Integration Analysis of Heterogeneous Data on Mind Externalization of Elderly People at Home

Sinan Chen[1(✉)], Hayato Ozono[1], and Masahide Nakamura[1,2]

[1] Graduate School of System Informatics, Kobe University, 1-1 Rokkodai-cho, Nada, Kobe 657-8501, Japan
{chensinan,ozono}@ws.cs.kobe-u.ac.jp, masa-n@cs.kobe-u.ac.jp

[2] RIKEN Center for Advanced Intelligence Project, 1-4-1 Nihonbashi, Chuo-ku, Tokyo 103-0027, Japan

Abstract. As the aging population around the world, figuring out the reason for changes in the health status of elderly adults at home is pressing. In our research group, to comprehend the scientific self-care of elderly adults at home, a core concept called "mind externalization" that retrieves the elders' thoughts as much as possible using spoken dialogue agent technology has developed swiftly. The purpose of this paper is to consider an approach to elucidating reasons for health changes in the elderly at home. Our key idea is to merge the results of health status, dialogue logs, and emotional values (recognized from images and audio during the spoken dialogue) into a time series. More specifically, we describe an approach for extracting the features of changes in health data (i.e., heart rate, stress, sleep quality, step, and activity level from the wearable device). It intends to add health data retrieved from a wearable device and unite heterogeneous data (i.e., health data and dialogue data). Based on the integration between health data and dialogue data (i.e., text logs, audio, and images), we discuss an approach to estimating the reasoning context before and after the period. In this way, assisting elderly adults at home by grasping their daily living in detail can be appreciated. Meanwhile, executing personalized self-management is promising.

Keywords: Elderly at home · Mind externalization · Spoken dialogue · Wearable device · Smart healthcare

1 Introduction

Population aging is currently a big issue in Japan, Germany, and Italy. Specifically, the number of people aged 65 years has reached 28.4% in Japan. It exceeds 21% of the national total, and the country is confronting a **super-aging society**[1]. As the population and disease structure change, the demand for nursing

[1] https://www8.cao.go.jp/kourei/english/annualreport/2020/pdf/2020.pdf.

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care is expanding year by year. In particular, many chronic diseases (e.g., mild cognitive impairment, disease syndrome) require long-term care. However, the shortage of facilities and humans for medical welfare and nursing care is becoming more severe. As the trend toward conversion from **institutional care to home care** continues, the number of elderly adults (requiring nursing care) at home is expanding more swiftly. Furthermore, the number of individual cases is also expanding, such as one elderly adult caring for another, and elder adults living alone.

Encouraging **self-care** among elderly adults within differences between households is a big challenge. For example, the degree of completion of *activities of daily living (ADL)*, the degree of achieving a regular rhythm of life, and the degree of physical and mental health are important indicators. In recent years, research on *assistive technology* applying engineering technology to support the lives of the elderly has been spreading around the world. A representative technology is to monitor elderly adults at home. It mainly utilizes the *internet of things (IoT)* and *information and communication technology (ICT)*. A machine monitors the situation (called *context*) of the elderly adult instead of the family caregiver and communicates with the family caregiver **only when required**. In this way, enhancing the *quality of life (QoL)* of the elderly and decreasing the burden on their families is promising.

Our research group is studying various systems and services from two perspectives: the "environment" and "humans" in houses. Related research from the perspective of the environment includes environmental sensing [20], behavior estimation [21], and context recognition [5]. On the other hand, related research from the perspective of the elderly includes facial expression recognition [10], health monitoring [19], and mental externalization through a virtual agent (VA) listening service [14]. However, in the VA listening service conducted in previous research, various kinds of heterogeneous data (e.g., text, image, and voice data in a time series) that acquired and accumulated remain. We have not yet been able to conduct an **integrated analysis of the health status (e.g., heart rate, stress) and the "mental state" of the elderly**.

The purpose of this paper is to consider a method to elucidate the reasons for causing changes in the health status of elderly adults at home. Figure 2 shows an image diagram of integration analysis of health data and dialogue data for elderly people at home. As an approach, we add health data retrieved from a **wearable health device** (i.e., an activity meter worn on the arm) and consider an integrated analysis of heterogeneous data (health data and dialogue data) in a time series. Our key idea is to merge the results of health status, dialogue logs, and emotional values in a time series. In our approach, we consider the following five concrete steps:

- **Step 1:** VA Listening Service and Wearable Health Installation
- **Step 2:** Acquisition and Storage of Heterogeneous Data
- **Step 3:** Extraction of Health Feature Changes in Time Series
- **Step 4:** Analysis of Interrelationships Among Changing Features
- **Step 5:** Context Estimation Based on Past Feature Analysis

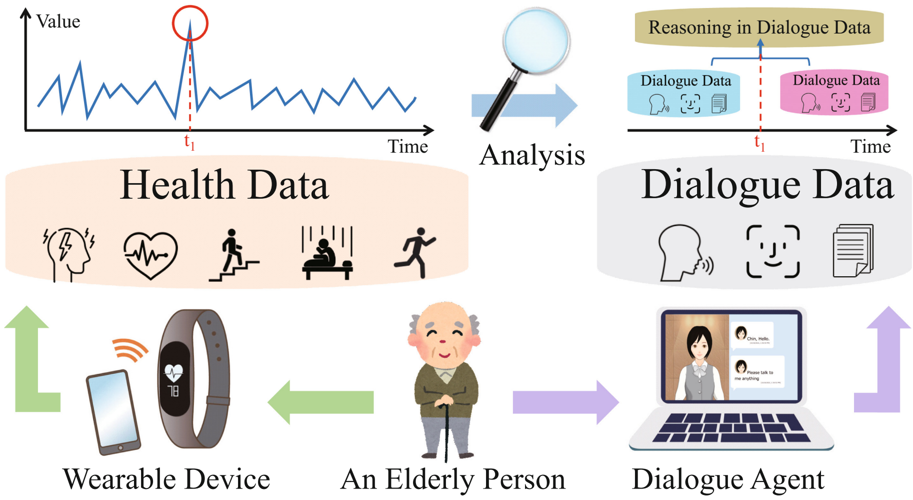

Fig. 1. Integration analysis of health data and dialogue data for elderly people at home.

In the discussion, the advantage of the research approach is that it provides a more multifaceted analysis of the elderly at home by utilizing heterogeneous data. The abundance of available data has likewise improved, allowing for a more granular understanding of the daily living conditions of the elderly at home. As for a limitation of the research approach, we have not yet resolved the problem of dealing with missing data in time series. Furthermore, we anticipate the interrelationships among different types of data. They have not evaluated for individual elderly adults. In particular, the correctness of the acquired data requires investigation. It also requires checking the effects of these data in case studies.

2 Previous Study: Monitoring Assistance for Elderly People at Home

This section depicts the background surrounding the current situation of the elderly at home. It presents previous studies aimed at understanding the mind of elderly adults.

2.1 Mental Externalization of the Elderly at Home

The "externalization of the mind" of the elderly refers to the act of blurting out to the outside world as much as possible of what is on the "mind" of the elderly. In recent years, with the aging of the world's population, **the shortage of nursing care facilities and human resources** [16] has become a social problem. In Japan, which is confronting a super-aging society, the number of elderly people at home is expanding every year as the structure of the population and diseases alter in line with the shift from conventional **institutional care to home care**[2]. The number of elderly people living at home is expanding year by year. While caring for the elderly in their own homes is habituated, it places a heavy burden on family members, and the problems of "elderly couple care each other," "people with dementia care each other," and elderly people living alone at home are becoming more severe.

The implementation of independent living for the elderly at home is not an easy task. The decline of physical and psychological functions, nursing care, and long-term medical treatment have limitations on self-care, and assistive technologies are required. One of the typical technologies is to **monitor elderly people at home**. In the previous study, we studied the two aspects of "physical" and "psychological" monitoring. For monitoring the physical aspects, we estimated daily life behaviors [21], recognized contexts [5], and measured and analyzed physical activities [6]. On the other hand, for observing mental aspects, there are virtual agent listening services, microservice execution by voice dialogue, and multimodal diary services [4]. In this paper, we focus mostly on psychological monitoring and support technologies.

2.2 Virtual Agent Listening Service

Virtual Agent (VA) technology refers to a technology that is equipped with a software (i.e., virtual) interface. It acts as an intermediary to promote smooth interactions between machines and humans. In our previous study, we proposed a VA listening service with voice interaction function to listen to the "feelings" of elderly people in their daily lives. Figure 2 shows the components of the VA listening service in the edge and cloud environments.

In the VA listening service, the components are described in detail from two aspects: hardware and software. The hardware component consists of IoT sensors (i.e., *Phidgets*[3] motion and pressure sensor modules) and a general-purpose computer (i.e., including built-in speakers, cameras, and microphones). On the other hand, we explain the details of the software components from two perspectives: local and cloud. First, the local component consists of a sensor driver, a VA (i.e., *MMDAgent* [13]: including speech synthesis and character materials), a local server (i.e., *Apache Tomcat* [15]), and a Web browser (i.e., including speech recognition by *Web Speech API* [1] and display of dialogue contents by *Web user interface*). Next, the cloud-side component consists of a cloud server (i.e., *WebSocket* and *Pub/Sub* [12]) and a database (i.e., dialogue scenarios (including gestures, time periods, and questions) and dialogue logs).

By linking the IoT sensor with a general-purpose computer, it is possible to drive the VA Listening Service in two modes: "passive mode" and "active mode". In the "passive mode," the VA listening service is automatically activated when an elderly person at home approaches the motion sensor. Based on the user-defined time of day and the questions to be asked, the VA listening service can

[2] https://www.mhlw.go.jp/english/policy/care-welfare/care-welfare-elderly/dl/establish_e.pdf.
[3] https://www.phidgets.com/?tier=0&catid=3&pcid=8.

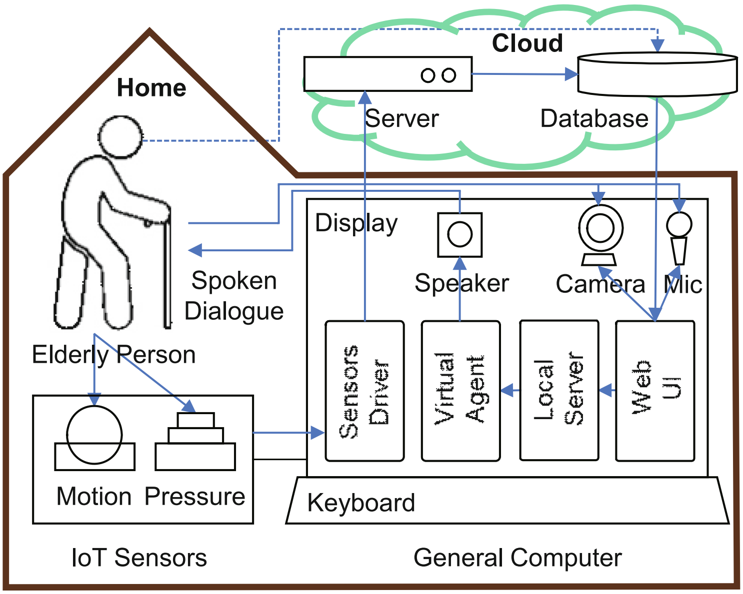

Fig. 2. Component structure of virtual agent listening service

ask about the person's mood, physical condition, eating and drinking status, etc. In the "active mode," the VA listening service is automatically activated when the elderly person at home presses the pressure sensor. When the elderly person tells the VA any tale by voice, the VA can give a random response (e.g., "Is that so?", "Yes", etc.) by voice. Through interaction between the VA listening service and the elderly person at home, thoughts and concepts in daily life, as well as answers to specific questions, can be extracted, recorded, and stored externally (i.e., externalization of the elderly adult at home).

2.3 Microservice Execution Through Voice Interaction

The use of various **microservices**, such as contents and services on the Web, as well as the externalization of the mind through voice dialogue between elderly people at home and VA is also promising. In our previous study, we aimed to help elderly people who are not accustomed to operating smart devices (e.g., computers, smartphones, etc.) to smoothly use Web services and information based on the spoken dialogue function described in Sect. 2.2. The key idea is to apply the application programming interface (API) to microservices in Web services (e.g., calendar, video watching, to-do management, etc.) and incorporate the appropriate content into the VA dialogue scenario. The approach includes two parts: (1) User information and microservice management. (2) Configuring VA behavior at API runtime. To demonstrate the effectiveness of the proposed framework, we linked the "ToDo management service" and the "YouTube watching service" with user information. This allows the elderly to control the execution and stopping of microservices through voice interaction.

2.4 Multi-modal Diary Service

Although VA listening services have made it possible to record and accumulate dialogue data, the **diversity** of dialogue data and the lack of analysis and reuse still pose challenges. In a previous study, we proposed a multimodal diary service that records and analyzes dialogue data from a variety of perspectives. The key idea is to retrieve not only text logs, but also audio and images during the dialogue as dialogue data, and to perform multimodal visualization. In the proposed method, we executed heterogeneous data extraction, Web API development, multimodal diary generation, and heterogeneous data analysis. To extend the heterogeneous data, we also considered text-based negative judgment, speech-based emotion detection, and image-based emotion estimation approaches. Using the proposed method, the elderly can better recall the past for themselves. Hence, a more precise improvement in self-care and health management of individual elderly adults is promising.

3 Development of Advancing Technology: Wearable Health

This section describes the challenges and measurement items for wearable health devices for the elderly at home, based on smart healthcare technology.

3.1 Smart Healthcare of Elderly People at Home

The use of information and communication technology (ICT), internet of things (IoT), and artificial intelligence (AI) technologies to support the traditional **healthcare** of the elderly at home (e.g., visiting hospitals, managing health, receiving care from family members, etc.) has been accelerating. The introduction of smart sensors (i.e., environmental sensors, opening/closing sensors, etc.), smart speakers, and 360-degree cameras to make the homes of the elderly into an environment similar to that of a facility has enabled safety confirmation [11], status confirmation [17], and automatic operation of home appliances [2]. However, these smart devices and approaches are only capable of sensing external environmental conditions, including the externalization of the elderly as described in Secti. 2, and are not capable of **monitoring the health** of individual elderly people, including changes in heart rate and stress, distance traveled, and number of steps taken.

3.2 Emergence of Wearable Health Devices

Wearable health devices are emerging to monitor the health of the elderly at home. Smart apparel (i.e., clothing-type devices) include Xenoma[4] and Hamon[5]. On the other hand, arm-worn smart watches (i.e., activity meters) include Garmin[6] and Fitbit[7]. Through the use of these devices, smart healthcare technology can be deployed in various areas such as fitness, sleep, and nursing care. By collaborating with local facilities and hospitals, it is possible to provide preventive medicine or telemedicine by utilizing health data. However, wearable health devices may not be suitable for bedridden elderly people and may be **invasive to their daily lives**. In the case of clothing-type devices, the user has to change and wash the related clothing regularly, which increases the **burden of daily life**.

3.3 Collection of Health Data by Activity Tracker

In order to **minimize the existing challenges**, we focus on the collection of health data by arm-worn activity tracker. Specifically, here is an example of handling health data from the following six items:

- **Number of Steps:** Measuring the number of steps and the intensity of exercise leads to the prevention of lifestyle-related diseases and the extension of healthy life span.
- **Sleep Quality:** The quality of sleep (i.e., REM/non-REM sleep) is expressed by analyzing heart rate, heart rate variability (i.e., HRV, the change in the length of the heartbeat with each beat), and activity level data.
- **Stress:** Estimates the factors that influence stress, such as training and physical activity, by measuring heart rate variability.
- **Heart Rate:** The heart rate is measured continuously for 24 hours using an optical heart rate monitor.
- **Calories burned:** The total number of calories burned during exercise/rest.
- **Body Battery:** This unique Garmin feature measures remaining physical energy by analyzing heart rate variability, stress levels, sleep quality, and activity levels.

4 Considering Approach: Integration Analysis of Heterogeneous Data

4.1 Technical Challenges

We are considering the following two technical challenges to elucidate the factors that cause changes in the health status of the elderly at home.

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[4] https://xenoma.com/products/eskin-sleep-lounge/.
[5] https://www.mitsufuji.co.jp/en/service/.
[6] https://www.garmin.co.jp/minisite/health/guide/ (in Japanese).
[7] https://healthsolutions.fitbit.com/.

The first is the **lack of richness** in data types. In our research on support systems for elderly people living at home, we have studied the extraction of biometric data (e.g., heart rate, blood pressure, amount of activity, etc.) using sensor devices and dedicated devices, the collection of multimedia data (e.g., text, voice, images, etc.) using IoT devices, and the collection of environmental data (e.g., temperature, illumination, humidity, etc.). Sensing of environmental data (e.g., temperature, illumination, humidity). However, many studies have been conducted using each of these methods independently, and there have been few studies using different types of data together.

Second, there is a **lack of integration analysis** among the data used. In order to elucidate the factors that contribute to changes in the health of the elderly at home, it is not enough to collect and analyze each piece of data, but an integrated analysis (meta-analysis) among the data is necessary. Integration analysis refers to the integration of the results of multiple studies and analysis from a higher perspective, or methods and statistical analysis for this purpose[8]. In particular, by supplementing and verifying the results obtained from heterogeneous data, multifaceted relationships can be clarified. For example, heart rate variability in the elderly may be related to temperature.

4.2 Goal and Key Idea

The purpose of this study is to examine methods to elucidate the factors that cause changes in the health status of elderly people at home, based on the previous studies described in Sect. 2. The key idea is to integrate and analyze health data, dialogue data, and the results of further analysis of dialogue data in a time series.

4.3 Overall Architecture

Figure 3 shows the overall architecture of the study approach, which consists of five steps: In Step 1, the elderly person wears a wearable health device and the VA listening service with voice interaction is set up. In Step 2, health data and interaction data are acquired and stored through the wearable health device and the VA listening service. In Step 3, we extract the typical changes in health data over time. In Step 4, we focus on dialogue data during health changes and analyze the interrelationships among different features. In Step 5, we search for personal rhythms from the previous feature analysis and consider context estimation from the latest data. More specifically, each step is described below.

4.4 Flows of Considering Approach

Step 1: VA Listening Service and Wearable Health Installation
In Step 1, we first deploy the VA listening service to the homes of the elderly based on previous studies. In addition, the elderly will wear a wearable health

[8] https://en.wikipedia.org/wiki/Meta-analysis.

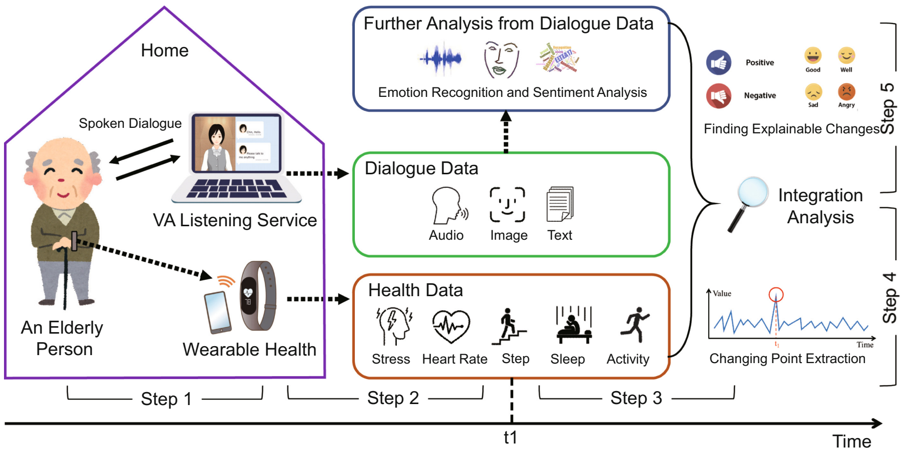

Fig. 3. Overall architecture of considering approach.

device on their arms. In this research, we chiefly focus on arm-worn activity meters (e.g., Garmin vivosmart 4[9]).

Step 2: Acquisition and Storage of Heterogeneous Data
In Step 2, we first acquire voice data, text data recognized from the voice, and image data taken at one-second intervals during the voice dialogue process between the elderly person and the agent based on the VA Listening Service, and send them to the cloud database. AI techniques such as emotion analysis are applied to these data, and the recognized results are also sent to the cloud database. With regard to health data, activity meters are generally linked to a dedicated smartphone application via *Bluetooth*, and by manually opening the dedicated application, health data is transmitted and sent to a cloud database. In order to transmit health data to the cloud database on a regular basis, we also introduce a dialogue scenario that reminds the user to open the dedicated application, and the agent asks the user to do so once a day.

Step 3: Extraction of Health Feature Changes in Time Series
In Step 3, we first develop a *Web Application Programming Interface (API)* that can retrieve health data for each item (see Sect. 3.3) to the computer local (edge). `GET` or `POST/date={yyyy-MM-dd}/data={data}` in the format of REST API [3] to retrieve the relevant health data by specifying the date and data item. Although each health data has a different measurement interval, the following five measures of feature change are defined to create a feature extraction program from past health data.

- **Maximum value**: $m_1 = max\{x_1, x_2, \cdots, x_n\}$ $(n = count(x_i))$
- **Minimum value**: $m_2 = min\{x_1, x_2, \cdots, x_n\}$

[9] https://www.garmin.co.jp/products/wearables/vivosmart-4-gray-r/.

- **Difference value**: $d_i = |(x_i - x_{i+1})|\ (1 \leq i \leq n)$
- **Average value**: $\bar{x} = \frac{1}{n}(x_1 + x_2 + x_3 + \cdots + x_n) = \frac{1}{n}\sum_{i=1}^{n} x_i$
- **Variance value**: $s^2 = \frac{1}{n}(x_1 - \bar{x})^2 + (x_2 - \bar{x})^2 + \cdots + (x_n - \bar{x})^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$

Step 4: Analysis of Interrelationships Among Changing Features
In Step 4, we utilize the following three computational approaches to evaluate the interrelationship between the values of the health change features and the dialogue recognition results. For example, we consider whether the negative score of the dialogue content rises or not when the stress increases swiftly. We likewise examine the change in the score of emotion analysis using facial expression and voice during the dialogue. Unlike real-time health data acquisition, it is challenging to cope with missing dialogue data.

- **Correlation coefficients**: $r_{xy} = \frac{s_{xy}}{s_x s_y} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} = \frac{1}{n}\sum_{i=1}^{n}\frac{x_i - \bar{x}}{s_x}\cdot\frac{y_i - \bar{y}}{s_y}$
- **Partial correlation coefficient**: $r_{xy\cdot z} = \frac{r_{xy} - r_{xz}r_{yz}}{\sqrt{1 - r_{xz}^2}\sqrt{1 - r_{yz}^2}}$
- **Covariance**: $s_{xy} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})$

Step 5: Context Estimation Based on Past Feature Analysis
In Step 5, we first consider the interrelated feature data from the past as training data. Next, we estimate the context by applying lightweight machine learning (e.g., supervised learning) to them. Context refers to an individual's emotional state and negative/positive changes. Through context estimation, we expect to understand the individual's emotional state and negative/positive changes by analyzing and estimating the health change characteristics obtained from the wearable health device even during the time when the VA listening service is not used.

5 Discussion

This section summarizes each of the main points regarding the advantages and limitations of the approaches considered in Sect. 4, and discusses the specifics.

5.1 Advantage

The following two advantages of the research approach are considered:

- **Utilization of heterogeneous data**: Unlike previous related research, we will utilize different devices and approaches to collect and warehouse data. This allows us to enhance the richness of the data types utilized. It can also be used to enhance the scalability of existing systems.
- **Expansion of multifaceted analysis**: In addition to the utilization of heterogeneous data, the analysis of interrelationships can be anticipated to infer the factors behind changes in the health status of the elderly at home from a more multifaceted perspective. Furthermore, it can promote and enhance the implementation of self-care for the elderly at home.

5.2 Limitation

We examine the following two limitations of the research approach:

- **Trouble in dealing with missing data**: There are times when the wearer is not wearing the wearable health device (e.g., recharging, taking a bath, etc.), and there are times when the wearer is not utilizing the VA listening service. During these times, data acquisition is not feasible, and it is hard to deal with missing data.
- **Problems with data acquisition accuracy**: Depending on the tightness of the wearable health device's belt, there are subtle differences in the data values such as heart rate attained. There are also occasional problems with mis-recognition of dialogue text gained by speech recognition, negative judgments, and emotion analysis.

6 Related Work

Two researches related to the approach considered in this study are described below. Research [7] proposed a web-based medical data integration and management platform that collects heterogeneous types of health-related medical records and real-time lifelog data. Unlike the wearable health used in this study, the proposed platform in this study provides the ability to manage real-time data such as heart rate, blood pressure, and activity information extracted from medical devices and send them to a server. It also applies machine learning tools to analyze risks based on domain knowledge and individual differences, and dynamically visualizes the results to patients and doctors based on how the information is simplified.

Research [8] described all these important aspects of smart healthcare wearable sensors, body domain sensors, advanced pervasive healthcare systems, and new IoT technologies for big data analytics. Unlike the focus of this work on integrated analysis in heterogeneous data, we identify new perspectives and focus on issues such as scalability, interoperability, device-network-human interface, and security. We also present the results of an evaluation of the applicability of knowledge in the field of *CAD*, such as large-scale analysis and optimization methods, to key *eHealth* problems.

7 Conclusion

In this paper, we focused on the self-help of the elderly at home in the super-aged society, and we organized and discussed the flow of considering the approach of integrating and analyzing heterogeneous data in order to elucidate the factors of health status change.

However, in order to obtain health data, the wearable health device to be used still has the challenge of being invasive to daily life. The wearable **remote** health monitoring device [9] is expected to provide a portable health care system and facilitate the provision of decentralized health care, as opposed to the traditional centralized clinical care. The correlation between non-verbal data (e.g., facial expression, posture, etc.) and health status of the elderly also needs to be verified in evaluation experiments. In research [18], facial features that convey a sense of familiarity were associated with a decrease in patients' pain perception.

As future work, we will conduct case studies and evaluation experiments using the study approach to clarify the correlation between actual interaction data and health data of elderly people at home. In addition, we will utilize data on daily behavior, daily rhythms, and environmental conditions to examine the correlation with changes in health status.

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