Invited Paper

Sensing and Changing Human Behavior for Workplace Wellness

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Abstract: Recently, companies have begun to care more about the well-being of their employees. With the spread of sensors, the Internet of Things, and artificial intelligence, the movement to build a better working environment by utilizing these technologies has been spreading. Especially, research on behavior that can change lifestyle habits is becoming popular. In this paper, we summarize workplace behavior research and projects for sensing and changing human behavior in a workplace and aim to improve the productivity and wellness of employees. Also, we introduce concepts for future workplaces and some of our related achievements. For physical state sensing, we have developed a continuous posture-sensing chair, which will soon be available commercially. For internal state sensing, we propose a method for estimating quality of life with wearable sensors. Our system have already achieved to estimate QoL (Quality of Life) around 90% with only 9 questions. In addition, we propose interactive digital signage to provide habit-changing reminders. Through one month experiment, we confirmed that our system can be feasible in daily life.

Keywords: sensing behavior, workplace, behavior change, wellness, office productivity, quality of life

1. Introduction

In recent years, due to prolonged working hours and deterioration of the working environment, increases in depression and production costs have become a social problem. According to a 2016 survey on time use and leisure activities [*1], people working in metropolitan areas have been shown to have longer commute times and shorter sleep times. Moreover, as shown by the world job satisfaction survey [*2] conducted by Indeed Inc., Japan ranks lowest among 35 countries around the world, and the need to reform work methods is urgent. Last year, the Japanese government widely promoted work style reforms [*3], and many companies are trying to improve their working environment.

Approaches to improving the workplace environment can be roughly divided into two categories. The first is human-based improvement, such as counseling and workshops. Several companies have held walking events as part of welfare programs. In addition, some wellness companies offer solutions for easily providing such welfare services. Employees are given incentives to join the program and also benefit from becoming more healthy by walking. Workshops are also a widely used approach for improving the working environment, especially for interpersonal relationships. Job crafting [1] and Civility, Respect, and Engagement in the Workplace (CREW) [2] are famous workshop programs held in many Japanese companies.

The second approach involves structural workplace improvements, such as changing desk layouts, furniture, and working space. Efforts have been made to analyze employee trajectories using sensors and cameras [3], and to change the office layout to make communication easier. In addition, many ergonomic chairs that can relieve physical stress and height-adjustable desks that allow standing work are becoming more popular. In addition, a strategy called activity-based working (ABW) is spreading. ABW provides employees an opportunity to change the workplace according to their work activities and mood.

In order to know the current status of the workplace and employees and to measure the effect of the above mentioned effort, questionnaire surveys are usually conducted before and after such efforts. Representative questionnaires are UWES (Utrecht Work Engagement Scale) [4] to measure work engagement and SF-36 [5] to measure QoL (Quality of Life). Quantitative assessment of stress can be also done by measurement of salivary cortisol and amylase levels [6], or Low Frequency/High Frequency (LF/HF) obtained from a heart rate, but paper-based questionnaires are widely used from the viewpoint of scalability and cost.

To understand the current status of the workplace and employees and measure the effects of improvements, surveys are usually conducted before and after such efforts. Representative questionnaires are the Utrecht Work Engagement Scale (UWES) [4] to measure work engagement and the 36-question short-form survey (SF-36) [5] to measure quality of life (QoL). Stress can also be quantitatively assessed by measurement of salivary cortisol and amylase levels [6] or the low-frequency/high-frequency (LF/HF) ratio obtained from a heart rate, but paper-based questionnaires are widely used because they are scalable and cheap.

Due to the progress of information technology, activity trackers

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*1 http://www.stat.go.jp/data/shakai/2016/pdf/gaiyou2.pdf
*2 http://blog.indeed.com/hiring-lab/indeed-job-happiness-index-2016/
*3 Follow-up Meeting for the Work Style Reform (The Prime Minister in Action) https://japan.kantei.go.jp/98_abe/actions/201810/_00039.html

and smartphones have become cheap and are widely used. Even a 3,000 JPY activity tracker has an optical pulse heart rate sensor. By using the inertial measurement sensor built into a smartphone, it is possible to distinguish locomotion between vehicles (cars and trains), walking, and stair climbing. The latest wearable devices include sensors for electroencephalography and respiration rate that encourage meditation, and eyeglasses exist that can measure the degree of concentration. Many researchers have attempted to utilize such widespread wearable devices to sense the state of workers and encourage behavioral change. For example, the Apple Watch has a function called "activity reminder," and when the user sits for a long time, it urges him or her to stand up, or when the heart rate is higher than usual, it urges him or her to take a deep breath. This function is thought to be useful for prevention of lifestyle-related diseases and is also called digital medicine. Teeriniemi et al. [7] reported the effect of information systems for weight control empirically through a large-scale (1,000 subjects) and long-term (2-year) experiment.

In this paper, we introduce our research related to physical and physiological state sensing in a workplace. Based on the sensing result, we aim to change human behavior for better well-being. For physical state sensing, we will introduce a continuous posture sensing chair that can distinguish 18 typical postures. For physiological state sensing, we will introduce QoL and Work Engagement estimation using smart devices. To change behavior using this information, we will introduce digital signage that interacts with workers to change their next action.

This paper is organized as follows. In Section 2, we explain related work. After that, our past achievements will be introduced in Section 3. We discuss the future challenges that we need to overcome in Section 4.

2. Related Work

In this section, we introduce some past research related to sensing and changing human behavior in a workplace. Various companies have already started making efforts to improve the office environment. Also, various projects and promotions that cooperate with multiple research fields for employee well-being have been launched in several countries [8].

2.1 Walking Promotion

Walking is the most common and acceptable activity in our life [9]. Therefore, various companies promote walking for wellness. Some companies encourage employees to walk more as part of welfare programs in which the employees can receive rewards based on points earned according to the number of steps.

Not only companies but also countries and municipalities have promoted walking. For example, Singapore started a health promotion, "The National Steps Challenge [*4]," based on walking in 2015. It encourages Singaporeans to take 10,000 steps every day.

2.2 The Fun Theory

Since 2009, Volkswagen has had a promotion called "The Fun Theory," which introduces gamification [10], [11] or nudges [12] into our society to change our behavior. "Piano Stairs" [*5], "Speed Camera Lottery" [*6], and "The World's Deepest Bin" [*7] are well-known examples that place attractive triggers in the environment. Through those social experiments, Volkswagen proved that "fun" can change people's behavior.

Gamification has already been applied to the workplace for improving the motivation [13], [14]. It can be used for improving the efficiency of a campaign to increase physical activities, such as "use the stairs." From the viewpoint of sustainability, the strategy of the fun theory is important.

2.3 Mobile Applications for Digital Health

Mobile wellness applications can be developed for the various sensors built into smartphones. Today, many companies and researchers are attempting to measure mental health and productivity using these sensors [15], [16], [17]. This is called digital health [18] or digital medicine [19].

The mPerf project, which uses mobile sensors to support productivity and employee well-being, [*8] is a widespread project in the United States that aims to improve productivity and well-being of employees by using mobile applications. It was funded by the American Intelligence Advanced Research Projects Activity in 2017. In this project, several universities (including Memphis, Minnesota, and UCLA) and their research departments (such as computer science, industrial psychology, and medical science) collaborated.

Promo@work [*9] is a part of the "Evidence-Based Health Promotion in Workplaces" consortium project funded by the Strategic Research Council at the Academy of Finland. The Finnish Institute of Occupational Health and several universities (Oulu, Tampere, and Koln) are collaborating.

Promo@work is a work health promotion for micro entrepreneurs whose health programs are not managed like those of large companies. It provides a mobile application for supporting diet, sleep, exercise, work recovery, stress, sedentary work, effective work hours. Along with the diversification of working methods, there are increasing ways to work remotely at home or at a cafe, instead of the traditional working style in which all employees work at the same time and place. Small startups often adopt nontraditional working styles, and their employees tend to work continuously, regardless of day and night, to develop products quickly with a small number of people. Unfortunately, unlike large companies, they often have no-one tasked with managing employee mental health. Thus, Finland focused on this problem and established a research team for employee wellness in small businesses.

*4 National Steps Challenge Season 4 is here!: https://www.healthhub.sg/programmes/37/nsc

*5 Piano Stairs: https://www.youtube.com/watch?v=2lXh2n0aPyw

*6 Speed Camera Lottery: https://www.youtube.com/watch?v=iynzHWwJXaA

*7 The World's Deepest Bin: https://www.youtube.com/watch?v=cbEKAwCoCKw

*8 mPerf: Using mobile sensors to support productivity and employee well-being, http://mperf.md2k.org/

*9 Promo@Work: Work health promotion for micro entrepreneurs, https://ohjausvuorovaikutus.fi/

2.4 Workplace Experiments

Many researchers have conducted experiments in actual workplace and university environments. Some of these research results are discussed here.

2.4.1 Effect of Desk Layout to the Productivity

Ref. [3] investigated whether the office layout affects communication and productivity in the workplace. In this study, a unique wearable sensor was used to measure vocal interactions. The experiments were conducted at two International Fortune 500 companies, and the desk layout was changed from the conventional isolated layout to an open layout. This decreased direct vocal communication by 70% and increased e-mail communication by 22% to 56%. Moreover, productivity fell.

2.4.2 Sensing in a School and a Nursing Home

Haines et al. [20] tried to promote walking and wellness and to improve the health of college faculty and staff.

In the StudentLife project [21], the authors tried to sense mental health, academic performance, and behavioral trends of college students using smartphones.

We also tried to measure the activities of elderly persons in a nursing home [22], [23] by using Bluetooth Low Energy Beacon, which is the same technology used for our another system explained in Section 3.4.

2.5 Measurement of Psychological State

Measurement of psychological state can be classified into two types, questionnaire-based measurement and quantitative measurement.

2.5.1 Questionnaire-based Measurement

In the occupational health research field, questionnaire-based investigations have been used as a way to know the psychological state of employees. An advantage of questionnaires is their high scalability and low cost. Investigation of many employees is easy because they respond on paper. Recently, it has become even easier because of the widespread use of smartphones that can use to answer questions anytime and anywhere.

Typical psychological states that can be measured by questionnaire are workaholism [24], work engagement [25], work motivation [26], depression and anxiety [27], and QoL [28], [29]. A shortcoming of questionnaire-based investigation is that it might include memory bias and psychological bias because it is based on subjective answers.

2.5.2 Quantitative Measurement

Currently, the most widely used quantitative stress measurement method is to measure salivary amylase or salivary cortisol [30]. These biomolecules are known to change in association with the activity of the sympathetic nervous system and can be used as a biomarker for stress. Because a salivary amylase monitor and chips are commercially available, we can easily measure those values. The weakness of this method is that it is influenced by the oral environment, such as what someone ate last.

Another stress measurement method focuses on the activity of the autonomic nervous system [31]. Disorders in this system can occur when human beings are stressed. These disorders can be observed with an electrocardiogram (ECG), and the LF/HF ratio calculated from the inter-beat interval is often used as a stress index. Currently, as wearable ECG devices become more popular, ECG-based stress measurement is becoming easier.

Another quantitative stress measurement technique is to measure galvanic skin response (GSR), the electric resistance of the skin. This is the same principle as that used in a lie detector, and it utilizes the fact that stress promotes perspiration. Because GSR sensors are installed in smartwatches, such as Microsoft Band 2 *10 and Empatica E4, this method might be the easiest way. However, we need to consider that perspiration also changes with other factors, such as exercise, clothing, and weather. In our previous work, we embedded a heart rate sensor and humidity sensor into a computer mouse [32]. However, now we can buy a commercial mouse, Mionix Naos QG *11, in which the GSR sensor and a heart rate sensor are already embedded.

2.6 Behavior Change Support System

Behavior change means to change people's customary habits. Much counseling-based research has been conducted on personal health care, such as smoking cessation and dieting. For public health in the workplace, several intervention methods, such as Job crafting [1] and CREW (Civility Respect and Engagement) [2] have been proposed.

Particularly, due to the spread of information technology in recent years, behavior change using smartphones and smart devices has attracted attention. One of the most famous information systems that prompts a behavior change is the "activity reminder" of Apple Watch. This wearable device monitors the physical state (stand/sit) and physiological state (heart rate) and urges you to stand up or take a breath for your health.

Harri et al. defined a theory to design such an information system to change human behavior [33]. The theory is called the behavior change support system, which is defined as "a sociotechnical information system with psychological and behavioral outcomes designed to form, alter or reinforce attitudes, behaviors or an act of complying without using coercion or deception." We adopted this theory to our proposed system explained in Section 3.4.

3. Future Workplace with Sensors and Behavior Change Support

Based on related research, we are studying the features of the next-generation workplace. In the future, many sensors will be deployed for sensing employee activities, and devices that cause behavior changes based on the sensing result might be installed. This section explains the experimental environment where we realized our concept for the future workplace and introduces three research results from experiments in this environment.

3.1 Experimental Environment

Figure 1 shows the settings for our experiments. We set up various working spaces in our laboratory because ABW (Activity-based Workplace) [34], [35], which prepares various environments in one office, is becoming popular. In the main working space, we prepared an adjustable desk and cycling desk aiming

*10 https://www.microsoft.com/microsoft-band/en-us
*11 https://mionix.net/naos-qg

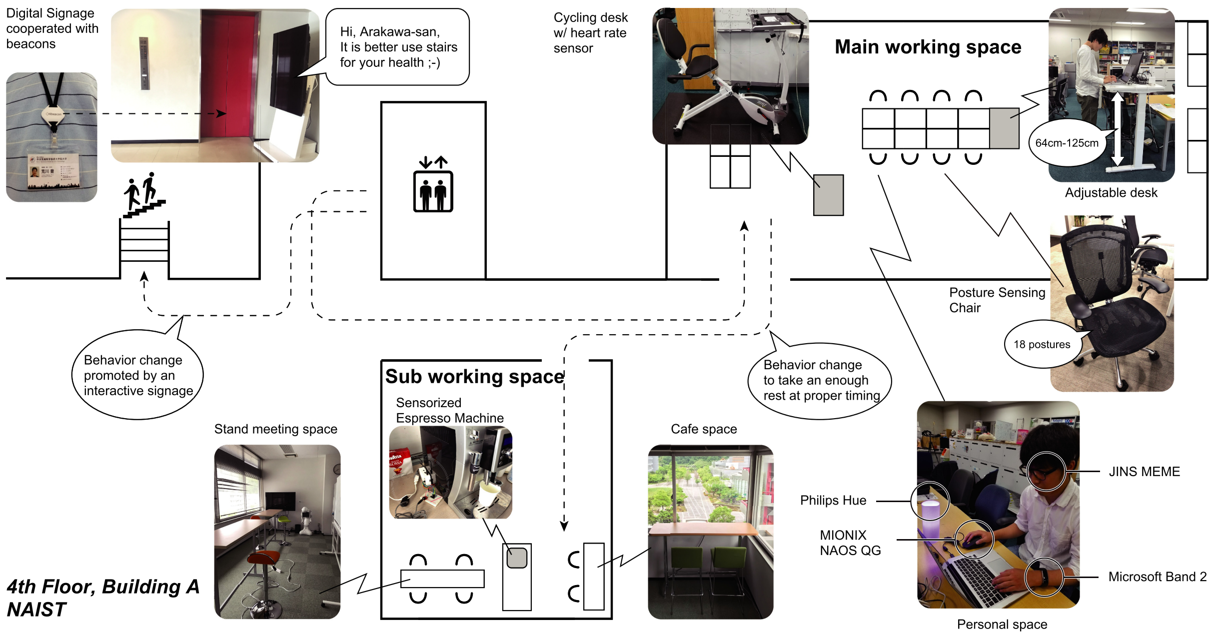

Fig. 1 Our concept of smart office.

to change the attitude of workers by changing their working posture. In addition to the main working space, we set up a subsidiary working space in a different room. This is a cafe-like space with an espresso machine and a snack corner. Because many people are working in the main working space, we expect that a person who wants to concentrate will move to the subsidiary working space. To sense the stress of workers, we integrated various sensors. Specifically, the workers wore JINS MEME eyewear [*12], which has an Electro-Oculography (EOG) sensor and motion sensor for sensing the degree of concentration. The result appears as a colored light on the desk side. The purpose of the light is to display the worker's cognitive state to prevent unexpected interruptions from colleagues. In addition, we prepared Microsoft Band 2 and Mionix Naos QG. Both devices have a heart rate sensor and GSR [36] sensor for detecting stress.

In addition, we prepared wearable beacons for workers, which are attached to a neck strap. These interacted with digital signage deployed at various locations. We expect that the beacon function will be installed into an integrated circuit (IC) card, the use of which has already spread to most companies. Although it is now used for tasks such as opening and closing doors, paying at internal cafes, and using copiers, in addition to a beacon function, some sensors might be embedded in the card. For example, Hitachi has developed a name tag incorporating an infrared sensor and an acceleration sensor, and has released a system that quantitatively evaluates social communication [37]. We also developed a name tag in which multiple energy harvesting elements are used for activity and place recognition [38].

3.2 Physical State Sensing

As one way to sense the physical state sensing, we introduce the development of a posture sensing chair that can continuously measure an employee's posture while working. Although there are related studies that used a depth camera [39], [40] and a motion sensor attached to a person [41], or pressure sensors installed on the seat surface [42], [43], [44], [45], [46], [47], it is difficult to take measurements during long periods without disturbing the work or reducing the comfort of the chair. Therefore, we proposed a method to estimate the posture from the deflection of the chair by attaching the acceleration sensors to the back of the seat surfaces [48].

3.2.1 Definition of Sitting Postures in a Workplace

In this study, we focused on recognizing 18 sitting postures that combine two types of sitting positions (shallow or deep), three types of sitting postures for leaning forward-backward, and three types of sitting postures for leaning left-right, as shown in **Fig. 2**. These sitting postures were defined based on research that monitored the sitting postures of office workers [49], conducted by the Okamura Corporation [*13]. In addition to the above sitting postures, we also targeted recognition of the non-sitting condition.

3.2.2 Developed sensing chair

Figure 3 shows the implementation of the sensing chair. Our target sensing chair is an ergonomic office chair in which the seat and back are made of mesh fabric that molds to the body for different postures and physiques. The sensing chair has two accelerometer sensors attached to the back and six accelerometer sensors attached under the seat, for a total of eight accelerometer sensors placed in the positions shown with red squares in Fig. 3. We attached each accelerometer to the back side of the mesh fabric so as to not deteriorate the chair performance in conforming to the person using it.

3.2.3 Classification Method

To classify 18 sitting postures with seat movement, the tilt angles of the accelerometer θ_{ini}, ψ_{ini}, and ϕ_{ini} at the time of seat movement was acquired in advance as an initial state. Thereafter, the variation of angles θ', ψ', and ϕ' between the tilt angle of the

[*12] https://jins-meme.com/en/

[*13] https://www.okamura.com/

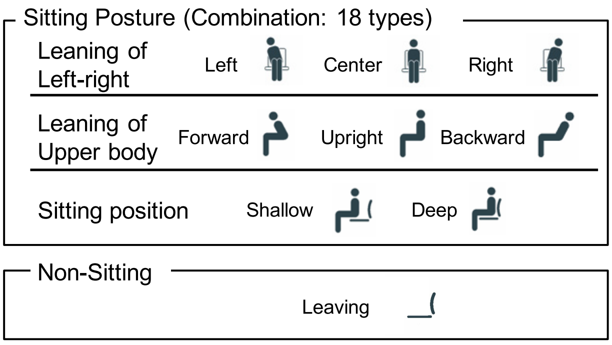

Fig. 2 Target sitting postures.

Fig. 3 Implementation of posture-sensing chair.

chair while sitting and the tilt angles θ, ψ, and ϕ of the initial state is calculated as follows:

$$\theta' = \theta - \theta_{ini}$$
$$\psi' = \psi - \psi_{ini}$$
$$\phi' = \phi - \phi_{ini}$$
$$\boldsymbol{x} = [\theta'_1, \psi'_1, \phi'_1, \theta'_2, \psi'_2, \phi'_2, \ldots, \theta'_8, \psi'_8, \phi'_8]$$

The change in the relative tilt angle of all accelerometers are taken as features $\boldsymbol{x}$, and a learning model was constructed by using Random Forest classification.

3.2.4 Accuracy

To evaluate the accuracy of the sitting posture classification method, data were collected from 20 volunteers with various physiques (male: 19 / female: 1, height: 171.8 ± 8.1 cm, weight: 66.1 ± 12.5 kg). The sensor data for θ', ψ', and ϕ' were collected as the volunteers performed 18 types of sitting posture and seat movement.

Each participant assumed these postures five times. The sensor data were collected when they were in a stationary state for each posture. Therefore, the dataset contained 1,900 data points from 20 participants, 19 postures (18 sitting postures plus no sitting), and 5 repetitions. We evaluated classification methods by leave-one-participant-out cross-validation. The result of the classification is shown in **Fig. 4**. This confusion matrix shows that the classification accuracy was 80.2%.

3.3 Internal State Sensing

As one method for internal state sensing, we introduce research on health-related QoL (HRQOL) estimation by sensors. HRQOL represents a QoL directly influenced by health, disease, and medical intervention. It is measured by using a questionnaire, such as Sickness Impact Profile (SIP) [50], Short Form-36 (SF-36) [29], World Health Organization QoL (WHOQOL) survey [28], and WHOQOL-BREF [51]. Inquiries using questionnaires can be conducted at a large scale with low cost, but they have problems in that answers to many questions are subjective and there is recall bias. Therefore, we developed a method to estimate HRQOL by using a smartphone or smartwatch [52].

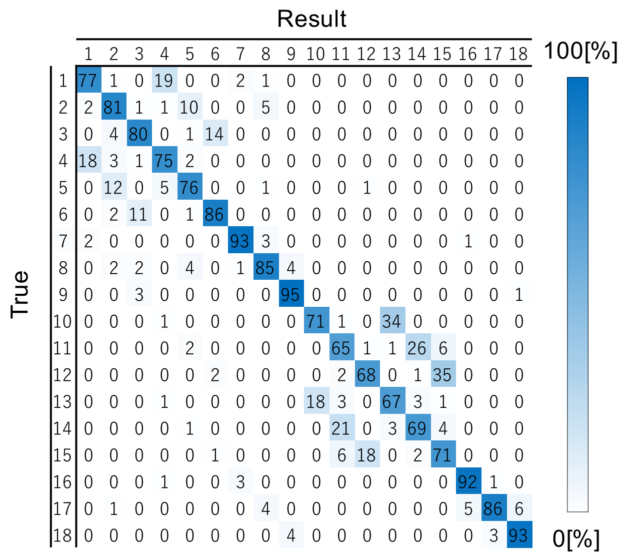

Fig. 4 Classification result.

3.3.1 Proposed System: Estimating QoL by Sensors

We developed a simplified HRQOL measurement method to estimate the HRQOL score from the bioactivity log data measured by smart devices, as shown in **Fig. 5**. The log data were collected by an Empatica E4 wristband [53] and smartphone. The HRQOL estimation model was constructed by the random forest algorithm, which is used in machine learning. The E4 wristband is a smart device that can measure acceleration, electro-dermal activity, blood-volume-pulse, heart rate, inter-beat interval, and skin temperature. We calculated seven features (total, average, median, standard deviation, variance, maximum, and minimum) for each sensor. Also, we used sleeping time (today/yesterday), activity time, blood-volume-pulse-LF/HF ratio [54], and heart rate-LF/HF ratio as features. We applied feature selection based on the Gini index for each questionnaire and selected the best feature combination. For reference data, the WHOQOL-BREF questionnaire results from each participant was used.

3.3.2 Evaluation

To evaluate the accuracy of the models, we conducted a leave-one-out cross-validation for a total of 15 weeks of data collected from one participant. In the evaluation, we also analyzed the effect of features for each question.

Table 1 shows estimation accuracy against each of the 26 questions in WHOQOL-BREF, which covers four domains: physical health (PHY), psychological (PSY), social relationships (SOC), and environment (ENV). From these results, we confirmed that the answers for some questions can be estimated by our proposed system. For example, estimation accuracy was better than 80% for questions 12, 13, 21, 24, and 25.

Next, we evaluated the correlation coefficient of the final HRQOL score, which is calculated by the following equations:

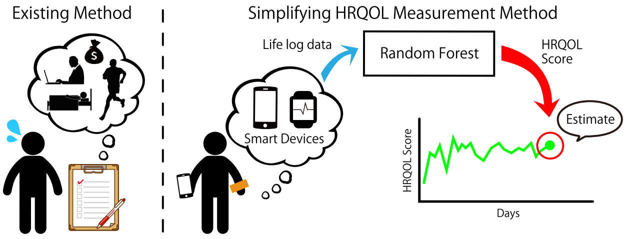

Fig. 5 System for estimating HRQOL.

Table 1 Accuracy against each questionnaire of WHOQOL-BREF.

Questionnaire No.	Domain	F-value	Num. of features
1	-	63.1	41
2	-	56.3	19
3	PHY	49.5	5
4	PHY	51.3	20
10	PHY	54.7	30
15	PHY	51.4	33
16	PHY	50.2	26
17	PHY	60.7	15
18	PHY	52.0	6
5	PSY	54.2	18
6	PSY	60.9	27
7	PSY	50.9	21
11	PSY	66.1	20
19	PSY	59.4	46
26	PSY	55.7	14
20	SOC	57.8	18
21	SOC	93.6	2
22	SOC	75.4	10
8	ENV	60.6	18
9	ENV	52.5	36
12	ENV	93.1	2
13	ENV	87.8	3
14	ENV	49.0	8
23	ENV	88.2	2
24	ENV	94.6	5
25	ENV	86.2	8

$$HRQOL = (PHY + PSY + SOC + ENV + Q1 + Q2)/26$$
$$PHY = (6-Q3)+(6-Q4)+Q10+Q15+Q16+Q17+Q18$$
$$PSY = Q5 + Q6 + Q7 + Q11 + Q19 + (6 - Q26)$$
$$SOC = Q20 + Q21 + Q22$$
$$ENV = Q8 + Q9 + Q12 + Q13 + Q14 + Q23 + Q24 + Q25$$

Figure 6 shows the results for correlation coefficients against each question asked in a conventional way. Of course, if we ask each subject all 26 questions, the correlation coefficient becomes 1.0. If we estimate all answers without asking any questions, the correlation coefficient becomes 0.643. To achieve an accuracy better than 90%, it is necessary to ask 9 questions, and our proposed system can estimate the answers for the remaining 17 questions.

3.4 Changing Workplace Behavior with Nudges

Changing behavior in the workplace is an extremely challenging task. Its purpose is to improve productivity, mental health, workplace communication, and employee comfort. "Nudging" is a concept in behavioral science, which means providing an unconscious bias or trigger to change human behavior. We believe that information-technology-based nudges can be used to improve employee well-being and health.

Examples of nudges in the workplace are as follows: (1) The smell of someone's coffee provides the motivation to take a break.

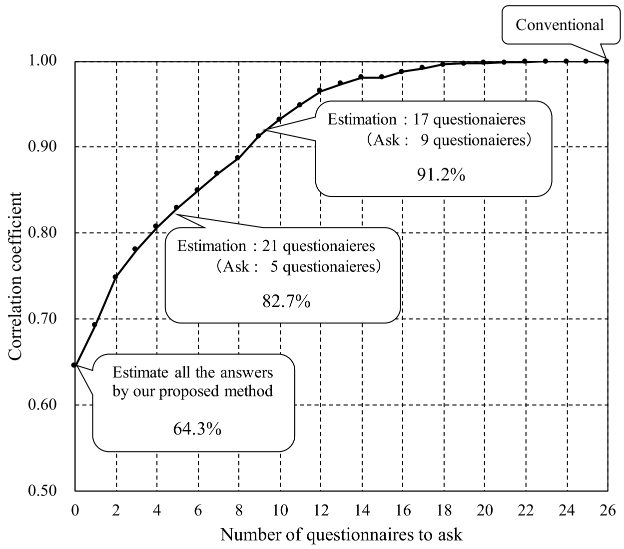

Fig. 6 Correlation coefficient vs the number of questionnaires to ask.

(2) In the breakroom, the microwave power is interlocked with a health check. By connecting a weight scale with the power controller, the user is prompted to check his or her weight before using the microwave. (3) When the microwave starts, a stretching exercise video streams in the microwave window so the waiting time can be used to improve health. In this way, it is possible to encourage health monitoring and exercise routinely in the office.

We also considered incorporation of gamification techniques [10], [11], [55], [56] into the workplace. For example, gamification and sensing techniques can be used to solve reservation problems in offices. The reservation problem here is the balance between the room capacity and the actual number of people using it. To prompt the users to reserve a room that matches the proper number of participants, comfort can be the reward. By interlocking the air conditioner and an IC card reader, for example by requiring a certain number of IC cards to touch the sensor to activate the air conditioner, the users' behavior probably will change.

3.4.1 Interactive Signage for Behavior Change

Here we introduce an experiment conducted at our university to induce small behavior changes for health, such as determining one's weight, and for encouraging cooperation between group members, such as checking a room to determine whether someone is present. To trigger such behavior changes, we developed interactive digital signage with the function of identifying and interacting with people using a Bluetooth low-energy beacon [57], [58].

Figure 7 shows the layout of the proposed interactive signage deployed in our building. We asked all participants to wear a tiny Bluetooth low-energy beacon for identification. The beacon was attached to the neck strap used daily to carry the user's student ID. Compared with the existing signage system, which uses a camera for user identification, the beacon-based identification system is robust against variations in angle and distance between the user and signage.

Our digital signage monitors the beacon signal, and if it detects the approach of a target subject, it talks to the passing user to provide visual and auditory stimuli. It also has a touch control

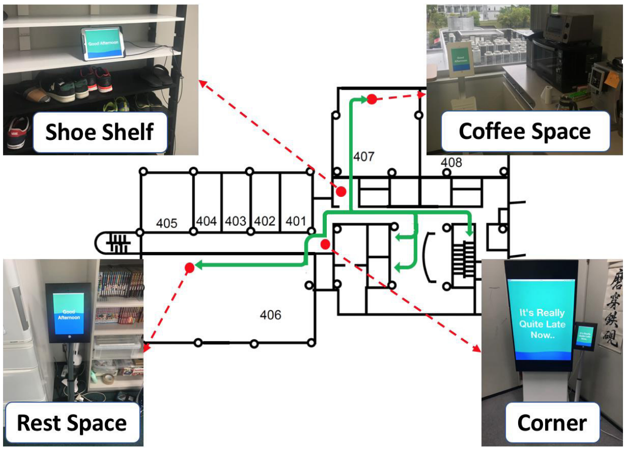

Fig. 7 Layout of our proposed interactive signages.

function to obtain a response from the subject.

3.4.2 Interaction Procedure

Our system interacts with the approaching person by the following procedure:

Step 1) User detection

We set a unique ID for each beacon and recorded the relationship between the ID and the user in the database. Therefore, our signage can easily identify an approaching person from the beacon signal. If the signage detects more than one beacon signal, it selects the closest user by comparing the received signal strengths.

Step 2) Scenario selection

We prepared various scenarios for interacting with the approaching person. The scenarios included not only questions aimed at behavior change but also common conversation. The digital signage selects a proper scenario from among all scenarios according to the time of day, user attributes, the status of previous scenarios, and the location.

Step 3) Interaction

The digital signage presented information on a display screen in addition to speaking it. We intended to prepare two ways for the user to respond: button selection and free text input. Because simplifying the way to respond is important for preventing users from feeling bothered, we designed queries to be answered simply by selecting a choice. Currently, the voice recognition has low accuracy, and it was not used in the experiments.

Step 4) Finish and restart

The digital signage automatically goes back to the initial screen after receiving a response from the user. Also, we set a timeout to handle the situation when a user cannot reply or does not notice the signage or its message. In such a case, the result is recorded as "ignored." If the user does not respond to a task, the signage goes back to the initial screen after a certain time period. The results (including ignored and rejected responses) are uploaded to a server and stored in the database.

3.4.3 Actuation Scenario

We defined four different sets of scenarios (personal task, personal+ task, check task, and check+ task) in advance. A personal task is a task for collecting personal data, such as stress level. A personal+ task asks the user to perform an action task, such as checking his or her weight. A check task asks the user to make a contribution to the organization, such as checking the supply of consumable articles. A check+ task is a check task that includes an action. **Table 2** provides examples of the scenarios we prepared for this experiment. Each scenario in the table consists of the voice and text message content and the response options (answer button, reject button, and text input field) presented to participants.

Table 2 Example signage interaction scenarios.

Category	Content	Labor Cost
Personal	Are you feeling stressful now?	Push Button
Personal	Have you eaten your breakfast yet?	Push Button
Personal	Did you sleep well last night?	Push Button
Personal+	Have you check your weight recently?	Push Button
Action	Do you want to use the weight scale to check your weight?	Push Button & Use Weight Scale
Check	Are Secretaries in their Office now?	Check & Push Button
Check+	Is there anyone in A407 now?	Go to A407 & Check
Action	Could you please turn off the light if it's on?	Go to A407 & Turn Off the Light

Table 3 Response rate for each task type.

Type	with bias	w/o bias
Personal	87.74%	84.35%
Personal+	81.82%	83.33%
Check	89.86%	85.18%
Check+	83.33%	86.67%
Action	100%	88.24%

3.4.4 Experiment and Result

To investigate the effects of interactive-signage-based stimulation, we designed a survey experiment with consideration of bias because the experimenter and participants are members of the same laboratory. The experiment was planned to be held over 3 weeks. During the first week, we repeatedly encouraged participants to interact with the queries from our signage (we call this the "period with bias"). The second week was Japan's "Golden Week," (a holiday period) and many participants were absent from the lab. During the third week, our system was still working but we did not remind participants to respond to signage queries (we call this the "period without bias").

Table 3 shows the response rate for each task type during the first and third weeks ("bias" periods). Overall, the response rate was higher than we expected and it did not significantly decrease during the period without bias.

4. Future Challenges

Finally, we discuss the remaining problems and our ongoing research related to the sensing and changing of human behavior in a workplace.

4.1 Physiological Sensing

Last year, an ECG was installed in the Apple Watch. Soon thereafter, a person's life was saved by the detection of atrial fibrillation, a newsworthy event [*14]. At the CES 2019 show, a wearable blood pressure monitor, HeartGuide [*15], was announced by Omron. In the future, other physiological data, such as blood sugar levels, may be easily measured by a smart device. In this way, the remarkable technological progress of smart devices is expected to enable the use of sensor data from multiple devices to improve the accuracy of internal state estimation.

4.2 Micro-activity Sensing

The use of conferences and working groups in offices is increasing. Job crafting and CREW are examples of group-based efforts to improve the workplace environment. To carry out group discussions smoothly and efficiently, some skill is required. We are focusing on the details of actions during group activities, such as gestures and facial expressions of attendees, and are developing a system that can measure such behaviors quantitatively [59].

4.3 Chatbot Therapist

Artificial intelligence (AI) speakers and chat bots that interact with users have already been introduced to the public. Actually, Woebot [*16], an artificially intelligent chatbot based on the principles of cognitive-behavioral therapy to treating depression, has already launched and the effect of Woebot was reported from the Stanford [60].

It seems that opportunities for human-machine interaction will be increasing from now on. Voice synthesis technology has also recently achieved remarkable results. It has become sophisticated enough to make it difficult to distinguish between synthesized and human speech. However, with regard to dialogue scenarios, there is still much room for improvement because it is difficult to construct dialogue as naturally and flexibly as human beings do.

4.4 Personalized Actuation Scenario

The purpose of behavioral change is greatly diverse according to the company and individual. In the future, it will be necessary to design a scenario according to specific purposes, such as workplace productivity or individual engagement.

4.5 Strategy for Workplace Integration

Digital signage is spreading throughout major cities. In state-of-the-art offices and universities, digital tablets are increasingly used to display, for example, registration information at classroom entrances, and we are entering a world where information is displayed everywhere. The authors believe that in the future, it will be normal to have a conversation with signage, as it has already become common to hold an IC card near numerous objects (sensors and the devices to which they are connected) in the urban environment (including offices). However, appropriate strategies are needed to more fully implement this.

[*14] An Apple Watch told a 46-year-old man he had an irregular heartbeat. It was right. - ABC News, Dec 11, 2018 https://abcnews.go.com/beta-story-container/Health/apple-watch-told-46-year-man-irregular-heartbeat/story?id=59726093

[*15] HeartGuide — Wearable Blood Pressure Monitor — Omron https://omronhealthcare.com/products/heartguide-wearable-blood-pressure-monitor-bp8000m/

[*16] https://woebot.io/

5. Conclusion

In this paper, we summarized projects and research for ubiquitous computing, with a focus on improving employee well-being in the workplace. Sensing human behavior in the workplace environment involves problems of privacy, and the use of AI for human behavior intervention entails some ethical issues. However, it is necessary to think about how to overcome these problems and how to make pervasive technologies improve our wellness. In fact, the continuous posture-sensing chairs that we have developed are going to be commercialized by a large furniture company. QoL estimation using wearable devices also has attracted various companies, and experiments in five companies with 60 employees are in progress during January to February 2019. We hope that the era of ubiquitous computing will penetrate into the workplace in beneficial ways, including behavior change for improved wellness, and will help us work more happily and healthily with the help of sensors and AI.

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