reflecting arterial elasticity
t4 (Starting point to drop point)	Systolic phase of the left ventricle	h4 (Drop amplitude)	Peripheral resistance of arterial vessels
t5 (Drop to the end point)	Diastolic phase of the left ventricle	h5 (Heavy stroke amplitude)	Aortic elasticity

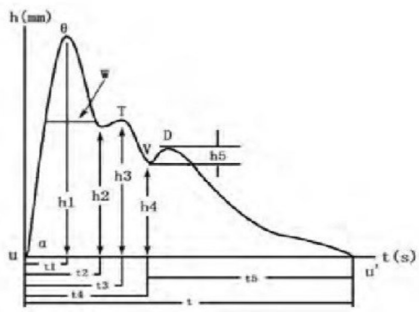

Figure 3-6. Pulse diagram

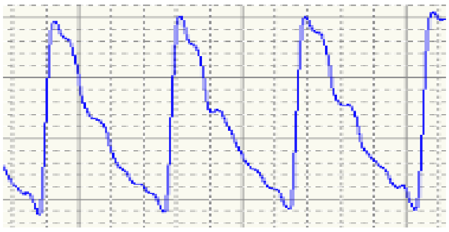

Figure 3-7. Pulse diagram (Actual measurement)

3.2.2.3 Research quality control

The pulse diagnosis instrument recording method was confirmed by a TCM doctor. All personnel involved in this investigation underwent rigorous training and assessment. During the investigation, data on the elderly were recorded accurately, and the notes were maintained in the research office. The results of the daily investigations were audited so that abnormities in the data could be verified. As two bracelets were found to be defective during the research process, the final analysis included 8 individuals.

3.2.2.4 Statistical methods

Amos 20.0 was used for statistical analysis. The structural equation model (SEM) was used to analyze causal associations between pulse and health indicators. After data preprocessed, a domain model was applied to data; this model was used to verify the relationship between variables or assumed latent factors in the SEM.

3.2.3 Results

Weekly pulse data was aggregated with health data for the corresponding date. The pulse data included pulse time (t1, t2, t3, t4, t5), pulse amplitude (h1, h2, h3, h4, h5) and pulse characteristics (position, strength, rate, and rhythm). The pulse position refers to “floating, medium, sinking”. The pulse strength refers to “powerful, medium, lack “. The pulse rhythm refers to the “pitch of the pulse”, that means the ratio per minute. The pulse rate refers to the number of beats per minute. Health data included personal information (age, sex, BMI), health habits (steps, sleep quality scores), and physiological indices (heart rate, blood pressure). This classification was approved by the TCM doctor. The pulse data and health data were imported into the structural equation model (Figure 3-8) (χ^2 =527.53; P<0.001; GFI =0.716; AGFI =0.642; RMSEA =0.124). It is necessary to adjust the model and delete the worse coefficient. “Sex” was deleted due to sample size, which may cause errors. “Position” and “Strength” were deleted because they were not quantitative data. The association between pulse and health indicators is shown in Figure 3-9 (χ^2 =169.63; P<0.001; GFI =0.858; AGFI =0.792; RMSEA =0.093). The influence of personal information, health habit, and physiological indices on pulse was 0.14, 0.18, and 0.05.According to the adjusted model; the SEM equation was (3-8):

$$\begin{aligned}\text{Pules} = \text{Pulse time} \times (-0.48) + \text{Personal information} \\ \times 0.14 + \text{Health habit} \times 0.18 \\ + \text{Physiological indices} \times 0.05 + \mathrm{e}_{24}\end{aligned} \tag{3-8}$$

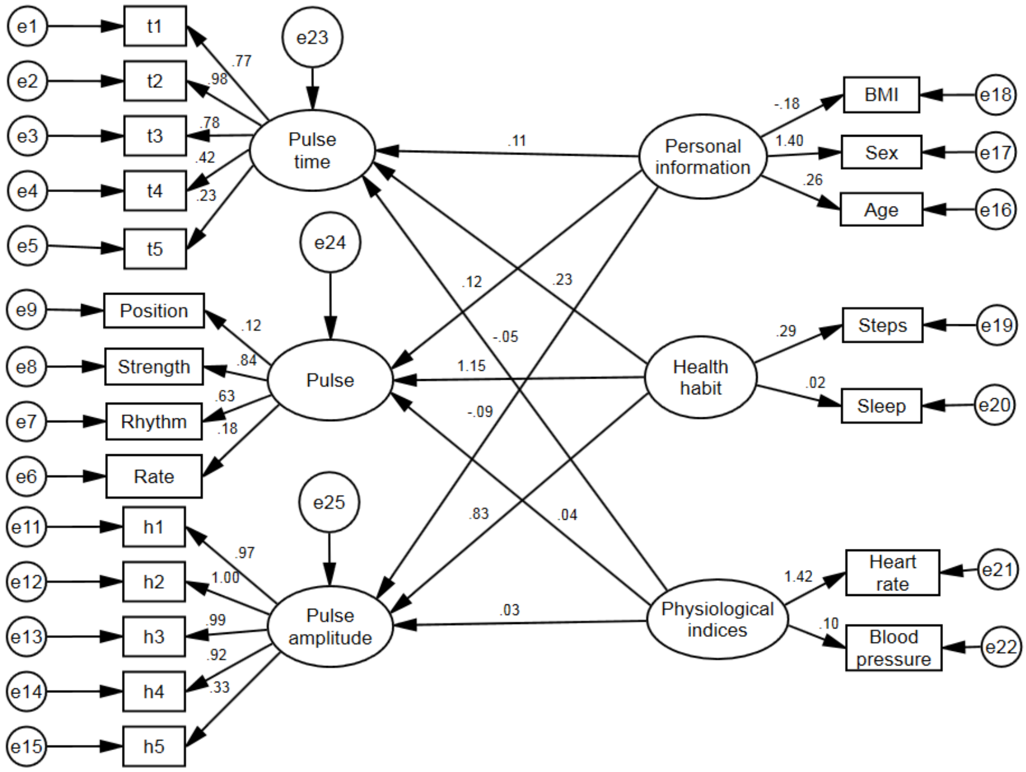

Figure 3-8. Association of pulse and health indicators (A)

(GFI =0.716; AGFI =0.642; RMSEA =0.124)

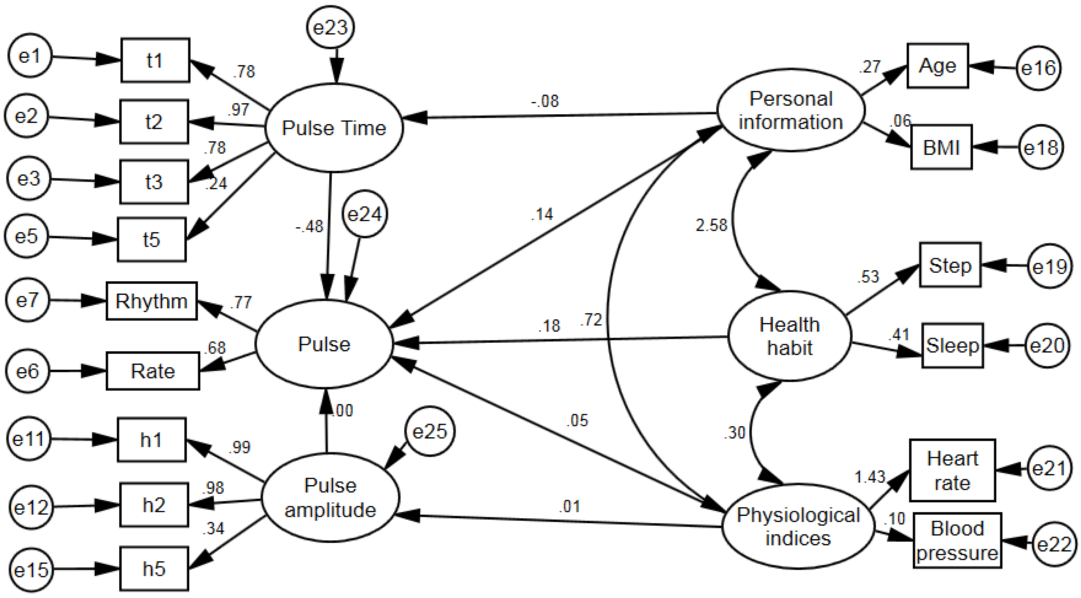

Figure 3-9. Association of pulse and health indicators (B)

(GFI =0.858; AGFI =0.792; RMSEA =0.093)

3.2.4 Discussion

Based on the concept of TCM, the pulse is the main indicator of human health. The association between pulse waves and hemodynamic parameters has been previously studied in hypertensive patients, and findings indicated that blood pressure values can be predicted by pulse waves [112].

In addition to physiological data, the present study incorporated personal health information and health habits, and comprehensively explained the association between pulse and health indicators. Age and BMI were classified into personal health information and were used to explain the effects on the pulse. Based on the SEM findings, personal health information can affect the pulse. This is also consistent with the process in which TCM doctors diagnose health problems of the elderly. Before diagnosis, the TCM doctor needs to know the age, height, and weight of the patient, acquiring this information is referred to “inquiry”.

Step and sleep are classified into health habits and used to explain the effects on the pulse. A previous study has shown that elderly who walk regularly or practice Tai Chi have a good constitution [113]. In terms of sleep, TCM pulse diagnosis is mainly reflected in the diagnosis of sleep quality (insomnia). A decrease in sleep quality can result in a change of pulse rate [114]. This study found that health habits have a significant impact on pulse.

Heart rate and blood pressure are classified into physiological indices and can be used to explain the effects on the pulse. Pulse diagnosis is used to assess the dialectical treatment and quality of life in patients with chronic coronary heart disease [115]. The pulse can be used as one of the criteria for feedback in cardiac function. The strength of vascular function is one of the principles developed by the pulse diagnosis instrument. Based on SEM, physiological indices can also affect the pulse. When the heart rate and blood pressure of the elderly are abnormal, the pulse will be abnormal. In diagnosis, if the TCM doctor finds that the patient's pulse is abnormal, patient is advised to perform an electrocardiogram or other examinations to confirm the diagnosis.

From the perspective of TCM, the pulse is divided into four aspects: position, rapid, physique, and tendency [125]. It is related to the frequency, rhythm, location, length, and width of the pulse as well as the smooth fluency of the blood flow and the strength of the heart rate. The difficulty in defining core parameters is how to correlate the pulse with health indicators. In previous studies, the pulse was mainly associated with the symptoms of disease [117]. Especially for patients with heart disease, their pulse is specific [118]. It is believed that the use of pulse data for determining the health of the elderly is also a way of summarizing the standardization of the pulse.

3.3 Prediction of step count by using wearable devices

3.3.1 Introduction

The use of information and communications technology (ICT) devices to measure pulse and health indicators for the evaluation of elderly health has been encouraged by government [6]. With the use of wearable devices and the accumulation of health data, the people can predict future health indicators. A study has shown that accurate predictions of the elderly health data can help prevent the occurrence of chronic disease risks [61].

The purpose of this study is to predict step count of the elderly by using wearable devices.

3.3.2 Subjects and methods

3.3.2.1 Subjects

10 elderly in Hangzhou, Zhejiang Province, China, were selected between March 15th and June 15th 2018. The sample included 5 men and 5 women, aged 65 to 76 years (average age 70.0 ± 3.9 years). Subjects were healthy elderly people who attend physical examination every year, and whose electronic health records (EHR) infer that they do not have chronic diseases.

This study was approved by the Waseda University Ethics Committee (ID: 2017-224).

3.3.2.2 Data collection methods

The health bracelet utilized is presented in Figure 3-10. This EHP health bracelet (model name: EHP-A86) was produced in Shenzhen, China. The specifications of the bracelet were: main dimension, 57×20×13.9 mm; weight, 24 g; senor, acceleration sensor, dynamic optical sensor; and system requirement, Android 4.3+ or IOS 7+. The bracelet can detect health data (blood pressure and heart rate) and record the step count and sleep quality. The implementation method consisted of: (1) communicating one-on-one with elderly subjects, teaching them how to wear the bracelet and use the application; (2) using the application data export function, and send weekly data to the researchers every week.

Figure 3-10. Wearable device (June 15, 2018, photograph by author)

The wearable device measured the step count, sleep quality, blood pressure and heart rate. The wearable device has a three-axis accelerometer that captures the data of the three dimensions in real time, and finally converts the data into step by the algorithm. The bracelets recorded the elderly blood pressure and heart rate hourly. The blood pressure and heart rate were automatically averaged daily. The step count was counted from 0:00 to 20:00 daily. The built-in body motion recorder of the wearable device measured the sleep quality according to the amplitude and frequency of wrist movement during sleep [118]. Sleep quality score interval is 0–100. Wearable device estimated the blood pressure by collecting the pulse waveform, the rising slope of the pulse wave, and the band time by a photoelectric sensor. Green light-emitting diode (LED) light of the wearable device was matched with a photodiode to illuminate the subcutaneous blood vessels of the wrist. Through the principle of blood reflecting red light and absorbing green light, wearable devices measure blood flow and calculate the heart rate [111].

3.3.2.3 Research quality control

All researchers involved in this investigation underwent rigorous training and assessment. During the investigation, data on the elderly were recorded accurately, and the notes were maintained in the research office. The results of the daily investigations were audited so that abnormities in the data could be verified. As two bracelets were found to be defective during the research process, the final analysis included 8 individuals.

3.3.2.4 Statistical methods

R version 3.5.1 and SPSS 20.0 were used for the statistical analysis. The data were expressed as "$\chi \pm s$." The experimental time was divided into 3 months. Based on the confirmation of the homogeneity of variance, one-way ANOVA was used to evaluate changes in the step count, blood pressure, sleep quality, and heart rate during the period. Box-Jenkins method was used to construct an autoregressive integrated moving average (ARIMA) model to predict health indicators.

3.3.3 Results

3.3.3.1 Health condition of the subjects

The health conditions of the subjects are showed in Table 3-8. Average blood pressure was high, but within the normal range [75]. Sleep scores were mostly in the range of 70–80, and the application inferred that the sleep quality was good and heart rate was maintained at 70–80 beats/min.

Table 3-8. General health information

	Age	Sex	Steps	Sleep quality (score)	HR (min)	SBP (mmHg)	DBP (mmHg)
A	65	Male	9,450.3±2696.8	71.7±7.9	73.7±4.5	130.6±5.8	87.4±4.7
B	68	Male	8,136.7±3271.1	73.1±13.2	77.4±4.9	128.7±5.7	86.0±6.4
C	68	Male	6,922.8±2939.1	74.7±8.7	77.6±4.7	137.3±4.4	98.0±7.3
D	75	Male	6,429.2±2636.7	81.2±6.3	69.1±6.3	134.6±6.5	87.5±4.8
E	72	Female	6,998.1±2537.2	80.4±6.0	69.7±5.9	130.1±5.6	82.9±4.6
F	76	Female	5,932.7±2346.7	77.1±4.3	69.7±6.1	136.7±5.0	87.7±4.8
G	67	Female	9,282.6±3266.9	74.6±8.5	70.7±5.6	127.6±4.8	82.8±4.8
H	69	Female	9,575.9±3242.4	65.5±9.1	69.2±6.1	127.3±4.8	82.9±4.6

SBP: systolic blood pressure; DBP: diastolic blood pressure; HR: heart rate

3.3.3.2 Changes in health condition

The experimental period was divided into 3 months, and changes in the step count, blood pressure, and heart rate was statistically analyzed. After one-way ANOVA, the step count had significantly changed (Figure 3-11). There was no significant change in sleep quality, heart rate, and blood pressure. However, the average daily step count had increased significantly at 3rd month compared with the previous 2 months.

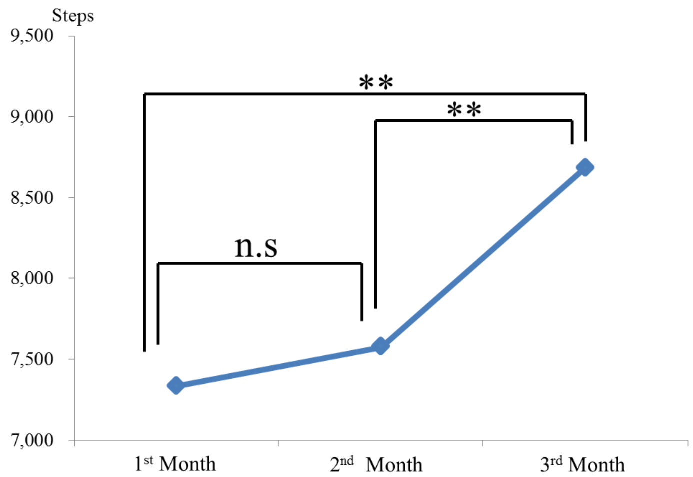

Figure 3-11. Changes of step count (One-way ANOVA)

3.3.3.3 Prediction of step count

The time series method was used to analysis the changes in the step count (Figure 3-12). After performing natural logarithmic transformation on the values, Box-Jenkins Method used to construct the ARIMA (*p, d, q*) model and determine the difference of 1 (*d*=1). Software derived the autocorrelation figure (Figure 3-13) and the partial autocorrelation figure (Figure 3-14), and set the values of *p* and *q* according to the reference legend (*p*=1, *q*=1). The model was confirmed as ARIMA (1, 1, 1). The ideal equation for this model was (3-9):

$$\begin{cases} y(t) = x(t) - x(t-1) \\ y(t) = a_1 \cdot y(t-1) + u(t) - b_1 \cdot u(t-1) \end{cases} \tag{3-9}$$

After model derivation (Table 3-9), the actual prediction equation was (3-10):

$$\{x(t) - x(t-1)\} - 21.435 = 0.117 \times [\{x(t-1) - x(t-2)\} - 21.435] + u(t) - 0.994 \times u(t-1) \tag{3-10}$$

It was predicted that the step count on day 94 should be 8,869 (Figure 3-15).

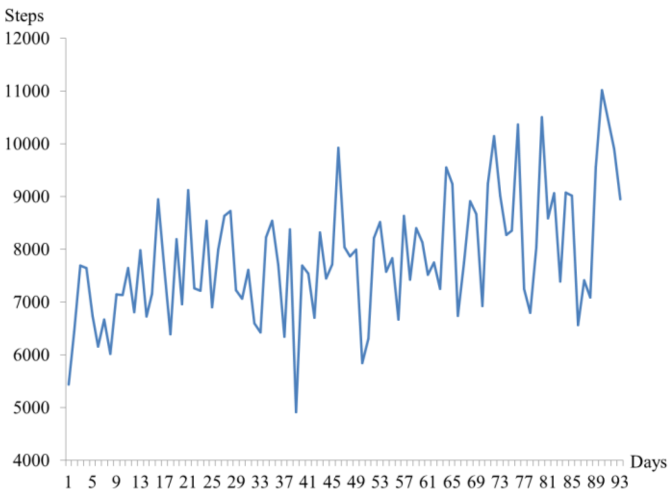

Figure 3-12. Changes of step count

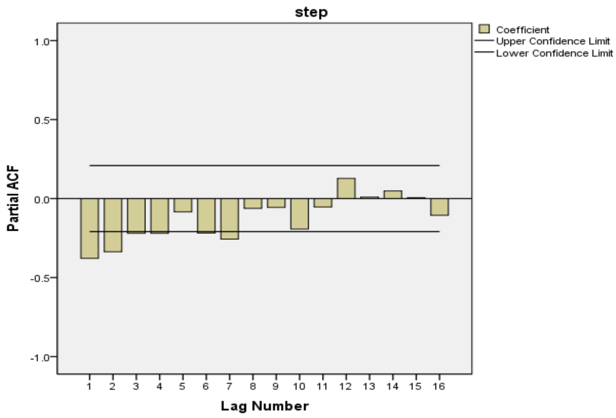

Figure 3-13. Autocorrelation in changes of step count

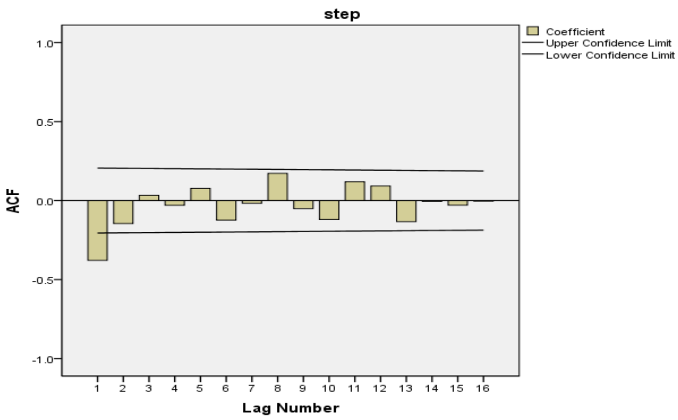

Figure 3-14. Partial autocorrelation in changes of step count

Table 3-9. ARIMA model parameters

		Estimate	SE	*t*	*p*
Step	Constant	21.435	6.025	3.558	0.001
	AR Lag1	0.117	0.119	0.986	0.327
	Difference	1			
	MA Lag1	0.994	0.299	3.324	0.001

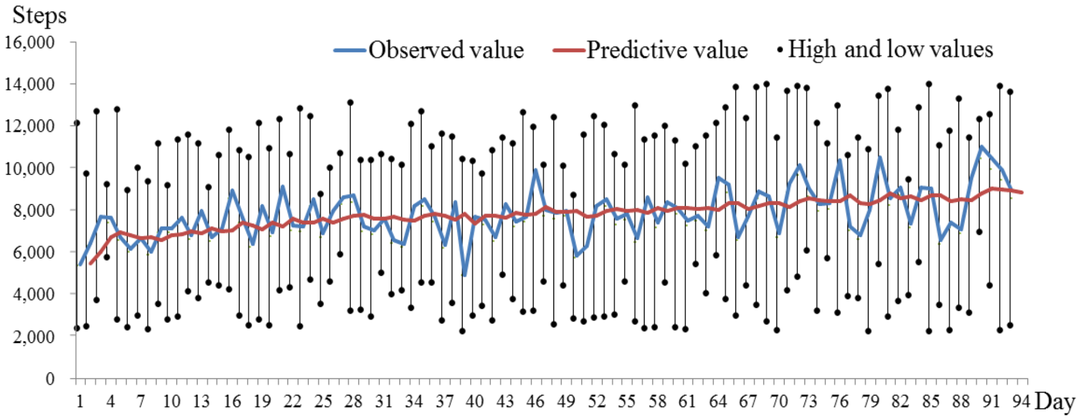

Figure 3-15. Changes of step count: trend and prediction

3.3.4 Discussion

3.3.4.1 Changes in health condition

The use of wearable devices can quantify health indicators and record health conditions [19]. The subjects had a relatively stable walking habit and walked more than 6,000 steps per day. During the study, the step count increased significantly. When using the wearable device, they could set personal goals, thereby increasing participation enthusiasm. A study showed that walking more than 4 hours per week can reduce the risk of cardiovascular disease [119]. Walking is the most common exercise for the elderly.

3.3.4.2 Prediction of step count

With the development of the discipline, time series study has gradually been applied to the health field. A Spanish study provided a mathematical model to predict the influenza situation in the second year of the outbreak and provided recommendations for disease prevention [120]. In this study, the step count predicted on day 94 was 8,869. In practice, the step count on day 94 was

8,267. The difference between the predicted step number and the actual step number was controlled within ± 10%. A previous study found that when the step counts of the elderly declines, the main cause of accidents may be due to the reduction in physical function [121]. When the elderly establish a health habit, the occurrence of an abnormal value can indicate a problematic health condition. Incorporating the time series method into wearable devices can predict the range of steps taken by the elderly in the future. A study showed that the location of the elderly can be determined by the GPS function of the wearable device [12]. In the case of an abnormal step count, it can be share health data with families through the sharing function of wearable devices to ensure the security for the elderly.

Chapter 4 Perceptions of TCM doctors on using wearable devices and TCM diagnosis instruments

4.1 Introduction

With the reduction of price, wearable devices have been widely used in people's daily life [145]. Gabriela et al. have used wearable devices to monitor postures in daily activities. This study found that wearable devices can recognize motion postures with 90% accuracy [122]. Dooley et al. applied wearable devices to monitor the health data of patients after ICU discharge, such as heart rate, and sleep quality [123].

Different from the use of wearable devices in daily life, TCM diagnosis instruments are mainly used in medical institutions. Zhen Qi et al. used digital image processing technology and machine learning methods to classify TCM tongue images [124]. The application of ICT in the field of medicine has become common, and TCM doctors have begun using these devices as diagnostic tools [89].

The purpose of this study is to explore TCM doctors' evaluation of wearable devices and pulse diagnosis instruments.

4.2 Subjects and methods

4.2.1 Subjects

The subjects of this study were TCM doctors who work at a TCM medical institution in Hangzhou, China. The inclusion criteria for TCM doctors were confirmed as: (1) graduated from TCM University; (2) worked in TCM hospitals for more than 10 years; (3) had doctor's qualification above an attending physician (TCM doctor qualification: chief physician, associate chief physician, and attending physician); (4) had experience in teaching students; (5) had experience in using wearable devices and TCM diagnosis instruments.

The recruitment time of this study was December 2018.

4.2.2 Study design

The interview was in January 2019. The researchers selected 12 interviewees who met the criteria, and 10 of them were willing to participate in this interview. This study used semi-structured interviews to collect data. Each interview begins with: "How do you feel about wearable device and TCM diagnosis instruments?" and includes: (1) the trustworthiness of wearable devices and TCM diagnosis instruments; (2) the role of wearable devices and TCM diagnosis instruments in different populations and place; (3) the role of wearable devices and TCM diagnosis instruments in the diagnosis; (4) suggestions for wearable devices and TCM diagnosis instruments.

If the interviewee does not spontaneously talk about these topics, the interviewer will ask these topics appropriately.

The researcher conducted semi-structured interview at the interviewee's office. Each interview lasted approximately 40 minutes. After communicating with the interviewees, the interviewer explained the study theme and goals, signed the informed consent, and collected information such as the age, qualifications, and number of years in treatment. In the interview, interviewees were allowed to use the recording device.

This study was approved by the Waseda University Ethics Committee (ID: 2018-278).

4.2.3 Statistical methods

This study used grounded theory to analyze interview data [125]. Grounded theory enables researchers to develop a theory to explain the phenomena. In other words, grounded theory is best suited to search for discovering new things. As the research progressed, the researchers' initial exploratory problems were gradually improved until they understood the topic of the research [126]. This method is applicable to the case of health care research [127]. The interview data was transcribed verbatim and uploaded to the NVivo 10 software, and the summarized data was separated and encoded by this software.

Data analysis can be divided into 5 steps (Figure 4-1): [125].

Step 1: Editing: read the interview data verbatim and understood the interview content.

Step 2: Open coding: coded the data line-by-line and grouped the contents.

Step 3: Intermediate coping: focused on the grouped concept, reclassified and defined them.

Step 4: Axial coding: used axis coding to define categories and concepts and classified them into higher-level headlines.

Step 5: Formation theory: integrated the final categories into the grounded theory

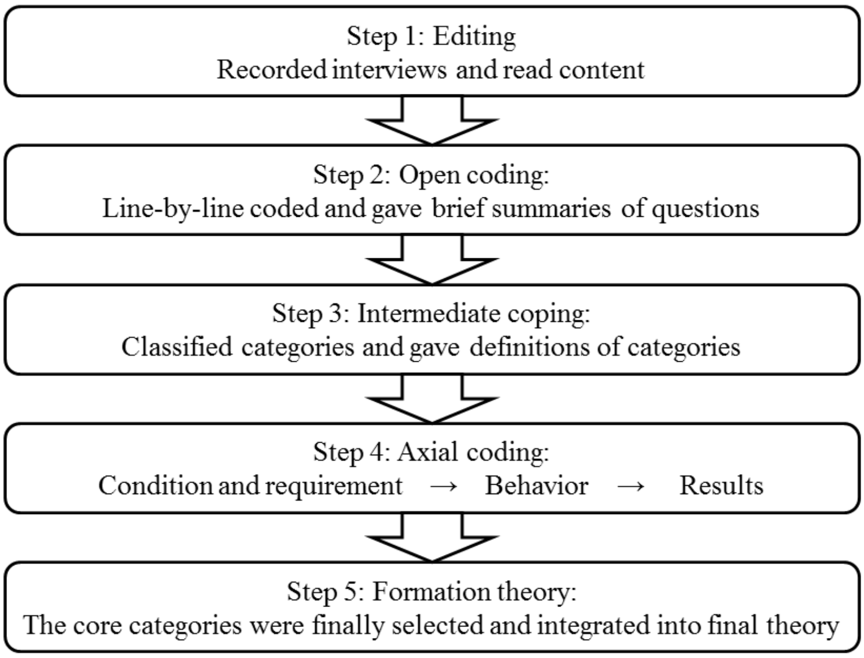

Figure 4-1. Research flow chart

4.2.4 Coding data

Grounded theory method was used in coded the interview data. All interview contents were transcribed verbatim and imported into NVivo 10 which was used for coding, sorting and retrieval of data. Based on grounded theory, this included the role of wearable devices and pulse diagnosis instruments in medical institutions, the user experience of TCM doctors, and the effect of TCM doctors' practices. Based on the interview data, the outline of the concepts, subcategories, categories and core categories were set up [127].

4.2.5 Trustworthiness

This study using NVivo 10 ensured that each stage of coding and clarified audit trails for deconstruction. Credibility was increased by iteratively reviewing the original transcribed interviews. The second researcher evaluated the coding, categories and applications of the data at the beginning of the analysis. Once the final main topics were derived, two researchers independently reviewed these topics to check for consistency.

4.3 Results

4.3.1 Subjects information

The interviewees consisted of 8 males and 2 females, aged 35 to 76 years and were able to clearly express their opinions surrounding the research questions. Participants' qualifications levels were higher, with 9 of them above the associate chief physician level, and the average years of TCM diagnosis was 23.7 ± 14.8 years. All TCM doctors had experience in using wearable devices and TCM diagnosis instrument. Among them, the most common wearable devices were wristbands, and the most common diagnosis instruments were pulse diagnosis instrument (Table 4-1).

Table 4-1. Subjects

ID	Gender	Age	Qualification	Years of working	Wearable device	TCM diagnosis instrument
Doctor 1	Male	55	Chief physician	32	Smart wristband	Pulse diagnosis instrument
Doctor 2	Male	49	Associate chief physician	15	Smart wristband	Pulse diagnosis instrument; Meridian diagnosis instrument
Doctor 3	Female	59	Chief physician	35	Smart wristband	Pulse diagnosis instrument
Doctor 4	Male	36	Associate chief physician	11	Smart wristband	Pulse diagnosis instrument; Meridian diagnosis instrument
Doctor 5	Male	39	Associate chief physician	12	Smart wristband	Pulse diagnosis instrument
Doctor 6	Male	76	Chief physician	54	Smart wristband	Pulse diagnosis instrument
Doctor 7	Male	42	Associate chief physician	15	Smart wristband; Smart watch	Pulse diagnosis instrument
Doctor 8	Male	67	Chief physician	37	Smart wristband	Pulse diagnosis instrument
Doctor 9	Male	41	Associate chief physician	16	Smart wristband; Smart watch	Pulse diagnosis instrument
Doctor 10	Female	35	Attending physician	10	Smart wristband	Pulse diagnosis instrument

4.3.2 Coding data

Table 4-2 shows an outline of the concepts, subcategories, categories and core category.

Table 4-2. Outline of the concepts, subcategories, categories and core category

Core categories	Categories	Subcategories	Concepts
Use feeling	Ease of portage	Volume	If the pulse diagnosis instrument is bigger than a PC, I think I will just use it in the hospital.
			If it is smaller than a PC, I can use it everywhere.
			Wearable devices which are larger than watches are not easy to wear.
			I hope it is to be designed as small as a watch.
		Weight	If the pulse diagnosis instrument is easy to move, it can be used in any medical institution.
			Now it is so heavy to move.
			I think a wearable device should be lighter than 100g so that I can wear it easily.
			If a wearable device is heavier than 100g I would not use it anymore.
	Comfort	Duration of use	If I used ICT devices for more than 3 months, it means that I believe that ICT devices help me.
			I generally use an ICT device for less than 3 months because it does not help me.
		Material	A metal device is comfortable for me.
			A plastic device is too hard to wear.
			A leather device is comfortable to wear.
	Convenience of operation	Screen size	The content is easy to read because of the large screen.
			The screen is small, and words are too small to read.
		Speed of respond	The health results respond quickly.
			The health result feedback slowly.
	Human interface	Humanized design	The humanized design is good for me to understand the meaning of the health indicators.
		Unfriendly design	I don't know the meaning of health indicators.
Sense of trust	Understanding of principles	Clear	I know the principle of the machine clearly.
		Unclear	The principle is too difficult to understand.
	Evaluation of accuracy	High accuracy	The step count has a high accuracy and I believe it.
		Low accuracy	It is just a single pulse with a low accuracy.
	Durability of the instrument	High durability	High durability is the foundation for using wearable devices.
		Low durability	The durability is not high.
Suitability for people	Age distinction	Elderly	Wearable devices are suitable for the elderly.
		Adult	Wearable devices are suitable for patients who need care.
	Disease differentiation	Chronic disease	Wearable devices are necessary for chronic patients.
		Acute disease	ICT device is not suitable for patients with acute disease.
Machine usage scenario	Daily life	Home	The wearable device can be used to record health indicators at home.
		Outdoor	I used a wearable device to record step count.
	Educational institution	University	Pulse diagnosis instrument is suited for teaching.
		College	I used this machine to teach students at college.
	Primary institution	Clinic	Clinics use devices to record health data.
		Pharmacy	Pharmacies use devices to record health data.
Combination of TCM and ICT	Ability to be worn	Wearable pulse instrument	If the pulse diagnosis instrument can be worn, it is valuable for our diagnosis.
	Interpretation of results	Analysis of risk	I think it is necessary to analyse the risk of fall.
		Predicate indicators	I hope the device can predict health in the future.

4.3.3 Categories

5 categories emerged to describe the TCM doctors' perceptions of using wearable devices and the TCM diagnosis instrument (Figure 4-2).

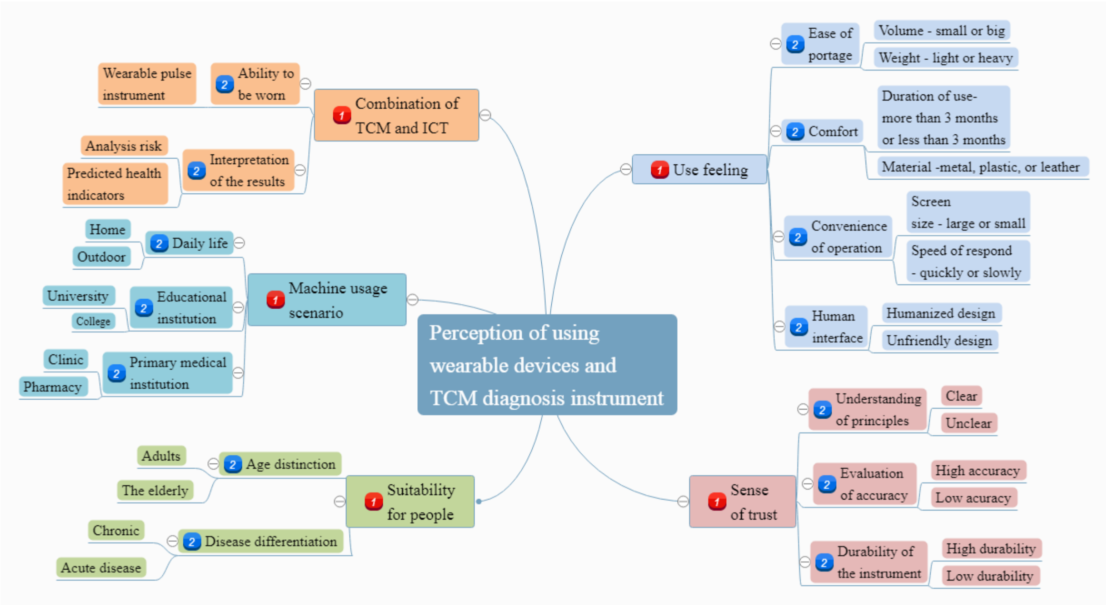

Figure 4-2. The category map of TCM doctors' perceptions of using wearable devices and the TCM diagnosis instrument (①Core category; ②Category)

Category 1: Use feeling. TCM doctors described user experience of wearable devices and TCM diagnosis instruments. For example, ease of portage, comfort, convenience of operation and human interface.

TCM doctors believe that "ease of portage" is depended on the volume and weight.

"If pulse diagnosis instrument is bigger than PC, I think I just use it in hospital. If it is smaller than PC, I can use it everywhere" (Doctor 1).

"Now wearable devices are usually bigger than watch, it is not suit for wearing. I hope wearable device can be designed as small as a watch" (Doctor 3).

"If pulse diagnosis instrument easy to move, it can be used in any medical institutions. But now

it is too heavy to move. And I think wearable device should lighter than 100g that I can wear it easily. If wearable device is heavier than 100g I would not use it anymore" (Doctor 4).

A TCM doctor used wearable devices for a long-term.

"I have been wearing bracelet for more than 3 months. I feel comfortable and it does not affect my daily work" (Doctor 2).

A TCM doctor reported that wearable devices were not used as watches.

"I wore the bracelet less than 2 months and I don't want use it any more. Because I feel the plastic material felt uncomfortable" (Doctor 5).

When using wearable devices for the first time, a TCM doctor reported that he was concerned about operability.

"The screen of this bracelet is too small. I can't see the contents of the screen. So I have not continued to use the bracelet" (Doctor 6).

TCM doctors thought that TCM diagnosis instruments were easy to operate.

"The pulse diagnosis instrument can connect to the computer. I can use the keyboard to directly input pulse information, and the result can be output quickly" (Doctor 2).

"The operation of the pulse diagnosis instrument is convenient, and it has a large screen to confirm the result" (Doctor 8).

Category 2: Sense of trust. TCM doctors described the trust in wearable devices and TCM diagnosis instruments. For example, the understanding of principles, evaluation of accuracy, durability of instrument.

TCM doctors have simply understanding of the principles of wearable devices and TCM diagnosis instruments, but they do not understand the details of the principles.

"The principle should be bionics, light perception and gravity sensors. This can mimic pulse diagnosis, and record data such as step count and heart rate. But I can't understand the detailed principle clearly" (Doctor 1).

"*The principle of pulse diagnosis instruments is not easy to understand*" (Doctor 2).

A TCM doctor believes that the sustainability of wearable devices affected accuracy.

"I think the accuracy of step count and heart rates are relatively high. These data were monitored for a long time. But blood pressure is easily affected by other external factors. I think the accuracy of blood pressure is low" (Doctor 3).

A TCM doctor also had doubts about the accuracy of TCM diagnosis instruments and thinks it is not replaced diagnosis by doctors.

"Pulse diagnosis has three steps, but pulse diagnosis instrument only has one step. Maybe the accuracy is high, but it is just a single pulse. TCM doctors used the three different diagnosis methods. Pulse diagnosis instrument cannot achieve this function" (Doctor 4).

TCM doctors have concerns the durability of wearable devices and TCM diagnosis instruments.

"Some patients have feedback that durability is not good. There are also sophisticated components in the devices. They are still easy to break" (Doctor 8).

"If wearable devices have high durability I believe most of people will like them" (Doctor 7).

Category 3: Suitability for people. TCM doctors described the objects for wearable devices and TCM diagnosis instrument. For example, age distinction and disease differentiation.

TCM doctors found that wearable devices are more suitable for the elderly.

"I feel that wearable devices are more suitable for the elderly. The data recorded by wearable devices can help the elderly understand their health" (Doctor 1).

"Some wearable devices have an anti-fall warning function, which is the most suitable function for the elderly" (Doctor 7).

A TCM doctor stated that wearable devices were suitable for the chronic patients.

"I think wearable devices are necessary for chronic patients. For example, for young hypertensive patients, we ask them to control blood pressure every day and monitor blood pressure in real time. Regardless of age, I recommend them using wearable device" (Doctor 5).

Category 4: Machine usage scenario. TCM doctors described the use scenarios of wearable devices and TCM diagnosis instrument.

TCM doctors believed that wearable devices should be used in daily life.

"Wearable devices should use in daily life. I think the most important function of wearable device is to detect abnormalities and record data" (Doctor 3).

"Wearable devices record health indicators, whether at home or outdoors" (Doctor 5).

TCM doctors reported that TCM diagnosis instruments should be mainly used at the TCM educational institution.

"The pulse diagnosis instrument is suitable for teaching. It is impossible for students to follow the teacher every day, and the pulse diagnosis instrument can be used as a practice object for teaching. It can be used at university" (Doctor 4).

"Nowadays, students rarely have the opportunity to diagnose the disease, and the pulse diagnosis instrument solves this problem. It allows students to have a basic understanding of the pulse" (Doctor 10).

TCM doctors suggested that TCM diagnosis instruments can be placed in primary medical institutions.

"The patients are actually very curious about their pulse diagnosis, but it is impossible for us to explain the patient one by one. TCM diagnosis instrument can be placed in primary medical institutions for patients to use" (Doctor 1).

"The pharmacy can also use the pulse diagnosis instrument to provide the pulse diagnosis while patient bought drug" (Doctor 3).

Category 5: Combination of TCM and ICT. TCM doctors described combination of TCM and ICT for wearable devices and TCM diagnosis instruments.

A TCM doctor believed that the combination of wearable devices and TCM diagnosis instruments are feasible.

"If the pulse diagnosis instrument can be worn, it is very valuable for our diagnosis. We can compare the pulse with other physiological indicators to make the correct diagnosis" (Doctor 6).

A TCM doctor recommends that the use of wearable devices and TCM diagnosis instruments should be more convenience.

"As a TCM doctor, I need to reveal the symptoms of patients more quickly. If the pulse diagnosis instrument can give results more quickly and accurately, it will help us to eliminate interference items and improve our diagnostic efficiency" (Doctor 3).

Multiple TCM doctors reported that the TCM diagnosis instruments could not explain results.

"The pulse diagnosis instrument cannot explain the pathology, and it has little effect on the diagnosis for TCM doctor. I hope the device could predict the health in the future" (Doctor 4).

"Wearable devices only have the ability to record data and lack of ability to analyse data" (Doctor 9).

4.4 Discussion

Use feeling, sense of trust, suitability for people, machine usage scenario, combination of TCM and ICT make up TCM doctors' perceptions around wearable devices and TCM diagnosis instruments.

4.4.1 Use feeling

Use feeling was composed of ease of portage, comfort, convenience of operation and interface humanity. Ease of portage is a characteristic of wearable devices and also is the main reasons why users buy devices. However, TCM diagnosis instruments have not been able to be miniaturised, which has affected the evaluation of TCM doctors. Furthermore, comfort is the foundation for long-term use of wearable devices for patients. A study showed data is important if patients wear wearable devices for a long time [128]. TCM doctors pointed out that the feedback of wearable devices is delayed. In terms of human interface, TCM diagnosis instruments have display screens and can directly feedback image data such as pulse images, which can be easily explained by TCM doctors. Human-computer interaction helped doctors and patients obtain valid data quickly and comprehensively [129].

4.4.2 Sense of trust

Sense of trust is composed of principle, evaluation of accuracy, and durability of instrument. TCM doctors are most concerned about the accuracy of instrument, which directly affects the TCM doctors' judgment on the diagnosis results. In the process of diagnosis and treatment, TCM doctors need to combine various indicators such as pulse and tongue [130]. Besides, TCM doctors have put forward higher requirements for the durability of instrument.

4.4.3 Suitability for people

TCM doctors are willing to use age and disease as a standard to distinguish which population suitable for use wearable devices and TCM diagnosis instruments. Although most young people use wearable devices now, TCM doctors recommend that the elderly are more suitable in using wearable devices. Wearable devices can objectively analyse the health data of the elderly and help them monitor health indicators [131]. TCM doctors also believe that wearable devices and TCM diagnosis instruments are suitable for people with chronic diseases.

4.4.4 Machine usage scenarios

In terms of machine usage scenarios, TCM doctors recommend that wearable devices are suitable for used in daily life, and TCM diagnosis instruments can be used in educational institutions and primary medical institutions. By monitoring heart rate and pulse, wearable devices provide users objective health indicators and perform them advices about the prevention of lifestyle diseases [133]. Taking pulse diagnosis instruments as an example, TCM diagnosis instruments can be used in universities to guide students for understand basic knowledge of pulse diagnosis [134]. Moreover, TCM doctors pointed out that TCM diagnosis instruments can be placed in primary medical institutions.

4.4.5 Combination of TCM and ICT

TCM doctors are expected to realize the miniaturisation of TCM diagnosis instrument, so that it can monitor TCM health indicators in daily life. TCM doctors also hope to improve the accuracy of the instrument.

The medical treatment decision support system not only relieves doctors from trivial work, but also enables them to dig deeply into cases to reveal hidden rules of medicine [141]. Used with TCM, medical treatment decision support system can be a better way to support TCM doctors in summarizing the experience of pulse diagnosis and accelerating the treatment decision. The use of this system can assist TCM doctors in improving the accuracy of the pulse diagnosis.

Chapter 5 Conclusions

5.1 Summary

The purpose of this study is to analysis the roles of wearable device and traditional Chinese medicine in health management of the elderly.

In Chapter 1, the literatures on the role of wearable devices and TCM in the health management of the elderly were summarized. A total of 34 articles were screened. Based on the stages of health management, the use of wearable devices and TCM in the health monitoring, health analysis, and health promotion stages were reviewed.

Chapter 2 presented the results of an analysis that examined changes in the health of the elderly that accompanied use of wearable devices. 18 elderly constituted the study sample. Health indicators were collected using wearable devices, which monitored step count, sleep quality, blood pressure, and heart rate. The results showed that, after using the wearable device for 4 months, the step count of the elderly increased significantly. Additionally, wearable devices are suitable for the elderly to record health indicators, and they were willing to continue using wearable devices. It is possible that the use of wearable devices may improve health awareness for the elderly.

Chapter 3 presented the roles of wearable devices and pulse diagnosis instrument for the elderly. The diagnostic accuracy of pulse diagnosis instruments was calculated using medical statistics and the machine learning method. The diagnostic accuracy of pulse diagnosis instruments was not high, but it was accurate in the diagnosis of "SE pulse." Compared with other machine learning methods (e.g., Random forest method), the *k*-NN method is suitable for the calculation of pulse two-class variables. Structural equation modeling (SEM) was used to analyze the association between pulse and health indicators. The elderly's step counts were successfully predicted within

10% of the actual step count. This result makes it possible to predict health indicators by using wearable devices.

Chapter 4 presented TCM doctors' evaluations of wearable devices and pulse diagnosis instruments. Interview data was analyzed by using grounded theory and 5 categories in evaluations of wearable devices and pulse diagnosis instruments were estimated. TCM doctors have different evaluative opinions about wearable devices and pulse diagnosis instruments.

5.2 Findings

This study examined the role of wearable devices and TCM in the health management of the elderly, the diagnostic accuracy of pulse diagnosis instruments, and the association between pulse and health indicators. TCM doctors' evaluations of pulse diagnosis instruments and wearable devices were also established.

5.2.1 Using wearable devices to record health data and raise health awareness

Information and communication technology (ICT) usage may help the elderly to maintain contact with social ties [135]. It is found that wearable devices can record health indicators in this study. In Japan, some researches have incorporated wearable devices into the health and medical care system (Figure 5-1) [149].

In Chapter 2, the trends in health data were summarized. Wearable devices helped the elderly understand their health indicators better and enhanced their willingness to take health-promoting measures. It was also found that wearable devices augmented the elderly's willingness to increase their social capital and expand their social networks [148].

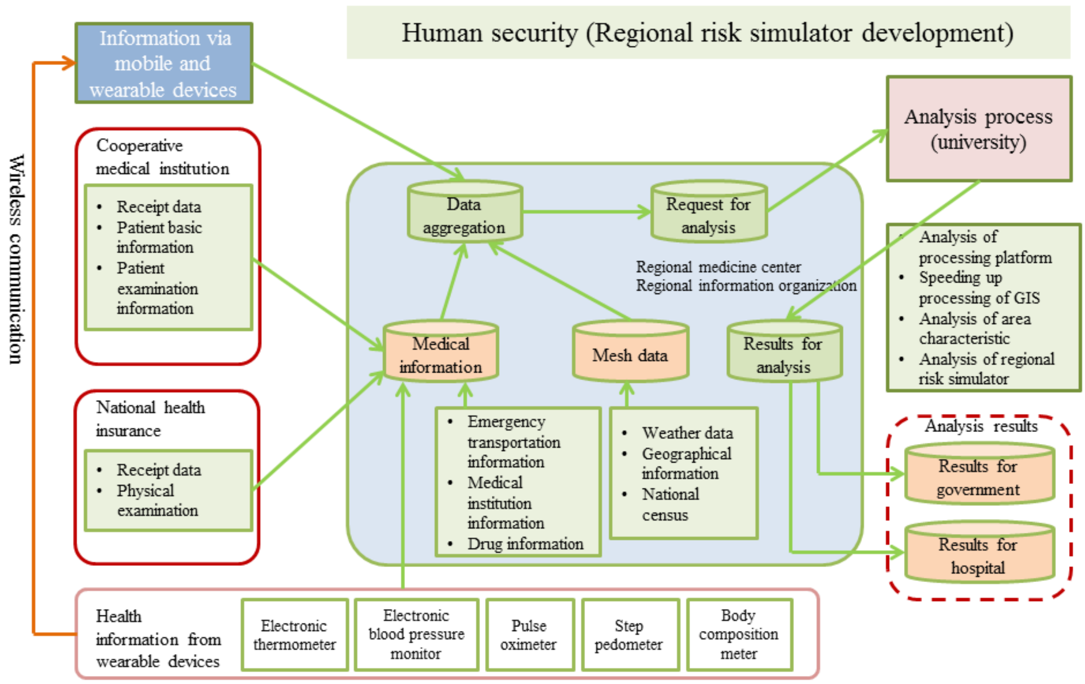

Figure 5-1. ICT development framework in Japan [149] (modified by author)

5.2.2 Pulse diagnosis instruments can support doctors' work

Pulse diagnosis instruments record pulses and can display characteristics of the recorded pulse. Further, the visualization function of pulse diagnosis instruments can help TCM doctors to explain pulse to patients.

Pulse diagnosis instruments can be used to teach pulse diagnosis to students. Specifically, it can be used to help students master their knowledge of pulse diagnosis. This can reduce the amount of teaching for TCM doctors. In addition to teaching pulse diagnosis, visualization of pulse can be used to help students practice pulse diagnosis by repeatedly comparing pulses [134].

5.2.3 Personal health data of the elderly can be used in health management

With the development of ICT, wearable devices have become integrated into daily life. They can be used to record health data and perform simple analyses. This study articulates how utilizing wearable devices to record daily health indicators and predict step count. The pulse diagnosis instruments were used to record pulse and provide information about healthy habits. In primary care institutions, the elderly can understand their own health conditions by using the results of pulse diagnosis instruments.

The EHR system can help hospitals to analysis health data (Figure 5-2) [149]. Based the health data, it can assist doctors to provide the elderly with more detailed health management plans [136].

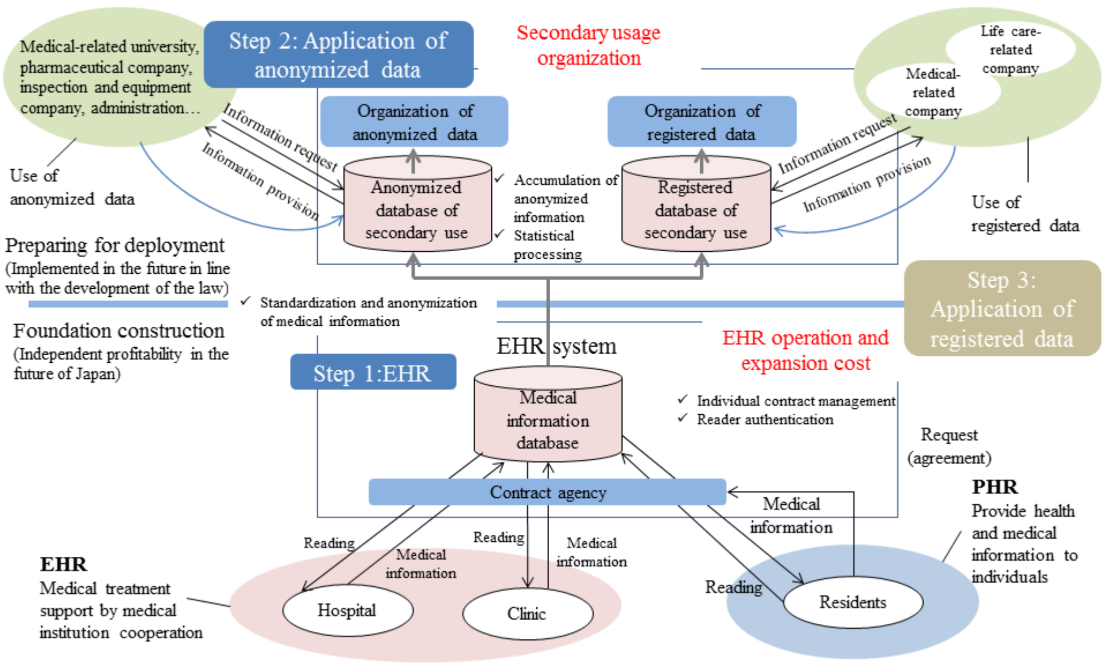

Figure 5-2. Application of EHR system in Japan [149] (modified by author)

Overall, the findings of this study suggest that the use of wearable devices helps the elderly understand their health conditions and facilitates health management. In the future, with the involvement of more data, it will be possible to use wearable devices to support health management of the elderly.

5.2.4 Evaluations by TCM doctor support the development of health instruments

The use feeling, sense of trust, suitable for people, machine usage scenario, combination of TCM and ICT make up the perceptions offered by TCM doctors in this study. TCM doctors believe that different places and different groups of people require different wearable devices and TCM diagnosis instruments. In the future, the use of wearable devices and TCM diagnosis instruments will help TCM doctors monitor health of the elderly. In addition, with regard to the development of wearable devices and TCM instruments, TCM doctors are looking forward to future wearable pulse diagnostic instruments.

5.2.5 Realistic applications

In Shanghai, wearable devices are tied to the mobile phones of the elderly, and help their families stay abreast of the health changes [137]. In Hangzhou, wearable devices are used to help the elderly attend exercise event and health management activities. The elderly can also set daily exercise targets based on their exercise plan [138]. Medical institutions have started providing pulse diagnosis services for adults [139]. In TCM hospitals, some TCM doctors have begun to use health data and pulse data as a reference for disease diagnosis. TCM diagnosis instruments have an educational function. Specifically, pulse diagnosis instruments can help visualize the pulse, and this prompts students to objectively understand the concept of the pulse, while also improving their knowledge of different types of pulses [134]. At Shanghai Chinese Medical University, pulse diagnosis instruments are used in TCM teaching courses (Figure 5-3).

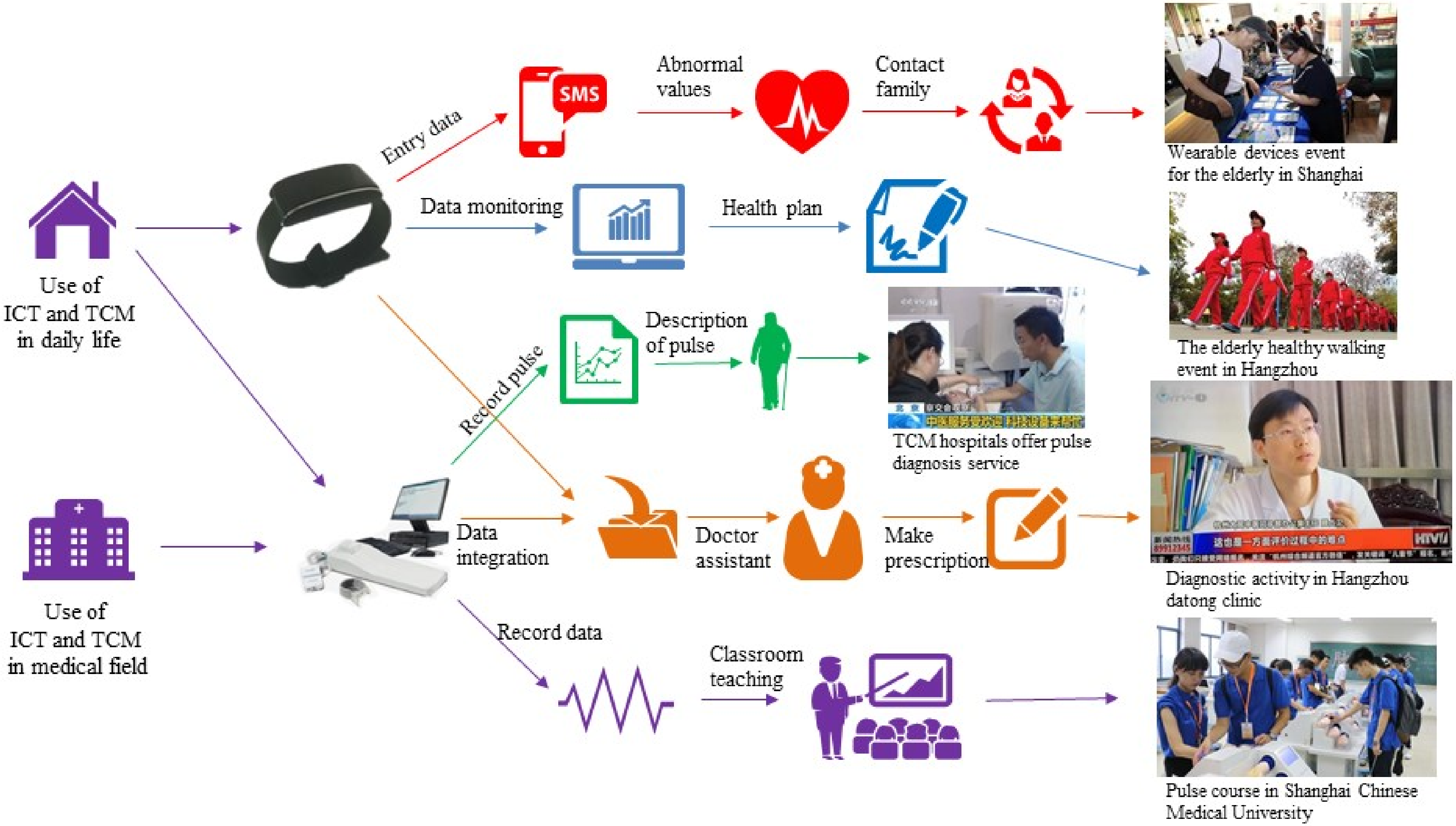

Figure 5-3. Realistic application

5.3 Implications for future work

The number of participants met sample requirements. However, the number of participants in this study was relatively low, and this may have impacted the results. The results would be more accurate if the sample size increased.

Step count, quality of sleep, blood pressure and heart rate were used as variables in this study. Variables such as emotions were not examined as factors in this study. Through emotions and similar variables, the observed association between pulse and health indicators can be further understood. This study did not use variables such as emotions because they are difficult to measure with wearable devices.

Future studies should use larger samples and have an extended duration of study (i.e., more than 12 months) to help us explore these results. In addition, other variables that affect the elderly' health should be examined. For example, analysis of the association between factors such as tongue diagnosis and health indicators can be explored. Additionally, the impact of emotional variables on the elderly's health can be investigated.

The addition of more variables can help build a model suitable for the elderly. The Ubi-Liven model is a safe and secure living environment centered on the elderly and including accommodations, families, nursing homes, local communities, and even tourist destinations. In order to comprehensively support the daily lives of the elderly, the authors designed a system that supports the elderly' networks and seamlessly integrates them with physical living environments that are powered by cloud storage, the Internet of Things, and personal big data analytics [140]. This model helps the elderly achieve healthy living by providing comprehensive health management (Figure 5-4).

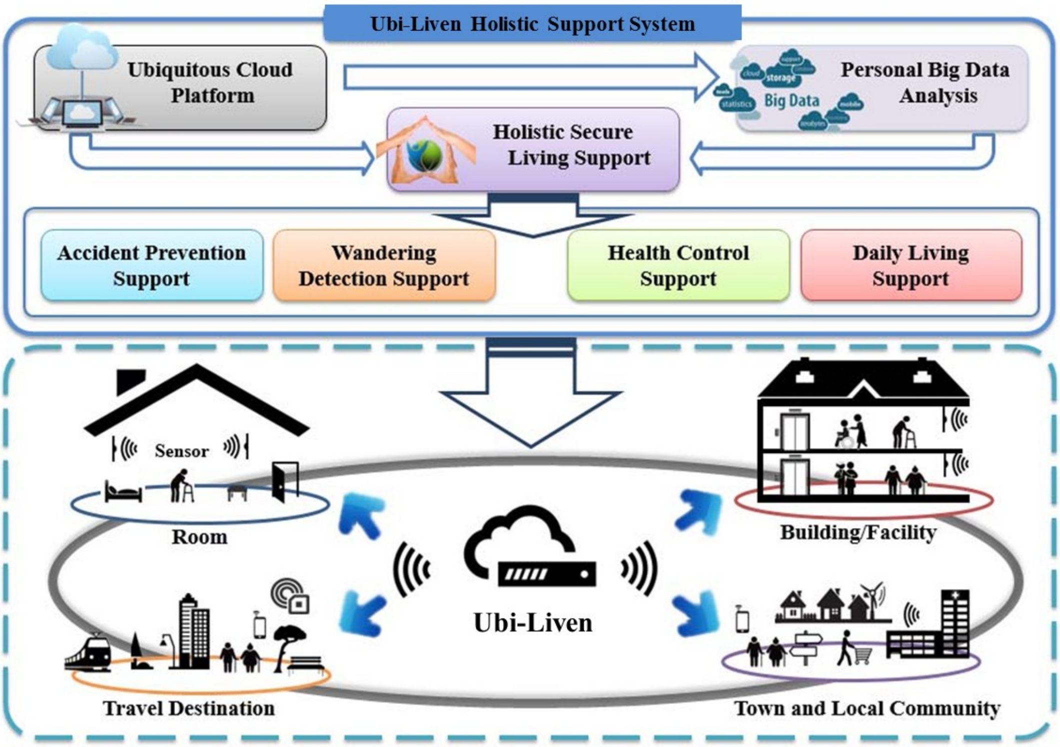

Figure 5-4. The Ubi-Liven model (Qun Jin 2016) [140]

During the implementation of this study, problem that related to human-computer interactions occurred. It is necessary to help the elderly feel comfortable of wearable devices.

It is possible to determine general health by using wearable devices to record continuous health indicators over a long-term. On the other hand, there is commonality between the TCM, which diagnoses by examining the whole body, and the wearable devices that record continuous health indicators. Combined with the development of ICT and predictive medicine, wearable devices and TCM contribute greatly to the health management of the elderly.

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Publication list related to this paper

1. Siyu Zhou, Atsushi Ogihara, Shoji Nishimura, Qun Jin. Analyzing the changes of health condition and social capital of elderly people using wearable devices. Health Information Science and Systems, 2018, 6(1), 4. DOI: 10.1007/s13755-018-0044-2
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