Digital phenotyping of geriatric depression using a community based digital mental health monitoring platform for socially vulnerable older adults and their community caregivers: A 6- week living lab single arm pilot study

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Abstract

Background: Despite a growing need for digital services to care for geriatric mental health, the development and implementation of digital mental healthcare system for older adults have been hindered by a lack of studies among older adult users and community caregivers.

Objective: This study aimed to identify whether digital sensing data on heart rate variability (HRV), sleep quality, and physical activity predicts same day or next day depressive symptoms among older adults in their ordinary living environments. In addition, this study tested the feasibility of a digital mental health monitoring platform to inform day-to-day changes in the health status of older adult users and their community caregivers.

Methods: A living lab pilot study was conducted with community-dwelling older adults (n = 25) and their community caregivers (n = 16) for 6 weeks. Depressive symptoms were assessed daily using PHQ-9 via scripted verbal conversations using a smartphone application chatbot, and digital biomarkers of depression, including HRV, sleep, and physical activity, were assessed using a wearable sensor (Fitbit Sense), which was worn continuously, except charging time, for 6 weeks. Daily individualized feedback on the health status of older adult users was displayed on the applications for the users and their community caregivers. Multilevel modeling (MLM), with within-person changes over time at Level 1 and between-person differences at Level 2, was utilized to examine whether the digital biomarkers predict same day or next day depressive symptoms after adjusting for age, gender, baseline depression, and chronic disease conditions.

Results: The MLM results showed that fluctuations in daily sleep fragmentation and sleep efficiency were associated with an increased probability of next day depressive symptoms for older adults. The feasibility test results indicated that older adults were able to use one or two functions of the monitoring platform 6 out of 7 days per week. However, the usability levels of older adults decreased from pre to post living lab due to experienced difficulties.

Conclusions: The findings indicate the feasibility of digital mental health monitoring platforms for socially vulnerable older adults. The results also suggest that wearable sensor assessments of sleep fragmentation and efficiency can be important indicators for passively sensing daily fluctuations of depressive symptoms in older adults.

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Digital phenotyping of geriatric depression using a community based digital mental health monitoring platform for socially vulnerable older adults and their community caregivers: A 6- week living lab single arm pilot study

Abstract

Background: Despite a growing need for digital services to care for geriatric mental health, the development and implementation of digital mental healthcare system for older adults have been hindered by a lack of studies among socially vulnerable older adult users and their caregivers in the natural living environments.

Objectives: This study aimed to identify whether digital sensing data on heart rate variability (HRV), sleep quality, and physical activity predicts same day or next day depressive symptoms among socially vulnerable older adults in their ordinary living environments. In addition, this study tested the feasibility of a digital mental health monitoring platform to inform older adult users and their community caregivers day-to-day changes in the health status of older adults.

Methods: A single arm, non-randomized living lab pilot study was conducted with socially vulnerable older adults (n = 25), their community caregivers (n = 16), and a managerial social worker for six weeks during and after the COVID-19 pandemic. Depressive symptoms were assessed daily using PHQ-9 via scripted verbal conversations using a mobile chatbot, and digital biomarkers for depression, including HRV, sleep, and physical activity, which were assessed using a wearable sensor (Fitbit Sense), which was worn continuously, except charging time. Daily individualized feedback utilizing traffic signal signs on the health status of older adult users regarding stress, sleep, physical activity, and, health emergency status was displayed on the mobile application for the users and a web/app for their community caregivers. Multilevel modeling (MLM) was utilized to examine whether the digital biomarkers predict same day or next day depressive symptoms. Study staff conducted pre and post-surveys in person at the homes of older adult users to monitor changes in depressive symptoms, sleep quality, and system usability.

Results: Among 31 older adult participants, 25 participants provided data for living lab and 24 provided data for pre-post-test analysis. The MLM results showed that fluctuations in daily sleep fragmentation (P = 0.003) and sleep efficiency (P = 0.001) were associated with an increased risk for daily depressive symptoms for older adults. Pre-post test results showed the improvements in the levels of depressive symptoms (P = 0.048) and sleep quality (P = 0.024) but not in the system usability (P = 0.185).

Conclusions: The findings suggest that wearable sensor assessed sleep quality maybe utilized to predict daily fluctuations of depressive symptoms in socially vulnerable older adults. The results also imply that receiving individualized health feedback and sharing it with their community caregivers may help improve mental health of older adults. However, additional in-person training may be needed to increase the usability (Registration for the main trials: Clinicaltrials.gov NCT06270121, https://clinicaltrials.gov/study/NCT06270121).

Keywords: depression; monitoring system; IoT; AI; wearable device; digital mental health phenotyping; living lab; senior care

Introduction

Geriatric depression and other psychiatric disorders have increased over the last two decades, while life expectancy and population aging have rapidly increased worldwide [1-4]. South Korea's suicide rate among older adults has been the highest in the Organization for Economic Cooperation and Development (OECD) countries since 2009, due to high rates of geriatric depression, economic poverty, and social isolation from the rapid nuclearization of the family [5]. With the fast pace of global population aging, caring for older adult family members with mental disorders has become an overwhelming task for the younger generations [6]. Despite the growing role of community services in caring for older adults with mental disorders, there are extensive shortages of budget in the local community and government's health department and skilled geriatric labor to meet the needs of these older adults with mental disorders.

The digitalization of mental health screening and intervention is expected to provide innovative solutions to challenges in mental healthcare for older adults. For example, digital phenotyping can facilitate early detection of depression and reduce the high rate of undiagnosed depression (50%) among older adults [7]. Digital phenotyping of mental health can be defined as "moment-to-moment quantification of the individual-level human phenotype of mental health status in real-life contexts using data collected from personal digital devices" [8]. Recent studies have suggested the possibility of digital phenotyping of depressive symptoms using ecological momentary assessments, including self-reporting of depressive mood [9]. In addition to momentary self-report, digital sensing technologies enabled unobtrusive passive sensing of depressive symptoms using smartphone applications, wearable sensors, and Internet of Things (IoT), which refers to the ubiquitous network of various devices for seamless data collection and intelligent monitoring and management to secure user's health and safety [10-13]. However, previous studies mostly examined digital phenotypes of depressive symptoms in young adults or small groups of depressive patients, which led to difficulties in using digital phenotyping technologies with older adults [3].

The underrepresentation of older adults in digital mental healthcare research is related to several barriers hindering older adults' participation in research with novel digital technologies. First, older adults often have sensory and cognitive impairments that require the application of different design principles than those that are effective with young or middle-aged adults [14-16]. For example, older adults generally prefer displays with simple layouts and multimodal command functions such as voice command in addition to touch screen interface. Second, implementation of digital healthcare services for older adults should involve both family and community caregivers who do not usually live with the older adult in addition to support from multiple community healthcare institutions [17, 18]. When learning to use a new technology, older adults need repeated in-person assistance and educational materials that were suitable for low digital literacy levels [14, 15]. Digital healthcare services are likely to benefit older adults when the digital service can connect them to needed healthcare services in the community. Third, the living environments of older adults are likely to hinder their use of digital mental healthcare services because considerable rates of older adults (40~60%) may not have internet connection or be equipped with a personal computer and other mobile devices [19, 20].

These functional, social, and environmental barriers highlight the need for proof-of-concept and feasibility trials for geriatric mental healthcare services among older adults and community caregivers in their natural living environments using living labs [3, 18]. Living labs are defined as "user-centered, open innovation ecosystems based on a systematic user co-creation approach, integrating research and innovation processes in real-life communities and settings to create sustainable impact" [21]. Living labs are essential to designing solutions for older adults. Digital mental health services will neither be acceptable nor sustainable if they are not designed to be compatible with the cognitive and physical capacity and natural living environments of older adults and the working environments of community caregivers via living lab testing [22, 23].

To fill the gap in the current geriatric health literature, this study aims to test the feasibility of a digital mental health monitoring platform that can be linked to existing community senior care services for prevention and early detection of declines in the mental health of socially isolated older adults. We conducted a single arm, non-randomized living lab pilot study with 25 socially vulnerable older adults who received individualized daily health monitoring in their natural living environments for six weeks during and after the COVID-19 pandemic. Their community caregivers (n = 16) and a managerial social worker at a community senior welfare center (community center, hereafter) also received the monitoring results of the older adult participants and implemented the information when they provided regular in-person senior caregiving services and emergency responses. Pre–post changes levels of mental health status (e.g., depressive symptoms and sleep quality) and usability of the monitoring platform were examined in older adults to test the health-improving effects and the system usability of the monitoring platform. In addition to feasibility testing, this study examined whether using digital biomarkers of geriatric depression detected by a wearable sensor can predict daily changes in depressive symptoms among older adults.

Methods

Overview

This single-arm, non-randomized living lab pilot study was conducted as a part of a larger study to develop a sustainable digital health monitoring platform that can be linked with a community-based public senior care service to promote the mental and physical health of older adults during and after the COVID-19 pandemic. We previously conducted formative research using surveys with older adults (n = 99) and focused group interviews with older adults (n = 16), community caregivers (n = 12), and social workers (n = 3) at the community center to identify the major health problems associated with older adults, the workflow of community caregiving services, and structures and features required for the health monitoring service platform. The current digital health monitoring platform utilized a chatbot on a smartphone, a smartwatch (Fitbit Sense, Google Inc., Mountain View, CA, USA), and a motion sensing camera (Azure Kinect SDK 1.3.0, Microsoft, Washington, USA) that was installed at home. The digital health monitoring platform aimed to improve the self-care capacity of older adults by providing daily mental and physical health status updates to older adult users compared to their own average taken during the first week of the living lab. The platform also aims to strengthen social support network of older adults by sharing their daily health status information and health emergency alarms with their community caregivers, who regularly provide the in-person senior caregiving service to the older adult user via the community center. Moreover, the information was shared with the managerial social worker at the community center to assist with any health emergencies during and after the COVID-19 pandemic. Before the pilot study, we conducted an informal pre-pilot test involving study staff (n = 6) to check for the overall functionality of mobile apps and processing algorithms. The results from the motion sensing camera, which was linked with experimental sessions outside the living lab, are reported separately from this study [24]. Trained research assistants and a community caregiver visited older adult participants in their homes in order to acquire informed consent and install a mobile application on the user's smartphone and digital devices. Participants were asked to respond to surveys at home before and after the living lab activities to measure usability of the platform and their mental and physical health status. The main RCT trials with both an intervention and a comparison group have been registered (Registration: Clinicaltrials.gov NCT06270121, https://clinicaltrials.gov/study/NCT06270121); however, there was no control group for the current pilot study. The study protocol was approved by the Institutional Review Board of Korea University (KUIRB-2021-0324-02).

Figure 1 presents the timeline of the living lab study procedure, which was conducted from September 2022 to August 2023. The living lab was conducted for six weeks, starting with a one week adaptation period. Older adults were asked to open the smartphone application in the morning; the application would automatically link them to a chatbot asking how they are doing and two questions on daily depressive symptoms. After using the chatbot, the participants could see their daily health status information for stress (via high frequency measure (HF) of heart rate variability (HRV)), sleep (via total sleep time and sleep fragmentation), and physical activity (via steps) on the previous day, compared to their own average during the first week of the living lab. The voice records, daily health status, and real-time emergency statuses of the older adult participants were sent to their matched community caregiver and the managerial social worker via the web/app. During the living lab period, the older adult participants were asked to wear a smartwatch continuously except while the battery was charging.

A pre- and post-survey was conducted by trained research assistants at the homes of older adults before and after the living lab to examine key changes in pilot trial outcomes, including depressive symptoms, sleep quality, and system usability. At the post-test survey, additional questions were asked about the frequency and types of functions in the platform they used during the living lab period and any other feedback to improve the platform in the main trials.

To help participants adapt to using the digital monitoring app and devices and prevent missing data, a member of the research staff visited participants to their home for two to three additional sessions of in-person training on how to use the verbal surveys and digital devices and how to check their daily health status during the second and third week of the living lab. If a participant's data was missed three days in a row, study staff called the participant over the phone, reminded them of the importance of responding to verbal surveys or wearing the smartwatch, and provided assistance if there were any technical issues hindering the older adult's participation. Community caregivers helped older adults to adapt to use the platform.

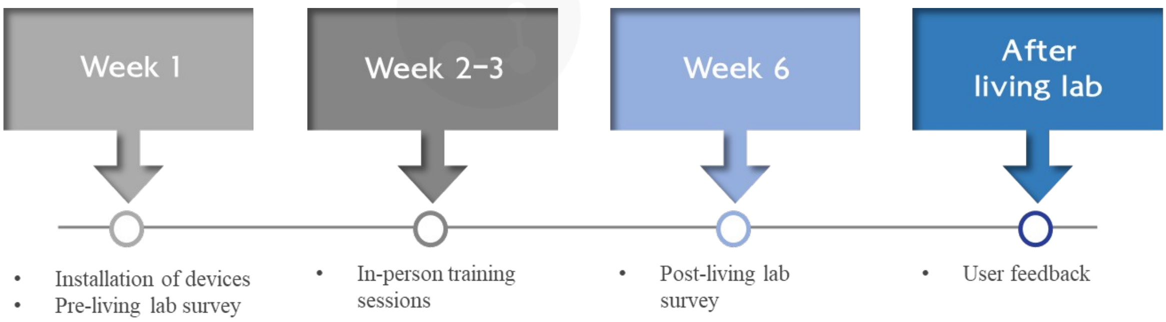

Figure 1. Timeline of the 6-week living lab pilot procedure.

Recruitment

Adults aged over 65 years old and their community caregivers were recruited at a community center in Seoul, South Korea. A meeting was held with the community caregivers and managers at the community center to explain the purpose and procedures of the study, ask for participation as a community caregiver, and help with recruiting the older adult participants. According to the formative research, community caregivers can be characterized as middle-aged women (mean age = 58.04 (SD = 3.17), 100% women) with one to two years of work experience. Each caregiver provided an in-person caregiving service to multiple older adults (a maximum of 16). Caregivers interested in participating in the study with their older adult service recipient explained the study protocol to the older adult during their next regular in-person visit. If both the older adult and their community caregiver were interested in participating, study staff visited the home of the older adult with their caregiver to receive informed consent.

The inclusion criteria were older adults who receive in-person senior care services because of their socioeconomic vulnerability (living alone with low income) and use the Samsung Galaxy smartphone (the mobile application was developed only for the Android smartphone, which is widely used by older adults in South Korea). Exclusion criteria were cognitive and functional impairments that could hinder study participation (eg, hearing loss) or those who live with other people in the same household, due to the technical difficulties of the motion sensing camera detection related to the larger study. The community caregivers who provide in-person public senior care services at the community center were eligible to participate in the study. A managerial social worker who was in charge of the in-person senior care service at the community center was also recruited to test the website of the monitoring platform.

Among 39 older adults who were recruited to participate in the study, 8 older adults declined participation mainly because of being busy and feeling burdensome about the long-term use of the platform. The remaining 31 older adults were consented to participate in the study.

Daily Verbal Survey

Textbox 1. The methods for assessing daily depressive symptoms via mobile application chatbot.

- **PHQ-9 Items on depressive symptoms**
  1. Do you feel down, depressed, or hopeless today?
  2. Do you feel little interest or pleasure in doing things today?
  3. Have you had trouble falling or staying asleep, or sleeping too much today?
  4. Are you feeling tired or having little energy today?
  5. Have you experienced poor appetite or overeating today?
  6. Do you experience trouble concentrating on things today?
  7. Are you feeling bad about yourself or that you are a failure or have let yourself or your family down?
  8. Are you moving or speaking so slowly that other people could have noticed?
- **5 items on daily greetings** (recommended by community caregivers during the formative research)

1. Did you sleep well last night?
2. Have you eaten your meal?
3. How are you feeling? Are you feeling pain in any part of your body?
4. What are you planning to do today?
5. Do you need to go to the hospital today?

- **An example daily voice survey scenario combining 1 randomly selected greeting item and 2 randomly selected PHQ-9 items**

Good morning, Ma'am!

[Greeting item] Did you sleep well last night? (Recording)

[PHQ-9 #1] Do you feel down, depressed, or hopeless today? (Recording)

[PHQ-9 #2] Are you moving or speaking so slowly that other people could have noticed? (Recording)

Thank you! Have a good day.

Patient Health Questionnaire-9 (PHQ-9).

The PHQ-9 was used to assess daily depressive symptoms via smartphone application chatbot, based on the formative research of the larger study on older adult users' difficulty to use a touch screen and their preference for verbal communication features to visual displays. The PHQ-9 is widely used to detect mild and clinical depressive symptoms in nonpsychiatric settings [25, 26]. Among the PHQ-9 items, one item on suicidal thoughts (Have you had thoughts that you would be better off dead, or of hurting yourself?) was excluded because of the potential risk of provoking negative thoughts among those who are at risk for depression.

In addition to the PHQ-9 items, we developed a chatbot script for daily greetings and safety checks with five commonly utilized questions recommended by community caregivers (See Textbox 1 for questions and script compositions). Older adult participants were instructed to open up the mobile application every morning, which automatically prompted the conversation with a chatbot (the first time the application was opened each day). Voice recording was activated for 30 seconds after each question, and the recorded file was instantly uploaded to the website for the community caregivers (Figure 2). The voice recording files were monitored during the living lab and coded later for existence of daily depressive symptoms (1 = *depressive symptoms indicated on at least 1 PHQ-9 item*, 0 = *no reports of depressive symptoms*) by two research assistants independently. A few disagreements between two coders were resolved by discussions among the two coders and an experienced supervisor.

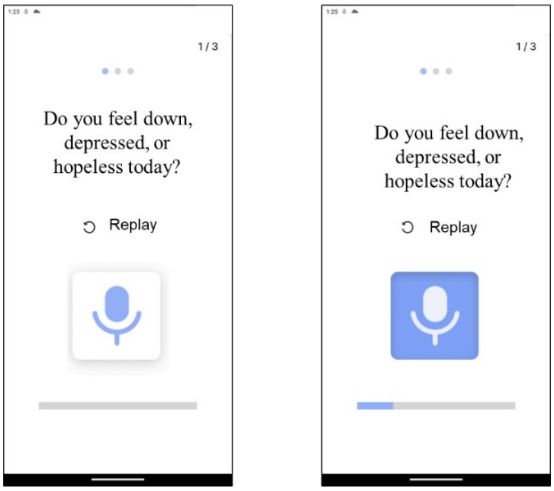

Figure 2. Mobile application function for collecting daily depressive symptoms; the chatbot voice asked two randomly selected PHQ-9 items and older adult participants' answers were automatically recorded. The blue bar and blue microphone icon indicate that voice recording has been activated.

Smartwatch Derived Measures

Daily sleep quality

Sleep quality was assessed by the total sleep time, sleep fragmentation index, and the number of long fragmentation episodes. The usual sleep time and wake time were examined at baseline by the PSQI items to confirm our sleep calculation algorithm, starting at 6PM and ending at 12PM the next day to capture all sleep periods. Additional adjustments were made for one older adult whose day and night cycles have reversed, to capture daytime sleep periods (n = 1). The Fitbit algorithm classified the activity level for each minute the older adult wore the sensor as either asleep or awake. Furthermore, the classification data were prescreened using the following seven criteria to improve the accuracy of actigraphy-assessed sleep detection based on previous studies [27, 28]: (1) If the previous four minutes were coded as awake, the first minute of the beginning of a sleeping period was corrected to sleep; (2) If the previous 10 minutes were coded as awake, the next three minutes were corrected to awake; (3) if more than 15 minutes before and (4) after sleeping less than 6 minutes were coded as awake, then the less than six minutes of sleep was corrected to awake; (5) if more than 20 minutes before and after sleeping less than 10 minutes were classified as awake, the less than 10 minutes sleep time was corrected to awake. The total time in bed was calculated as the time between the start and end of the sleep cycle. (6) The sleep start time was defined as the first time-block with at least 10 minutes of continuous sleep, and (7) the sleep end time was defined as the last 10 minutes of continuous sleep before getting out of bed. The total sleep time was calculated by summing the sleep minutes from sleep start to sleep end. The sleep fragmentation index was calculated by the number of times the participant awoke for more than 1 minute divided by the total sleep time [27]. Sleep efficiency was calculated by dividing the total sleep time by the time in bed [27].

Heart rate variability (HRV)

HRV was assessed by time and frequency domain indicators. The indicators were calculated every five minutes, 24 hours a day using the Python-based open-source program code Aura-healthcare (https://aura-healthcare.github.io/hrv-analysis). The code converted heart rate to R–R intervals, which refers to the time elapsed between two successive R-waves in the QRS signal on the electrocardiogram and is known to be influenced by the sinus node and autonomic nerve stimulation [29]. Then, the code was used to calculate the time domain indicators, including the standard deviation for the N-N intervals (SDNN), the normalized or filtered R–R intervals, and the root mean square of successive differences (RMSSD). The frequency domain indicators were calculated for the low frequency (LF) by high frequency (HF) ratio and HF after applying the fast Fourier transformation, which classified the power of heart rate into high, low, and very low frequency. The characteristics and reliability of HRV assessments using Fitbit have been reported in a previous study with a diverse population [30].

Physical activity (PA) indices

PA levels were assessed by Fitbit's indicator for steps and minutes of light, moderate, and intense activity for each day of the living lab participation. Fitbit uses a three-axis accelerometer to count steps and PA by the frequency, duration, intensity, and patterns of movements. The accuracy of Fitbit activity data was validated by previous studies [31-33].

Provision of Individualized Daily Health Status Feedback via the Mobile Application

The mobile application for older adults and their community caregivers provided customized daily health status feedback on stress, sleep, steps, and activity using traffic signal colors and detailed information as presented in Figure 3 (a). Applying the traffic signal colors, a green face in the health status for stress, steps, and activity domain signified a value higher than 1 standard deviation (SD) of the user's average in the domain. A yellow face indicated a value within ± 1 SD of the average of the health status domain score. A red face indicated a value lower than 1 SD of the average level. The ranges for the green and red faces were the inverse for sleep (via the sleep fragmentation) compared to the other measurable categories since a higher value indicates more fragmented sleep. Clicking each face on the initial page (Figure 3(a) on the left side) progressed the user to the next page, which presented details (Figure 3(a) on the right side) of the differences between today's value in the domain compared to the average during the first week and a weekly graph illustrating the pattern of changes in the weekly values.

The web/app for the community caregiver and the managerial social worker (Figure 3 (b)) was provided to enable the community caregivers' centralized monitoring for prompt emergency responses to older adults during and after the COVID-19 pandemic in addition to sharing the daily health status. The emergency signal was displayed if an older adult was continuously inactive over eight hours and/or had a heart rate of less than 30 bpm or higher than 140 bpm.

(a)

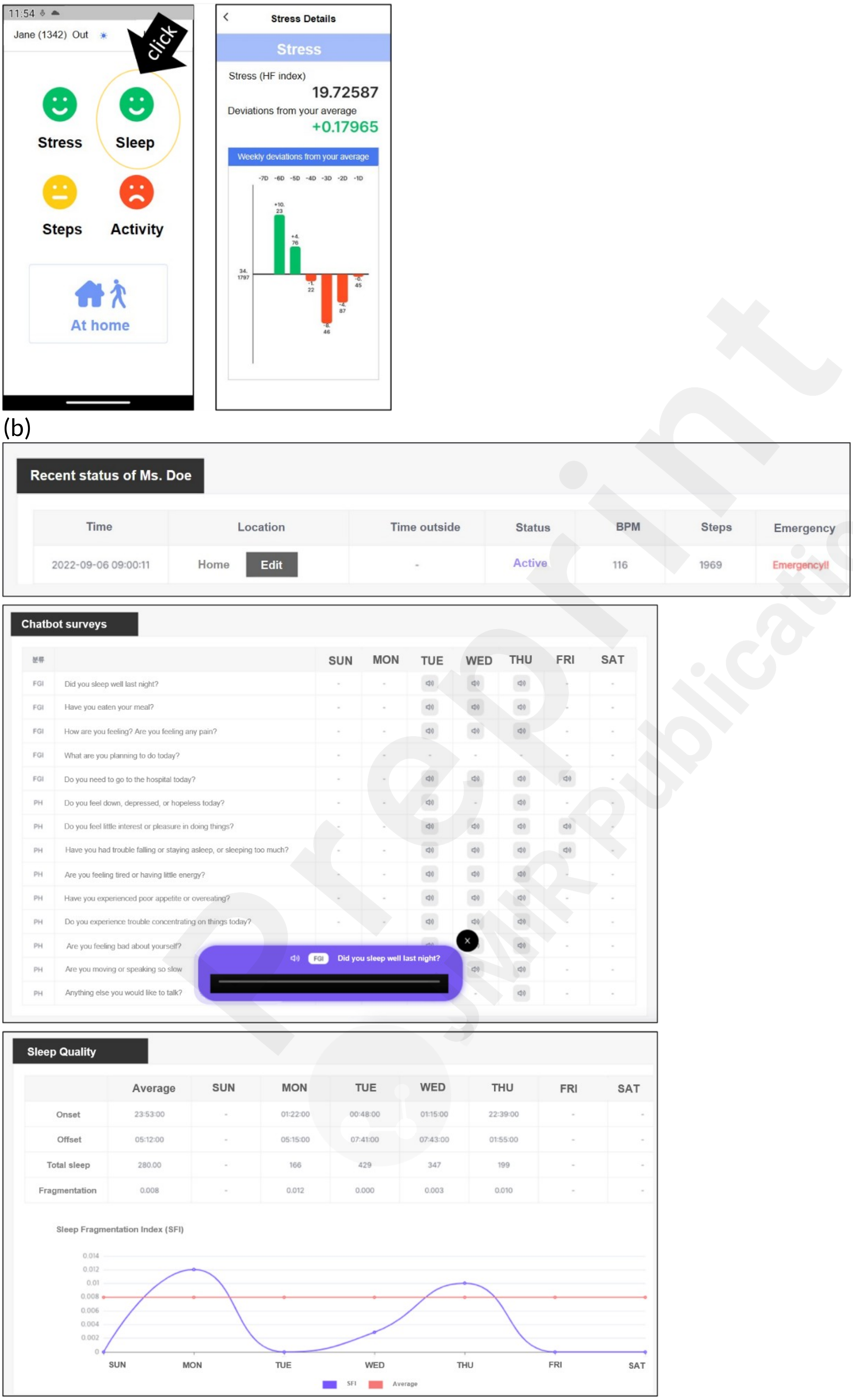

Figure 3. Example of customized daily health status feedback on stress, sleep, steps, and activity using traffic signal colors and detailed information via the mobile app for (a) the older adult users,

(b) the web/app for the community caregivers and the managerial social worker.

Pre and Post Survey Measures

Geriatric Depression Scale (GDS)

The 15-item version of the GDS [34, 35] was utilized to assess levels of depressive symptoms in older adults at the pre- and post-living lab surveys. Scores ranged from 0 to 15, with cutoff scores ≥ 5 and ≥ 10 indicating risk for mild and severe depression, respectively.

Pittsburgh Sleep Quality Index (PSQI)

Subjective sleep quality was assessed via the PSQI at the pre- and post-living lab surveys [36, 37]. The PSQI consists of 19 items and measures seven components of sleep during the past month. The total PSQI score was used to indicate level of overall subjective sleep quality, with the cutoff score ≥ 5 indicating risk for sleep disorders.

System Usability Scale (SUS)

The SUS was used to measure the older adults' levels of experience and difficulty using the digital monitoring platform at the pre- and post-living lab surveys [38]. The scale asks whether the participant uses digital technology frequently and feels that the technology is easy to use, among other questions, with a five-point scale that ranges from 0 = *strongly disagree* to 4 = *strongly agree*.

Most older adult participants had difficulty in identifying digital technology on which to base answers for this scale on the pre living lab survey, which was assessed on the day when the digital health monitoring platform was installed. Some examples of digital devices such as a smartphone or a kiosk at hospitals were enumerated to help them answer the survey. Post living lab assessments of the SUS were based on experiences using the developed health monitoring platform.

In addition to the SUS, we asked the number of days per week they used the platform and the number of functions they used on the platform on the post living lab survey. At posttest, participants were asked to provide qualitative feedback to improve the platform for the future trials, which was written in verbatim by a research assistant.

Covariates

Covariates were determined a priori based on extant literature summarizing demographic and health risk factors for daily depressive symptoms of older adults [7, 39]. In addition to the baseline levels of depression, demographic and health factors linked with depression (age, sex, and chronic health conditions) were used as covariates.

Statistical Analysis

Following analysis of missing data and distributions of key variables, the descriptive analyses and group comparisons between depressed and non-depressed older adults were conducted using t-test, (age, BMI, PSQI total score, daily depressive symptoms, wearable sensor assessments of HRV, sleep, and PA indicators), chi-square test (sex, education, income, chronic disease, sleep disorder categories), and Fisher exact test (smoking). Next, bivariate correlations were examined on baseline depression and person mean variables (daily depressive symptoms and wearable sensor assessments) across five weeks, excluding the first week for adaptation.

In order to identify digital biomarkers for daily depressive symptoms of older adults, multilevel modeling (MLM) analysis was used to examine daily fluctuations in depressive symptoms, smartwatch detected sleep quality, HRV, and activity levels over time using SAS PROC MIXED (SAS Institute, Cary, NC, USA). The application of MLM analysis of daily depression and smartwatch data enables the determination of the antecedents and correlates of daily depressive symptoms and the use of participants as their own controls [40]. For the multilevel models, the Level 1 equation examined whether daily sleep, HRV, and physical activity indices predicted the odds of reporting any depressive symptoms on the same day and on the next day. To examine the main effect of smartwatch indices on daily depressive symptoms, the main effect models for each of the sleep/HRV/activity model indices were used as Level one predictors and daily depressive symptoms on the same day or the next day as Level one outcome variables. In all MLM analyses, the Level two equations included personal characteristics such as participants' demographic and health covariates. Daily measures were person mean centered and Level two covariates were grand mean centered, so the estimates can be interpreted as probability of daily depressive symptoms when there were deviations in the predicting digital biomarker variable from the participant's own average across the five-week living lab period. The multilevel data structure of this study was presented in Figure 4. The Type one error rate was set at 0.05 for statistical analyses except the MLM analyses with the Bonferroni and Holm corrections for multiple testing that resulted in the Type one error rate of 0.005.

Finally, the pre- and post-test results were examined using a paired t-test for variables with normal distributions, such as system usability. Due to their skewed distributions, depressive symptoms and sleep quality were analyzed using the Wilcoxon signed-rank test. For the pre- and post-test results for usability, the age moderation effects were further explored using repeated measure ANOVA to test if the system usability differed between the oldest (75+ years old) and the rest (65–74 years old) using repeated measure ANOVA.

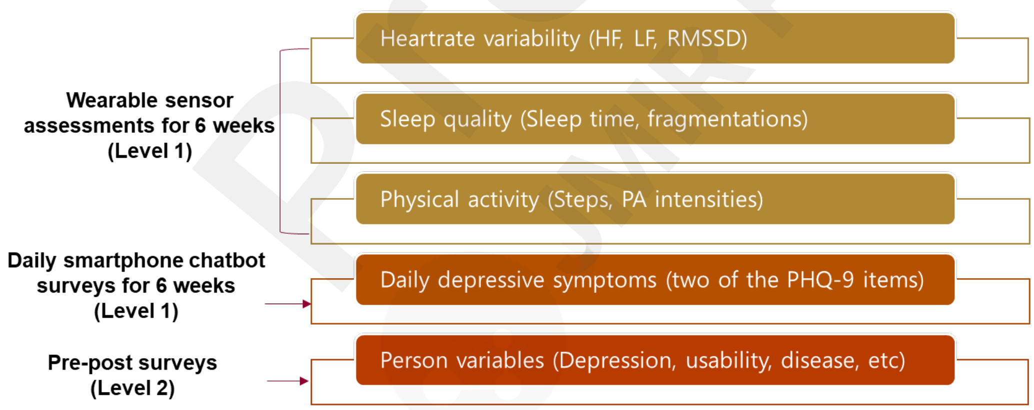

Figure 4. Multilevel data structure of this study with wearable sensor and daily depressive symptom survey data as Level one and pre and post-test survey data as Level two.

Power

The power analysis for multilevel model design is known to be complex. Previous studies have shown a compensatory relationship between the number of participants and the number of observations per participant [41, 42]. We collected a total of 807 days of observational data from 25 older adults (32.28 days per participant on average; range from eight to forty days). The variability of available days occurred for two primary reasons: participants' non-adherence to the data collection protocols (eg, forgetting to wear the Fitbit), and the schedules on which participants wanted the digital devices to be installed and removed from their homes (eg, 1 participant had to schedule the removal of devices one week later than other participants for personal reasons). A recent simulation study suggested acceptable levels of performance in terms of parameter estimations for a model with a sample size of 25 when combined with continuous data collection for 30 days [41].

Data Exclusion and Missing Data

Among the 31 adults who initially participated, we excluded data from six participants who dropped out of the study after the installation of sensing devices due to inconvenience and difficulties in using applications and digital devices. For daily usage of the platform, twenty-five older adults provided their responses to daily verbal surveys and wearable sensor data, which were included in the multilevel analyses with the primary outcome of daily depressive symptoms. Among 808 days of assessments (mean = 32.32 days per participant), there were 186 days (23. 01% of total days) with missing daily verbal survey data due to participants forgetting and no responses being recorded, 269 (33.29%), 440 (54.46%), and 298 days (36.88%) with missing HRV, sleep measures, and steps data, respectively, due to participants forgetting to wear a smartwatch during the day or night or problems with charging the device. Previous studies in missing data analysis suggest that multilevel analyses using the full information maximal likelihood estimation methods tend to be robust against estimation biases from data with partial missingness [43]. For pre-post-test effects, one participant did not complete the post-test survey due to their long-term traveling for family matters, which resulted in data from 24 older adults for the analyses.

Results

Descriptive Results

The demographic and health characteristics of the older adult living lab participants are presented in Table 1. Participants appeared to be older adults (average age = 76.40 years ± 4.23) with social vulnerabilities in terms of education and income levels. There were more women participants (n = 19) than men (n = 6). On average, participants reported four chronic disease conditions; 12% reported depressive disorders, and 40% arthritis or diabetes. The average level of sleep quality was poor, with 88% at high risk for sleep disorders.

Compared to those with low risk of depression at baseline, those with high risk were more likely to report daily depressive symptoms via verbal surveys and sleep longer but with lower efficiency, and less likely to engage in light, moderate, and intense physical activity (*P* values = <.001 ~ 0.023).

Table 1. Characteristics of older adult living lab participants [a-e]

	Total	Baseline depressive symptoms		*P*
		No	Yes	
Demographic characteristics	*n* = 25	*n* = 15	*n* = 10	
Age (years), mean (*SD*),	76.40 (4.23)	76.40 (4.42)	76.40 (4.17)	1.000

range				
Sex, *n* (%) of women	19 (76.00)	11 (73.33)	8 (80.00)	0.702
Education, *n* (%)				
Elementary school or less	14 (56.00)	7 (46.67)	7 (70.00)	0.514
Middle school	2 (8.00)	2 (13.33)	0 (0.00)	
High school	5 (20.00)	3 (20.00)	2 (20.00)	
College or more	4 (16.00)	3 (20.00)	1 (10.00)	
Monthly income, *n* (%)				
Less than 500,000 KRW [a]	4 (16.00)	2 (13.33)	2 (20.00)	0.951
500,000-1,000,000 KRW	16 (64.00)	10 (66.67)	6 (60.00)	
1,000,000-1,500,000 KRW	2 (8.00)	1 (6.67)	1 (10.00)	
1,500,000KRW or more	3 (12.00)	2 (13.33)	1 (10.00)	
Health characteristics				
Smoking, *n* (%)				
Current smoking	1 (4.00)	0 (0.00)	1 (10.00)	0.179
Past smoking	6 (24.00)	6 (40.00)	0 (0.00)	
Never	18 (72.00)	9 (60.00)	9 (90.00)	
Body mass index, mean (*SD*)	24.56 (3.94)	24.65 (2.44)	24.43 (5.68)	0.893
No. of chronic disease, mean (*SD*)	4.20 (1.71)	4.20 (1.37)	4.20 (2.20)	1.000
Arthritis, *n* (%)	10 (40.00)	5 (33.33)	5 (50.00)	0.495
Cardiovascular disease, n (%)	18 (72.00)	12 (80.00)	6 (60.00)	0.275
Diabetes, *n* (%)	10 (40.00)	7 (46.67)	3 (30.00)	0.405
Depression, *n* (%)	3 (12.00)	2 (13.33)	1 (10.00)	0.802
Dementia, *n* (%)	1 (4.00)	0 (0.00)	1 (10.00)	0.211
Baseline study variables				
PSQI Global sleep quality, 0-21, median (IQR)	8.00 (6.00, 10.00)	7.00 (6.00, 9.00)	9.00 (6.75, 11.25)	0.216
Sleep disorders, *n* (%) of PSQI > 5	22 (88.00)	12 (80.00)	10 (100.00)	0.132
Digital assessments (Person mean, SD)				
Daily PHQ symptoms, 0-1	0.37 (0.48)	0.31 (0.46)	0.48 (0.50)	<.001
HRV				
LF/HF	5.94 (1.33)	5.89 (1.30)	6.00 (1.36)	0.338
HF	26.02 (37.14)	23.75 (20.57)	28.71 (49.99)	0.138
SDNN	103.01 (41.89)	108.81 (44.73)	96.17 (37.22)	<.001
RMSSD	9.32 (3.87)	9.13 (3.58)	9.55 (4.19)	0.215
Sleep				
Total Sleep time	319.63 (163.08)	297.98 (166.73)	345.12 (155.30)	0.004
Sleep fragmentation index	0.02 (0.02)	0.02 (0.02)	0.02 (0.02)	0.612
Sleep efficiency	65.98 (20.86)	68.31 (21.18)	63.24 (20.20)	0.016

Physical activity				
Steps	3207.11 (3901.80)	3512.54 (4024.61)	2839.53 (3724.16)	0.053
Light PA	130.46 (101.55)	148.81 (107.43)	104.19 (86.19)	<.001
Moderate PA	14.05 (19.34)	15.75 (20.09)	11.62 (17.98)	0.023
Intense PA	21.89 (27.85)	24.40 (26.02)	18.30 (29.98)	0.020

[a] KRW = Korean Won, 1 USD = 1344 KRW; IQR = Inter Quartile Range; * The presence or absence of depressive symptoms was determined based on a score of 5 or higher on the Geriatric Depression Scale.

Figure 5 presents the 24-hour profile of heart rate on total days and days when older adults reported depressive symptoms. The patterns of heart rate on the days with depressive symptoms appeared to have more variations in levels of heart rate across a day compared to total days.

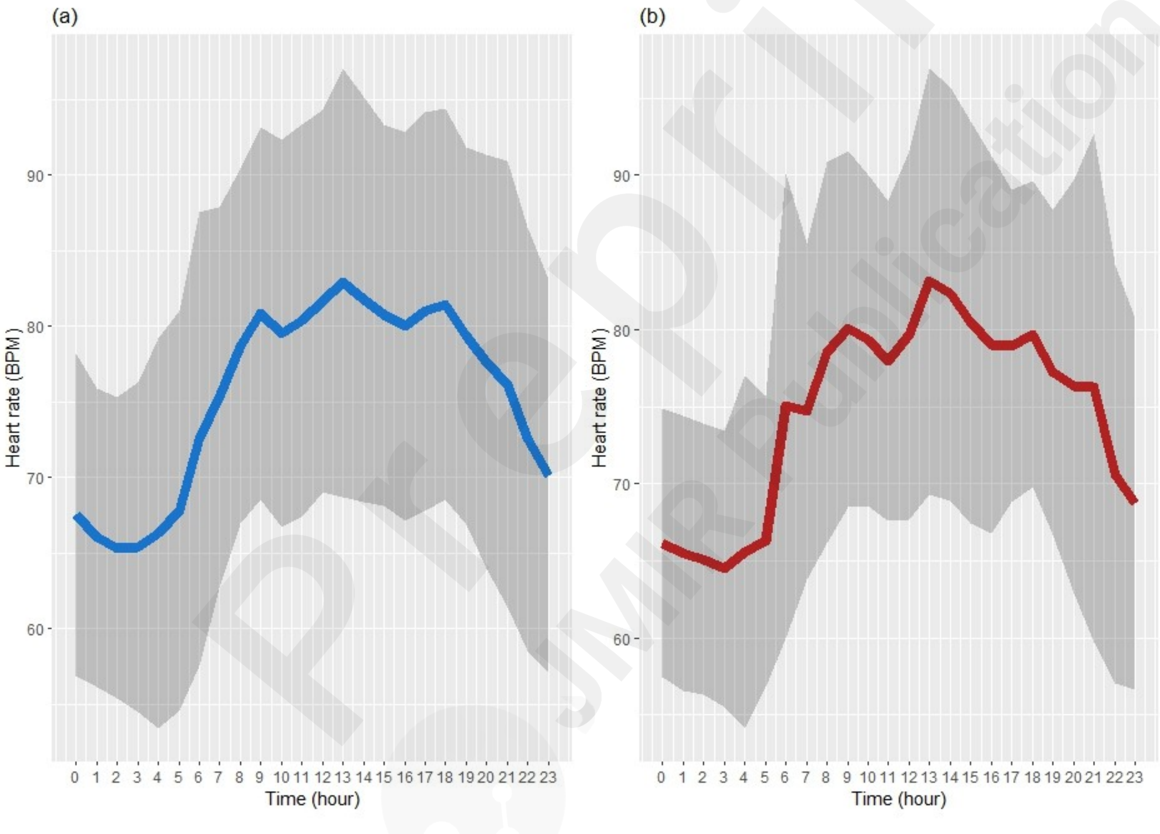

Figure 5. The average 24-hour profiles of heart rate on (a) total days, (b) days with depressive symptoms.

Figure 6 shows the bivariate correlation analysis results among baseline depression, the person mean score of daily depressive symptoms, and the smartwatch measures of HRV, sleep quality, and PA, along with distributions of the variables on the diagonals. First, as expected, baseline depressive symptoms were significantly associated with the person mean variable of daily depressive symptoms (r = 0.43, P = 0.032). Interestingly, the person mean of daily depressive symptoms was negatively associated with daily sleep efficiency (r = -0.47, P = 0.018) and the amount of moderate physical activity (r = -0.50, P = 0.024). In addition, the HRV, sleep, and PA indicators were correlated with each other such that person mean variables of daily HF and RMSSD were associated with daily sleep efficiency (*r* = 0.58, *P* = 0.003, and *r* = -0.51, *P* = 0.009, respectively). The person mean levels of daily HRV indicators were also associated with person mean levels of daily physical activity levels. HF was positively related to light PA (*r* = 0.49, *P* = 0.030), and SDNN was positively associated with light, moderate, and intense PA (*r* values = 0.45 ~ 0.59, *P* values = 0.006 ~ 0.046).

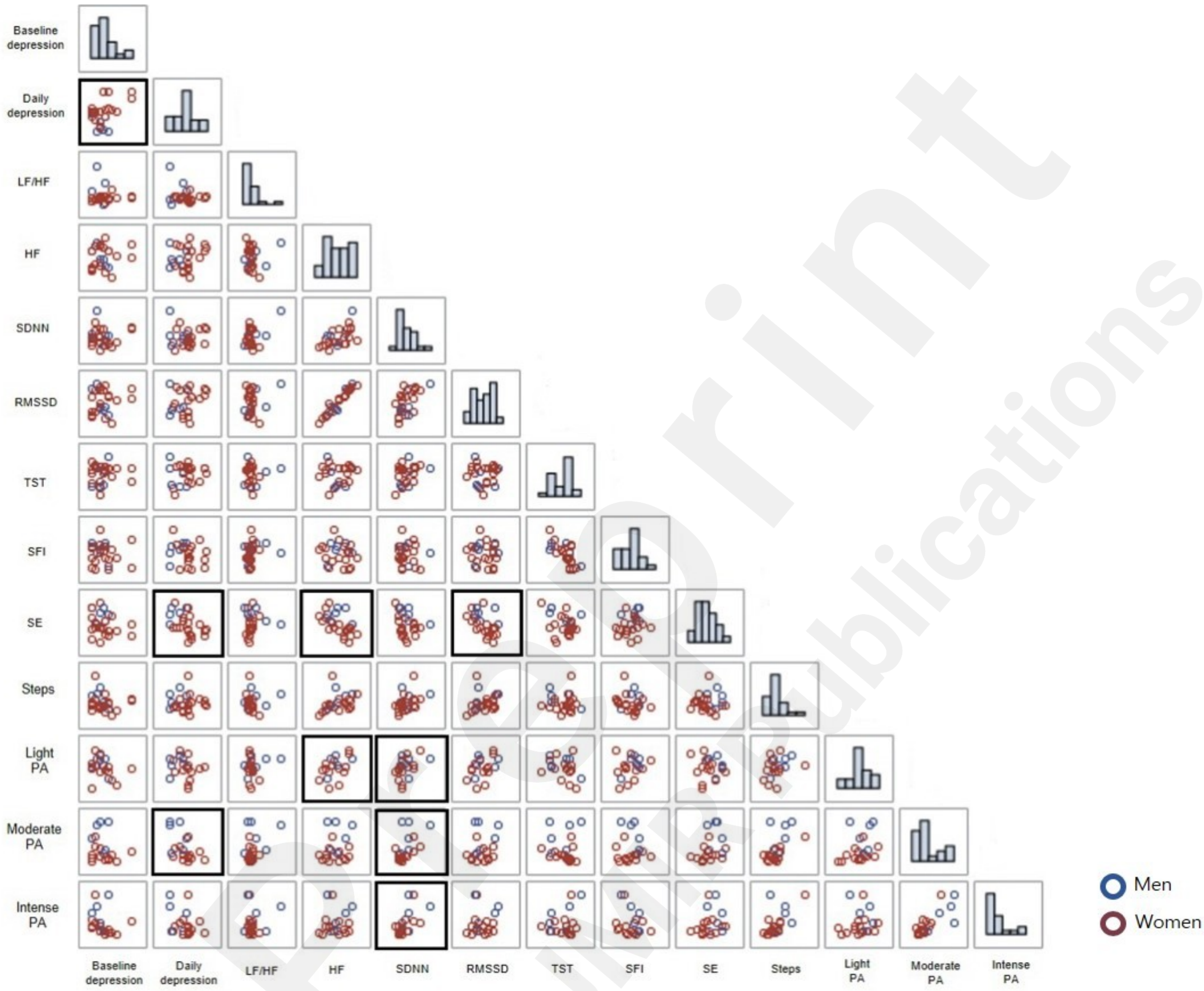

Figure 6. Bidirectional correlations among baseline depression, person mean of daily depression, and digital markers of heart rate variability indicators, sleep indicators, and physical activity measures (Bold box = significance at *P* < 0.05; red dots = women, blue dots = men; LF/HF = low frequency/high frequency power ratio, HF = high frequency power, SDNN = standard deviation of N-N intervals, RMSSD = root mean square of successive differences, TST = total sleep time; SFI = sleep fragmentation index, SE = sleep efficiency, PA = physical activity).

Principal Results

As presented in Table 2, the multilevel modeling results showed that daily sleep fragmentation index and sleep efficiency significantly predicted the occurrence of daily depressive symptoms that were measured during the next day even after adjusting for baseline depression, age, sex, and chronic disease conditions (OR (95% CI) = 2.066 (1.252, 3.411), *P* = 0.003 for daily sleep fragmentation; OR (95% CI) = 0.972 (0.955, 0.989), *P* = 0.001 for daily sleep efficiency). That is, on days following more fragmented sleep or lower sleep efficiency than their own average, older adult participants were more likely to report depressive symptoms via the chatbot survey. The effects of daily sleep fragmentation and efficiency on daily depressive symptoms remained significant after applying Bonferroni-Holm corrections for multiple testing. None of the daily assessments in HRV, sleep quality, or PA predicted the next day's depressive symptoms.

Table 2. The concurrent and lagged effects models of daily digital indicators on daily depressive symptoms.[a-e]

	Same day depressive symptoms		**Next day depressive symptoms**	
Digital predictors	OR (95% CI)	*P*	OR (95% CI)	*P*
HRV				
HF/LF	0.975 (0.790, 1.204)	0.817	0.929 (0.751, 1.148)	0.493
HF	0.987 (0.617, 1.579)	0.956	0.978 (0.632, 1.513)	0.920
SDNN	0.998 (0.990, 1.005)	0.574	1.001 (0.994, 1.008)	0.845
RMSSD	0.954 (0.866, 1.051)	0.342	0.998 (0.924, 1.078)	0.957
Sleep				
Total sleep time	0.999 (0.996, 1.001)	0.160	1.001 (0.999, 1.003)	0.351
Sleep fragmentation index	2.066 (1.252, 3.411)	0.003[c]	1.149 (0.750, 1.759)	0.775
Sleep efficiency (%)	0.972 (0.955, 0.989)	0.001[c]	0.999 (0.983, 1.016)	0.928
Physical activity				
Steps	1.000 (1.000, 1.000)	0.277	1.000 (1.000, 1.000)	0.213
Light PA	0.999(0.996, 1.002)	0.483	1.002 (0.998, 1.005)	0.334
Moderate PA	0.992 (0.971, 1.014)	0.478	0.985 (0.964, 1.006)	0.156
Intense PA	0.998 (0.985, 1.011)	0.734	1.002 (0.989, 1.015)	0.748

[a] All analyses were adjusted for age, sex, chronic disease conditions, and baseline depression.

[b] All digital predictors were person mean centered, so that daily values represent deviations from the individuals' own means across the participation days.

[c] The Bonferroni-Holm correction suggests that *P*-values indicating significance should be less than 0.005, with 11 multiple tests for each of the two outcome variables.

[d] OR = odds ratio; CI = confidence interval; PA = physical activity.

Pre-Post-Test Results

As presented in Table 3, the pre-and post-test results showed significant decreases in depressive symptoms (the pre–post difference (95% CI) = -1.000 (-2.000, 0.000), *W* = 143.500, *z* = -1.976, *P* = 0.048) and improvements in sleep quality (the pre–post difference (95% CI) = -1.500 (-3.000, 0.000), *W* = 165.000, *z* = -2.252, *P* = 0.024) after the six-week living lab than before. However, there were no significant changes in the levels of usability (the pre-post difference (95% CI) = -6.354 (-15.969, 3.261), *t* (23) = -1.376, *P* = 0.185). Age moderation was also not significant in the pre- and post-changes in usability (*F (1, 22)* = 437.682, *P* = 0.200). At the post-test survey, participants reported using the monitoring app 6.68 days per week on average (SD = 1.44) and using 1.58 functions (SD = 1.91) out of a possible five, including recording verbal surveys for daily depressive symptoms, checking individualized health feedback for stress, steps, physical functions, and sleep time.

Using open-ended questions to receive user feedback in the post-test survey, older adults expressed satisfaction with the chatbot survey that asked about their daily lives and health conditions. They felt cared for and safe, knowing their voice message would be delivered to their community caregiver daily. Yet, older adults expressed frustrations with the smartwatch malfunctioning. The older adults experienced technical malfunctions during the living lab period owing to difficulties regularly charging the smartwatch, accidentally turning off the smartphone's Bluetooth connection, and central server overloading.

Table 3. Pre-post-test changes in depressive symptoms, sleep quality, and usability levels

Variables	**Pre-test, median (IQR) or mean (SD)**	**Post-test, median (IQR) or mean (SD)**	***P***
Depressive symptoms (GDS)	3.000 (1.000, 6.000)	1.500 (0.250, 5.000)	0.048
Sleep quality (PSQI)	8.000 (6.000, 10.000)	6.000 (4.000, 7.750)	0.024
Usability (SUS)	53.333 (24.524)	59.688 (19.620)	0.185

[a] Wilcoxon signed-rank test was used to analyze depressive symptoms and sleep quality due to their skewed distributions.
[b] Paired t-test was used to evaluate usability based on a normal distribution of the usability scores.

Discussion

Principal Results

This study examined the feasibility of digital phenotyping of depressive symptoms and continuous digital mental health monitoring among a small group of socially vulnerable older adults (*n* = 25) in their ordinary living environments. Through daily verbal checks of depressive symptoms via chatbot and assessing daily changes in digital biomarkers via a smartwatch, this study suggests that two digital measures of daily sleep quality, sleep fragmentation, and sleep efficiency, predicted occurrences of daily depressive symptoms on the following day even after adjusting for potential confounders such as baseline depression, age, gender, and chronic disease conditions. To the best of our knowledge, this study is the first to examine the digital phenotyping of depressive symptoms in socially vulnerable older adults in their own living environments for an extended period of time. Additionally, the pre- and post-test results showed that depressive symptoms and sleep problems, but not system usability, improved after older adults used the platform with their community caregivers and received daily results of individualized health status for six weeks. Although the current findings are preliminary and do not include a comparison group, these results imply the possible health benefits of using a digital health monitoring platform for older adults when connected to an in-person community senior care service.

Comparison with Prior Work

By developing analytic algorithms for continuous sensing of sleep time, fragmentation, and efficiency, this study revealed that daily changes in sleep fragmentation and efficiency at night compared to one's average predicted daily depressive symptoms among older adults the following day. These results align with previous studies that reported a significant association between actigraphy-assessed wake time after sleep onset and sleep efficiency and one-time survey measures of depressive symptoms in adults with a history of clinical depression [12, 39, 44]. A meta-analysis of 38 studies with actigraphy assessments also reported significant differences in longer wake time after sleep onset between depressed patients and healthy controls [45]. The current results advance the literature by assessing daily changes in depressive symptoms among socially isolated older adults for an extended period of time and examining whether within-person fluctuations of sleep quality predict ongoing changes in depressive symptoms across days.

The current results showed that neither actigraphy-assessed heart rate variability nor physical activity measures significantly predicted daily depressive symptoms. Previous results have indicated mixed associations between heart rate variability and depressive symptoms, depending on diagnosis or severity of depression and cardiovascular health of the studied population. For example, a meta-analysis of 21 studies reported significant differences between depressive patients and healthy controls [46]. A previous study with depressed patients also reported a negative association between heart rate variability (eg, RMSSD) and cognitive symptoms of depression (eg, rumination) on the same day among depressed patients [47]. However, such associations between HRV and depressive symptoms were not evident in adults without clinical depression or those with cardiovascular health problems. For example, depressive symptoms were not significantly associated with ECG-measured HRV in healthy adults [48] or adults at risk of coronary artery disease [49]. The majority of older adults (72%) in this study had cardiovascular disease conditions, which was higher than the national prevalence in South Korea (40.36%) and worldwide (31.0~70%) for adults over 70 years old [50-52]. Future studies with a large sample of older adults are needed to examine associations between depressive symptoms and HRV among older adults with various chronic disease conditions.

Regarding the association between depressive symptoms and physical activity, daily fluctuations of physical activity did not predict daily depressive symptoms, which was contrary to previous findings. For example, a meta-analysis of 42 studies with actigraphy or pedometer assessments of physical activity reported significant associations between average physical activity and levels of depressive symptoms among adults with and without clinical depression [53]. Also, increased physical activity through intervention programs was associated with lower levels of depressive symptoms compared to the control group in adult populations without clinical depression [54]. There might be several possible explanations for the null effect of daily physical activity on daily depressive symptoms found in the current study. It is possible that long-term physical activity levels rather than day-to-day fluctuations may explain changes in depressive symptoms. In line with this possibility, the present results showed a significant negative association between person mean levels of depressive symptoms and person mean levels of moderate physical activity. Future studies are needed to identify possible factors that may explain the linkage between daily depressive symptoms and physical activity such as cumulative patterns of physical activity, specific types of physical activity (eg, group exercise), or external circumstances that may hinder physical activities (eg, the COVID-19 pandemic).

Finally, the pre- and post-test results showed that older adults experienced improvements in depressive symptoms and sleep quality after using the platform with their community caregivers. It should be noted that the participating older adults had previously been using the in-person senior caregiving service, which provided the same amount of regular phone calls and in-person weekly visits for safety checks and help with a hospital visit if needed. Yet, utilizing the current digital monitoring platform may have enabled the community caregivers to optimize the timing of the service provision to when older adults were most in need. For example, an older adult user received red lights on sleep and physical activity via the user app when they had poor sleep and skipped exercise due to a flare-up of chronic disease conditions. Their community caregiver received the same daily feedback and voice recordings from the older adults about health issues via the caregiver app. Subsequently, they phoned or visited each participant to check on the negative health changes for that day. The current findings support recent studies that showed the health-improving effects of digital healthcare services for older adults when mental health professionals providing in-person services [55, 56] or community health workers with intensive training [57, 58] were connected to the digital service. However, this study contributes to the literature by presenting preliminary findings indicating that community caregivers without a healthcare specialty or intensive training in mental healthcare may promote the mental health of socially vulnerable older adults by utilizing a digital health monitoring platform.

Contrary to the expectations, the usability test results of this study indicate older adults' experienced difficulties in using the mental health monitoring system and these difficulties did not improve over time. These results highlight the importance of providing sufficient in-person assistance, combining group lessons, in-person trainings, and troubleshooting visits for older adults when implementing a new digital healthcare service.

Limitations

These findings should be interpreted with caution due to several limitations. First, the sample size was limited to 25 older adults, which may not provide sufficient power to detect small effect sizes of associations between daily depressive symptoms and sensor-based daily indicators and pre-posttest changes in outcome measures. The current results may not be generalizable to other older adult populations or other countries because we purposely selected older adults with social vulnerabilities, including living alone with low income, who suffer more from lack of access to digital technologies than overall older adult populations [59]. The current study used multilevel modeling in order to examine the concurrent digital biomarkers of daily depressive symptoms, but other analytic approaches such as machine learning to classify older adults with high and low risk of depression may be desirable for future studies. Finally, strict implementation of COVID-19-related social restriction policies in 2022 may have influenced the current findings.

Conclusions

This study examined the feasibility of mental and physical health monitoring platforms for socially vulnerable older adults and their community caregivers in their ordinary living environments and explored whether passively sensed measurement of HRV, sleep, and physical activity predicted daily fluctuations of depressive symptoms in older adults. The results suggest that older adults were able to utilize the monitoring platform during the six-week study to check daily health status, which was also delivered to the community caregiver to improve the existing senior care service. The multilevel modeling results indicate same day associations between daily sleep quality indicators (sleep fragmentation index and sleep efficiency the previous night) and daily depressive symptoms. The pre-post test results suggest that older adults experienced improvements in depressive symptoms and sleep quality after using the monitoring platform that was linked with their existing community care services. These findings provide preliminary support for digital phenotyping of geriatric depressive symptoms using sleep measures from a wearable sensor. The current study also suggests a possible service delivery model for developing on-offline hybrid senior care service that can utilize existing community based senior care services for early detection and prevention of mental health declines in socially vulnerable older adults.

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Conflicts of Interest

The corresponding author and the first author developed the health monitoring platform software in collaboration with M2S+ Co. and owned the intellectual property rights. The Department of Health and Welfare of the Korean Government provided funding for the development of this platform and owned the right to utilize the developed platform as a public service for older adults.

Abbreviations

GDS: Geriatric Depression Scale
HF: high frequency measure of heart rate variability
HRV: heart rate variability
IoT: Internet of Things
KRW: Korean Won
LF: low frequency measure of heart rate variability
MLM: multilevel modeling
PA: physical activity
PHQ: Patient Health Questionnaire
PSQI: Pittsburg Sleep Quality Index
SD: standard deviation
SDNN: standard deviation of the N-N intervals
SFI: sleep fragmentation index
SE: sleep efficiency
SUS: System Usability Scale

TST: total sleep time
RMSSD: root mean square of successive differences

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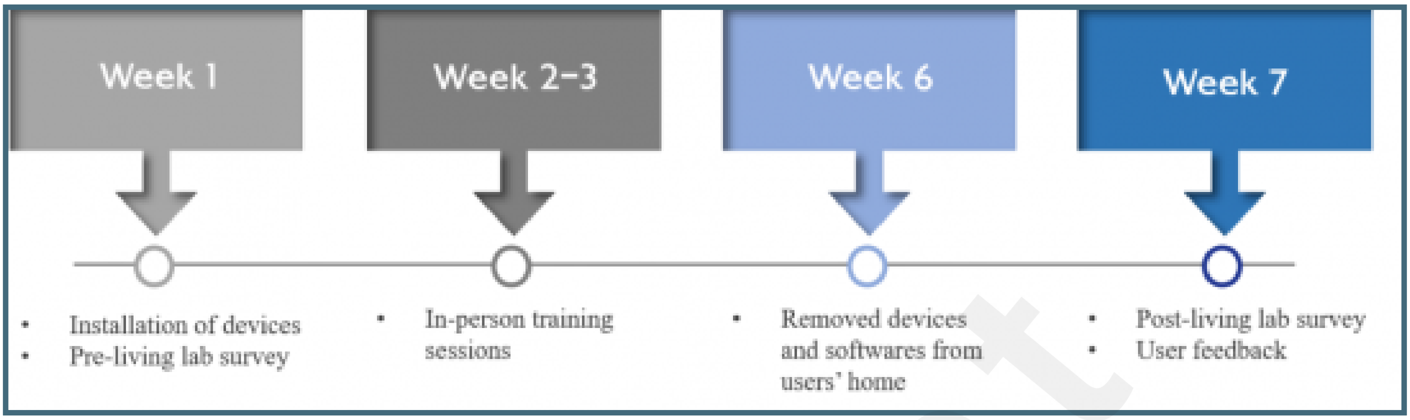
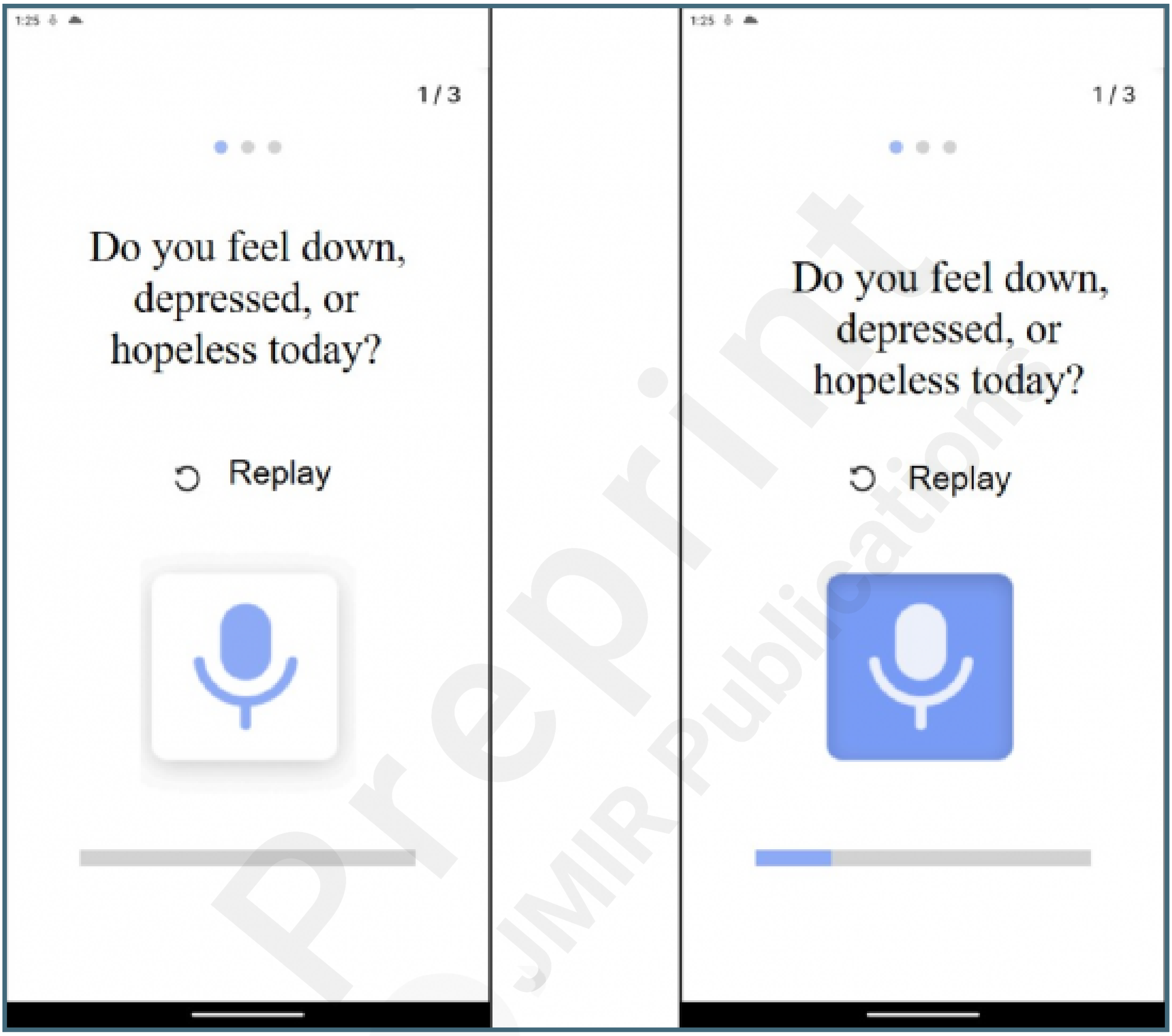
Supplementary Files

Figures

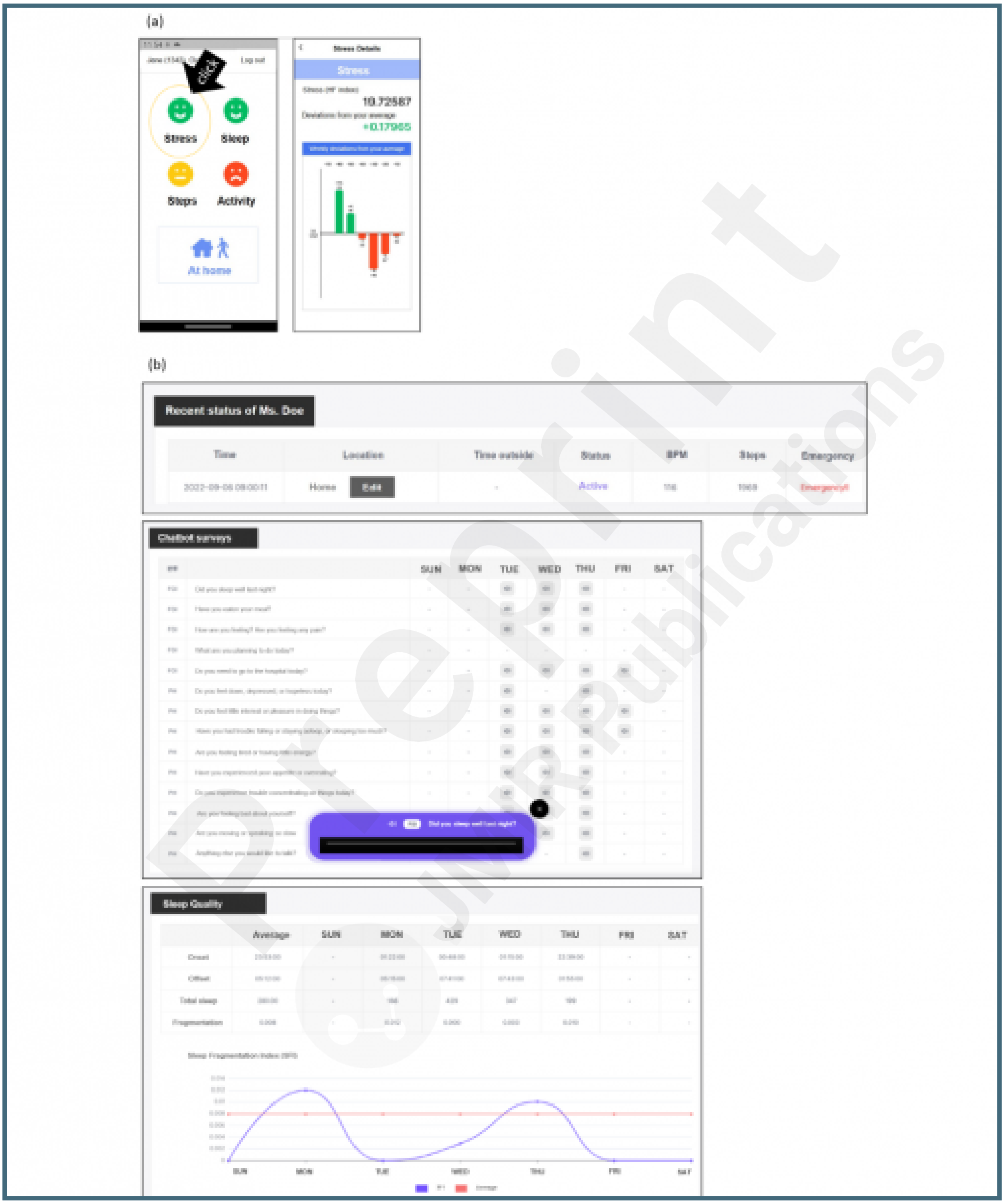
Timeline of the 6-week pilot living lab procedure.



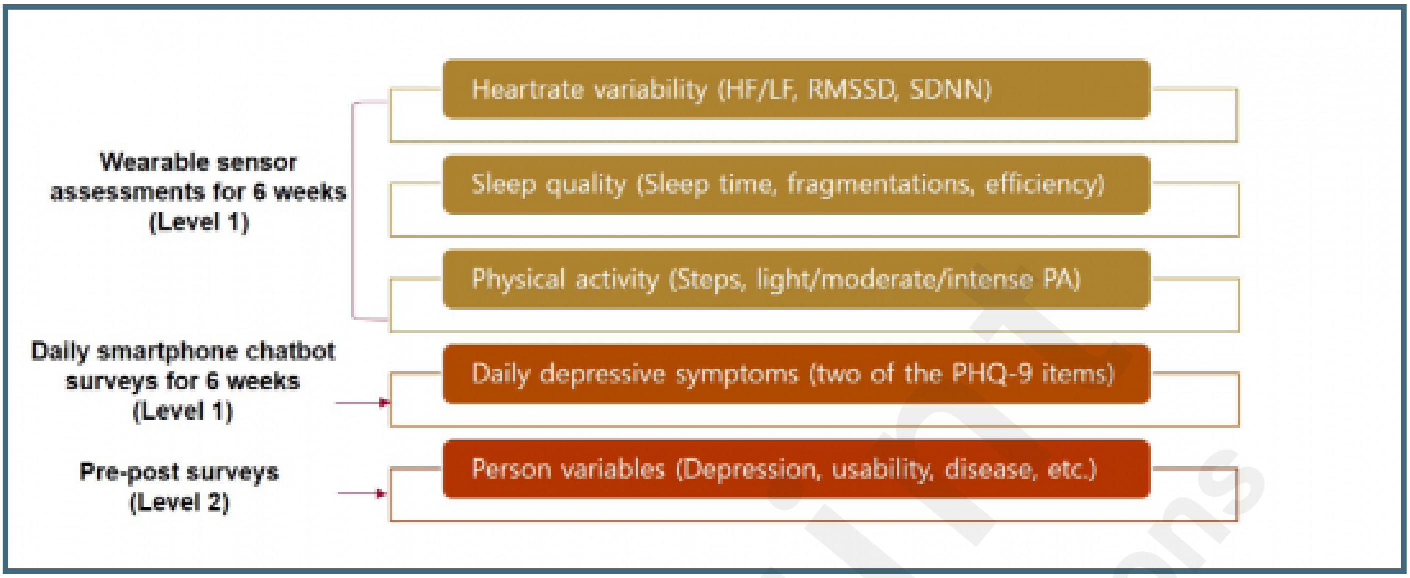
Mobile application function for collecting daily depressive symptoms; the chatbot voice asked 2 randomly selected PHQ-9 items and older adult participants' answers were automatically recorded. The blue bar and blue microphone icon indicate that voice recording has been activated.



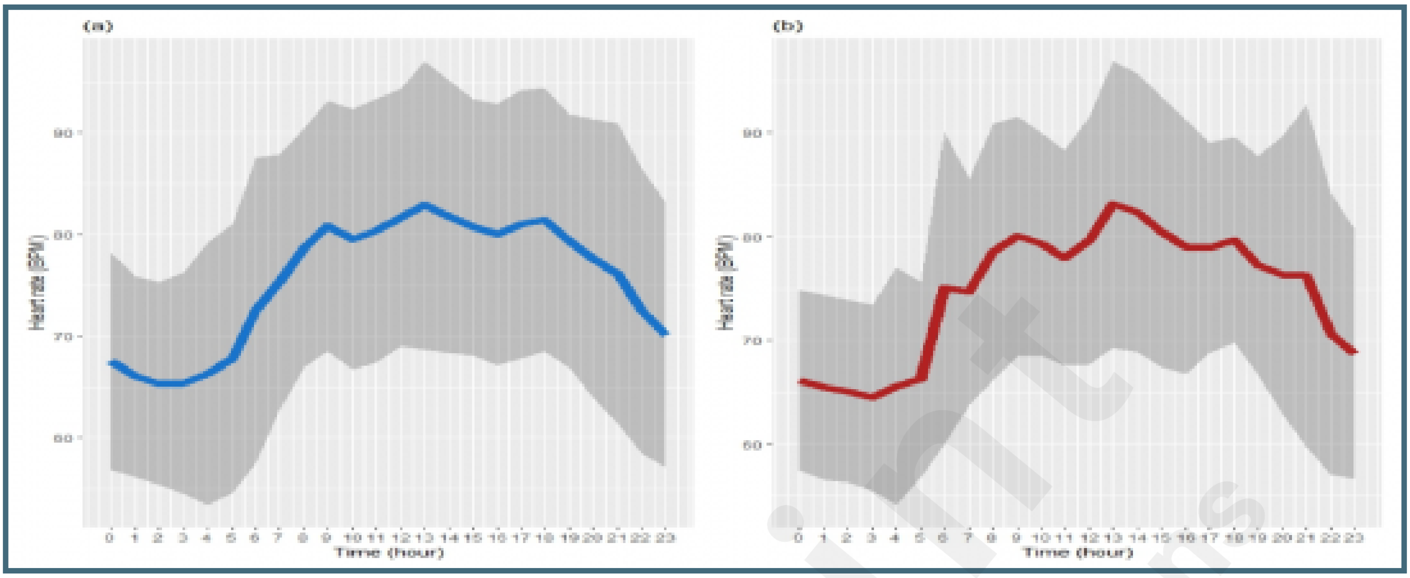
Example of customized daily health status feedback on stress, sleep, steps, and activity using traffic signal colors and detailed information via the mobile app for (a) the older adult users, (b) the web/app for the community caregivers and the managerial social worker.



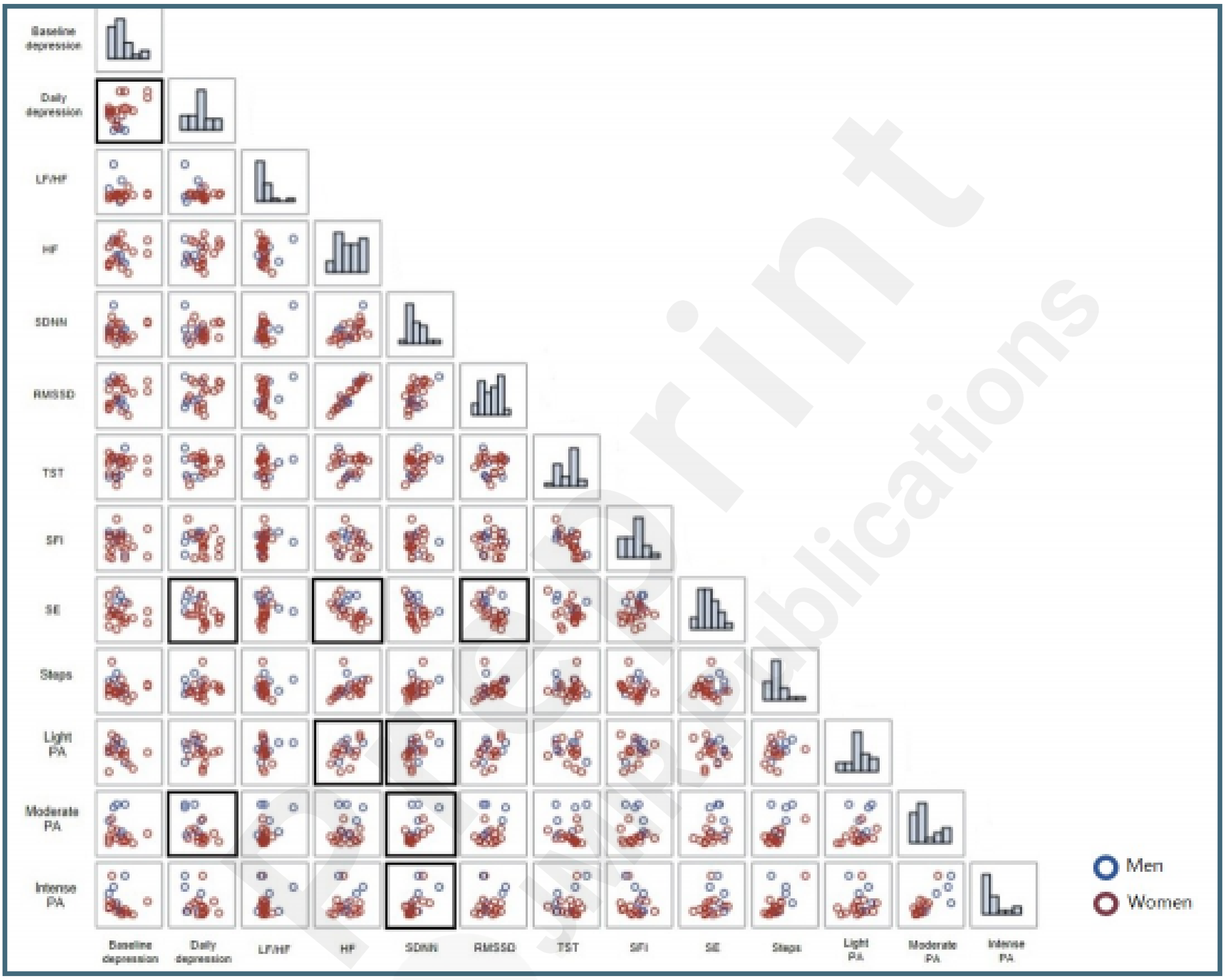
Multilevel data structure of this study with wearable sensor and daily depressive symptom chatbot survey data as Level 1 and pre and post-test survey data as Level 2.



The average 24-hour profiles of heart rate on (a) total days, (b) days with depressive symptoms.



Bidirectional correlations among baseline depression, person mean of daily depression, and digital markers of heart rate variability indicators, sleep indicators, and physical activity measures (Bold box = significance at P < 0.05; red dots = women, blue dots = men; LF/HF = low frequency/high frequency power ratio, HF = high frequency power, SDNN = standard deviation of N-N intervals, RMSSD = root mean square of successive differences, TST = total sleep time; SFI = sleep fragmentation index, SE = sleep efficiency, PA = physical activity).



CONSORT (or other) checklists

CONSORT E-HEALTH checklist V1.4 for the current living-lab pilot trials.
URL: http://asset.jmir.pub/assets/d1bdf80e91735a9b76744860276deada.pdf