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Enhancing the Quality of User Research Using Embedded IoT Sensors for Collecting Life Information

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Abstract
This study aims at developing a new user research method that uses IoT sensors embedded at users' homes to enable users to recall their memories. The proposed method was evaluated by experiments where four participants individually created user journey maps with quantity data that was collected for seven days. The results showed that IoT sensor data increased the quantity, clarity, and accuracy of recalled memories. This study argues that IoT sensors can be an effective approach to increasing user research quality by triggering users' memories without interfering with users' ordinary lives.

Keywords: user research, empathy, internet of things (IoT), user-centred design, design methods

1. Introduction

In creating new products and services, empathic understanding of users plays a significant role to identify latent user needs (Mattelmäki et al., 2014). The demand for high-quality user research is growing to support gaining a deep understanding of users' and contexts (Brawn, 2009). User research is conducted in several ways, such as interviews, focus groups, and observations, to identify latent user needs which users are not aware of (IDEO, 2011). Boeijen et al. (2014) divided the user research method into two categories depending on interaction types with users: communicating with users (CWU) such as interviews and investigating what users do, such as observation. CWU methods allow designers to understand the internal factors that motivate user behaviour, unlike researching what users do. However, CWU methods often result in identifying what users know consciously rather than unconsciously because they rely on users' self-reports (Boeijen, 2014). CWU methods do not have a role in knowing users' unconscious behaviour. However, CWU methods cannot completely elicit from users what users consciously know. Users may not always answer questions sufficiently and correctly because it is difficult to reconstruct memories that have been experienced too long ago (Norman, 2015). Therefore, many methods have been proposed to minimize the time gap by incorporating data from users' daily lives. One of them is Experience Sampling Method (ESM) which lets users write a daily diary in their daily lives. In ESM, participants answer questions sent by researchers during their daily lives. While the participants' memories are fresh, answering the questions frequently in their daily lives becomes a burden for the participants. The high respondent burden causes the problem that the burden decreases the response rate of the participants to the questions and the quality of the answers (Baxter et al., 2015). Hernandez et al. (2016) measured the difference in response time and the time required to select a response in ESM depending on the device used to interact with the researcher and examined the effect of device differences on the response rate. Isio and Abe conducted a survey on emotion using a wearable device combined with ESM. This method requires fewer efforts because the method uses biometric data to acquire affective states in episodes and does not require a response from the participant. However, Javier assumed a choice-based response method, and Ishio required text responses when investigating a wealth of feelings and behaviours other than quantitative emotion data, making it difficult to reduce the burden.

While in the above-mentioned research, data is mainly viewed by designers, quantitative data of users can also be used by users themselves (Kollenburg et al., 2018, Woo and Lim, 2020). Data-enable design uses collected quantitative data to gain insights for solving a problem, with the user intervening in the process (Kollenburg et al., 2018). Woo and Lim (2020) proposed a smart DIY system that allowed users to solve more problems by iteratively understanding their routines and reflecting on their functions. These studies focused on participatory design with users, which requires users' contributions in the entire design process rather than increasing user understanding in human-centred design where designers design for users.

In the context of user research, Arvola et al. (2017) confirmed that people could recall more memories when they reflect on their experiences with researchers based on videos recorded in their lives. However, it is difficult to capture the lives of unacquainted users with cameras due to privacy concerns. It is also difficult for the users to behave normally when the researcher also views the data from the camera after, which is a similar problem with observation methods (Boeijen et al., 2014). In addition, interviews with a huge amount of video recordings were very time-consuming.

Showing the sensor data to the user may help them to recall the memory as well as the camera logged. The data collected by sensors is quantitative data of the user's lives. Unlike cameras, the use of sensors is considered to interfere with users spending their daily lives to the less extent because users can know what is logged beforehand.

Therefore, this study developed a method to use IoT sensor data collected from a user's environment as a trigger to recall users' memories. The proposed method consists of three phases: (1) designers collect data on daily lives by the installed sensor, (2) users reflect their lives with sensor data, and (3) designers obtain the user's information based on users' reflection.

The purpose of this study is to verify whether the proposed user survey can achieve the following two points: (1) The user can live their lives normally without awareness of the presence of sensor during data collection, (2) during the reflection, the richness of their memories increases and becomes more accurate by viewing the sensor data.

2. Method

2.1. Outline

The proposed user-research method was verified by a case study under the theme "design satisfactory eating experiences of university students living alone". Four participants (P1-P4) joined the experiment, all of whom were 21-23 years old male university students living alone. The participants had friendship relationships with one of the authors. The participants were briefed that the experiment's purpose was to develop a user survey method using sensors that investigated the use of home appliances to improve the lives of students living alone. The participants were not informed that they would recall own lives after data collection. The experiments lasted nine days consisting of, installing sensors at participants' homes, seven-days data collection, and self-reflection sessions (Figure 1). On the day before data collection (Day0), one of the authors installed loT sensors on kitchen appliances and a camera shooting time-lapse videos in each participant's home. At the same time, researchers explained the purpose of the experiment: a study of user research methods investigating the usage of home appliances. Researchers did not inform the participants that they would recall their lives in the following self-reflection session. Sensors collected usage data for seven days (Day1-Day7). On the day after the week of data collection (Day8), the participants participated in the self-reflection session, where they drew the three types of user journey maps (UJMs) about their eating behaviours and associated emotions. First, the participants individually drew activities on eating behaviours on a UJM based on their memory (MemoryJM). Next, the participants drew another UJM by viewing the collected sensor data regarding the use histories of kitchen appliances (DataJM). Finally, the participants watched a time-lapse video of their lives with the camera and drew a UJM(VideoJM). MemoryJM and DataJM were compared to investigate an increase of richness and correction of the recalled memories by sensor data, and DataJM and VideoJM were compared to examine the lack of richness and accuracy of the recalled memories with the sensor data. After this session, a questionnaire and an interview were conducted to investigate participants' awareness of the sensors during data collection and their own perception of the changes in their memories when drawing UJMs.

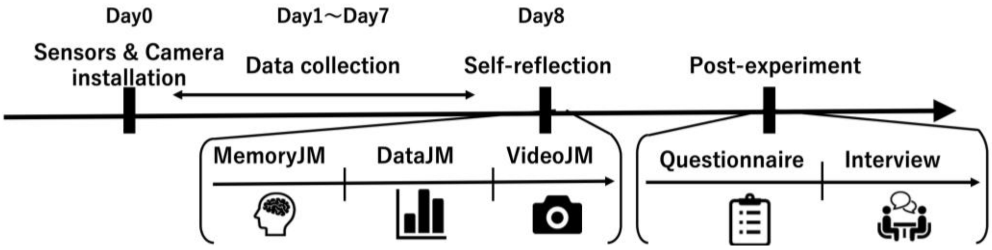

Figure 1. Flow of this experiment

2.2. Data collection at participants' home

The sensors were small IoT devices (MESH, Sony Group Corporation), each 24mm x 48mm x 20mm in size (Figure 2). The six types of sensors used were brightness sensors, human detecting sensors, motion sensors, temperature sensors, button sensors and magnetic sensors. These sensors were used to collect data on the usage time of kitchen appliances. Table 1 shows the correspondence between kitchen appliances usage data collected and whether data was collected by automatic or button sensor measuring use of appliance when the participants manually pressed the button. The sensor data was sent to Raspberry Pi installed in the participants' homes via Bluetooth and was recorded on a Google spreadsheet via the Internet, which allows real-time data viewing to confirm data collection went smoothly.

Figure 2. Pictures of the installed sensors

Table 1. Kitchen appliances collected usage data ＊mark represents a failure in data collection

	Rice cooker	pods	refrigerator	freezer	microwaves	kitchen	coffee machine	toaster
P1	button	button	auto	＊	auto	auto	-	-
P2	-	-	auto	＊	auto	auto	-	-
P3	＊	button	auto	＊	button	auto	auto	-
P4	auto	-	auto	auto	button	auto	-	auto

A camera shooting time-lapse videos was installed to record actual scenes of lives. The recorded videos were used to see the correctness of the memories recalled by the participants both with and without data. The videos were viewed only by each participant, which was informed to the participants before data collection. We limited the video viewers to the participant because it would be unethical for the researchers to see the participant's private lives at home. We also expected that the presence of a camera seen by the researcher might affect the results when asking the participant's awareness of the sensors. This camera took an image every 15 seconds, and a day was played back as a 10-minute movie.

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2.3. Self-reflection session

In the self-reflection session, participants reflected their lives by viewing sensor data, and then the authors obtained the user's information. In this experiment, verbal interaction such as interviews to verify memories that users recalled might influence users' memory and the influence was expected to disturb the comparison between memories with and without sensors seriously. Therefore, UJMs drawn by each participant were chosen to assess changes in their memories to avoid the influence of the order of recalling. UJMs is often used by designers to graphically show a timeline of user experience. In this experiment, UJMs were drawn by the participants themselves to visualize their eating behaviours and associated emotions (Figure 3-Left). UJMs has the horizontal axis showing time, and the vertical axis showing the satisfaction of the participants. The participants were instructed to draw one activity in one frame as Figure 3-Right shows an example. Other basic behaviours during a day were directly drawn on UJMs to know the time spent at home, which were time of waking up, going to bed, and going out. Of the seven days (Day1-Day7) data collection, the researcher selected the three days having the most data, which were considered to be the days with the many activities at home.

The participants drew UJMs of each of the three days on paper. First, the participants drew their MemoryJM of the three given days. The participants were also permitted to see their own data that could be viewed without using the proposed method, such as their own schedule, receipts of shops. Next, the participants annotated and corrected the information of MemoryJM with viewing the sensor data by using sticky notes and coloured pens (DataJM). Afterwards, additions and corrections were made to DataJM during watching the videos having recorded their eating behaviour (VideoJM). For this experiment, VideoJM was regarded as the UJM correctly representing the participants' activity because the authors could not watch the videos.

Figure 3. (Left)UJM drawing by participants (Right) Example of one activity in one frame

2.4. The post-experiment questionnaire and interview

After drawing UJMs, a questionnaire and an interview were conducted to assess the participants' awareness of data collection with sensors and perception of the richness of memories. The questionnaire was conducted with a 7-point Likert scale which had 1: " *I strongly disagree* ", and 7: "*I strongly agree*". The questionnaire consisted of two categories: awareness of the presence of the sensors and perceived difference in richness of their memories between before and after viewing the sensor data. Awareness of the presence of the sensors was asked for the beginning (Day 1-2) and the end (Day 6-7) of the data collection period separately. The items measured to what extent the participants were aware of the presence of the sensor during data collection. The perceived difference in richness of their memories between before and after viewing the sensor data was assessed by two points: quantity and clarity of the recalled memories. Quantity refers to the number of activities participants recalled, while clarity refers to the detailedness of the memory within an activity. Both quantity and clarity were assessed in terms of behaviour and emotion. The purpose of the interviews was to learn more about the reasons for the questionnaire responses and the reasons for the statements in UJMs, which were done orally by the author after the questionnaire. Examples of the questions were" why did you gave the score to this question in the questionnaire?" and "how did you recall the behaviours in this frame that were added on *DataJM?*"

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3. Result

3.1. Awareness of the presence of sensors during data collection

The results of the post-experimental questionnaire and interview assessed the awareness of the presence of the sensor and its cause. Table 2 shows the results of the questionnaire asking to what extent the participants were aware of the sensors.

Table 2. Awareness of the presence of the sensors

Questions during data collection (1: I strongly disagree ", and 7: "I strongly agree")	Score			
	P1	P2	P3	P4
Were you aware of the presence of sensors in Day1-Day2	5	5	5	5
Were you aware of the presence of sensors in Day6-Day7	5	4	2	4

All four participants scored 5 out of 7 on the questions which indicated that the participants were aware of the sensor during data collection. The interview suggests that the most significant cause was the presence of button sensors. Button sensors were installed in the houses of P1, P3, and P4, and the button had to be pressed when using the kitchen appliances to which button sensors were assigned. Therefore, they were worried about forgetting to press the button as shown in the following quotation of P1.

> *I'm afraid that I might have forgotten to push the button on the sensor. [P1]*

P4 was made aware of the sensor because the motion sensors' LED blinked whenever the sensor responded. As for another reason for keeping awareness, P2 thought that it would be better for this experiment to use the kitchen appearance which the sensor was installed.

> *I didn't know the (real) purpose of the experiment, so I thought it would be better to use the kitchen appliances (with the sensor installed) a lot. Although I did not try to use a lot more than usual, I felt I could contribute to the experiment when using it. [P2]*

Regarding the effect of the elapsed time, the awareness of P3 decreased, the scores of P2 and P4 slightly decreased. P1 did not get used to the button sensor within one week (Table 2).

> *I had gradually accustomed to the sensors and had come to take them for granted. [P4]*

3.2. Recalled memories by viewing sensor data

3.2.1. Changes of users' memories on their behaviours before and after viewing sensor data

This section describes recalled memories of behaviour based on UJMs and the post-experiment questionnaire and interview. Table 3 shows the number of frames drawn on the MemoryJM, the number of changes from MemoryJM to DataJM, and the number of changes from DataJM to VideoJM. The rows in Table 3 summarize the results for four UJMs. The changes in written behaviours were categorized into three types based on the difference: *addition of a new frame, addition of description within a frame*, and *correction of a frame*. *Addition of a new frame* means an increase of the recalled memory quantity and *addition of description within a frame* means an increase of recalled memory clarity. *Correction of a frame* refers to written description becoming more accurate. The difference between MemoryJM and DataJM shows the influence of viewing sensor data, while the difference between DataJM and shows the influence of watching the videos.
We qualitatively visualize each change which were summarized in Table 3, by showing examples of the UJMs shifts Figure 4 and the questionnaire Table 4 and interview results in the following section. In Figure 4, what the participants drew on MemoryJM is shown in the black frame, DataJM is in the blue frame, and VideoJM is in the red frame. One scale on the horizontal axis represents one hour.

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Table 3. The number of the change of frames: sum of P1 to P4 (P1/P2/P3/P4)

	The number of frames on MemoryJM	increase of	MemoryJM →DataJM	lack of	DataJM →VideoJM
Day1-Day2	12(-/4/1/7) 4UJM (-/1/1/2)	quantity	5(-/3/0/2)	quantity	7(-/1/4/2)
		clarity	0	clarity	0
		correction	3(-/2/1/0)	accuracy	0
Day 3-Day 4	19(13/-/4/2) 4UJM (2/-/1/1)	quantity	4(3/-/0/1)	quantity	3(2/-/1/0)
		clarity	2(0/-/0/2)	clarity	0
		correction	4(3/-/1/0)	accuracy	2(0/-/1/1)
Day5-Day7	20 (7/9/4/-) 4UJM (1/2/1/-)	quantity	3(0/3/0/-)	quantity	1(1/0/0/-)
		clarity	1(0/1/0/-)	clarity	0
		correction	2(1/0/1/-)	accuracy	0

Table 4. Participants' perception of the memory changes

Questions about when drawing DataJM (1: I strongly disagree ", and 7: "I strongly agree")	Score			
	P1	P2	P3	P4
Did you perceive an increase of quantity of your memories of behaviour	7	5	6	6
Did you perceive an increase of clarity of your memories of behaviour	7	6	6	3
Did you perceive an increase of quantity of your memories of emotions	6	4	5	3
Did you perceive an increase of clarity of your memories of emotions	2	1	3	3

Increase of quantity: Table 4 shows, all participants perceived that the sensor data made them recall behaviours. *The number of additions of a new frame* does not include sentences that describe what can be directly known from data. For example, a frame that says "*I used the pod*" were not counted. Therefore, *addition of a new frame* from MemoryJM to DataJM represents the increase of the participants' memory. Figure 4-(A) shows a typical example of the addition of new frames. In the case of P1, after being shown the microwave usage data, he could recall that he ate pork-stuffed green bell peppers from a supermarket. Figure 4-(B) shows the microwave and refrigerator usage data triggered P4 to recall heating rice and defrosting meat for cooking.

Lack of quantities: There were frames that participants couldn't recall until drawing VideoJM. The number of *additions of a new frame* from DataJM to VideoJM increased as time passed from the recorded behaviours. For example, P3 could recall little about his eating behaviours on day2 even after viewing the sensor data (Figure 4-(C)).

> *The more recent the memory is, the more I can recall by just looking at the data. If the memory is old, I need to watch the video. [P3]*

Increase of clarity: Table 4 shows three participants perceived that their memory became clearer due to viewing the data. Originally, P4 wrote down that he ate rice only. After seeing his sensor data, he could recall that he also fried some chicken and ate them together (Figure 4-(D)). After seeing his MemoryJM, P2 could recall with confidence that he went to a convenience store Figure 4-(E). These cases were considered that the episode at the time was clearly recalled.

Correction: Viewing the data made memories more accurate than memory itself did. The modification of time counted when the difference was more than two hours. In the following example, not only time but a major correction was made in frames. Figure 4-(F) shows that P1 first recalled eating lunch alone at school in his MemoryJM, but he noticed that he had lunch at home with his friends due to the sensor data showing that he was at home. The data made P1 recall he left his laboratory at the school and went home. Figure 4-(G) shows that although P3 first described that he ate his dinner once on his MemoryJM, the sensor data made him recall that he had actually eaten two separate meals with a 3-hour gap.

Lack of accuracy: There were two cases where participants drew inaccurate behaviour in DataJM, both cases were in Day3-Day4 UJMs. P1 interpreted the usage data of the refrigerator as that he opened it to check the contents in the refrigerator, while he actually opened it to take out condiments (Figure4-(H)).

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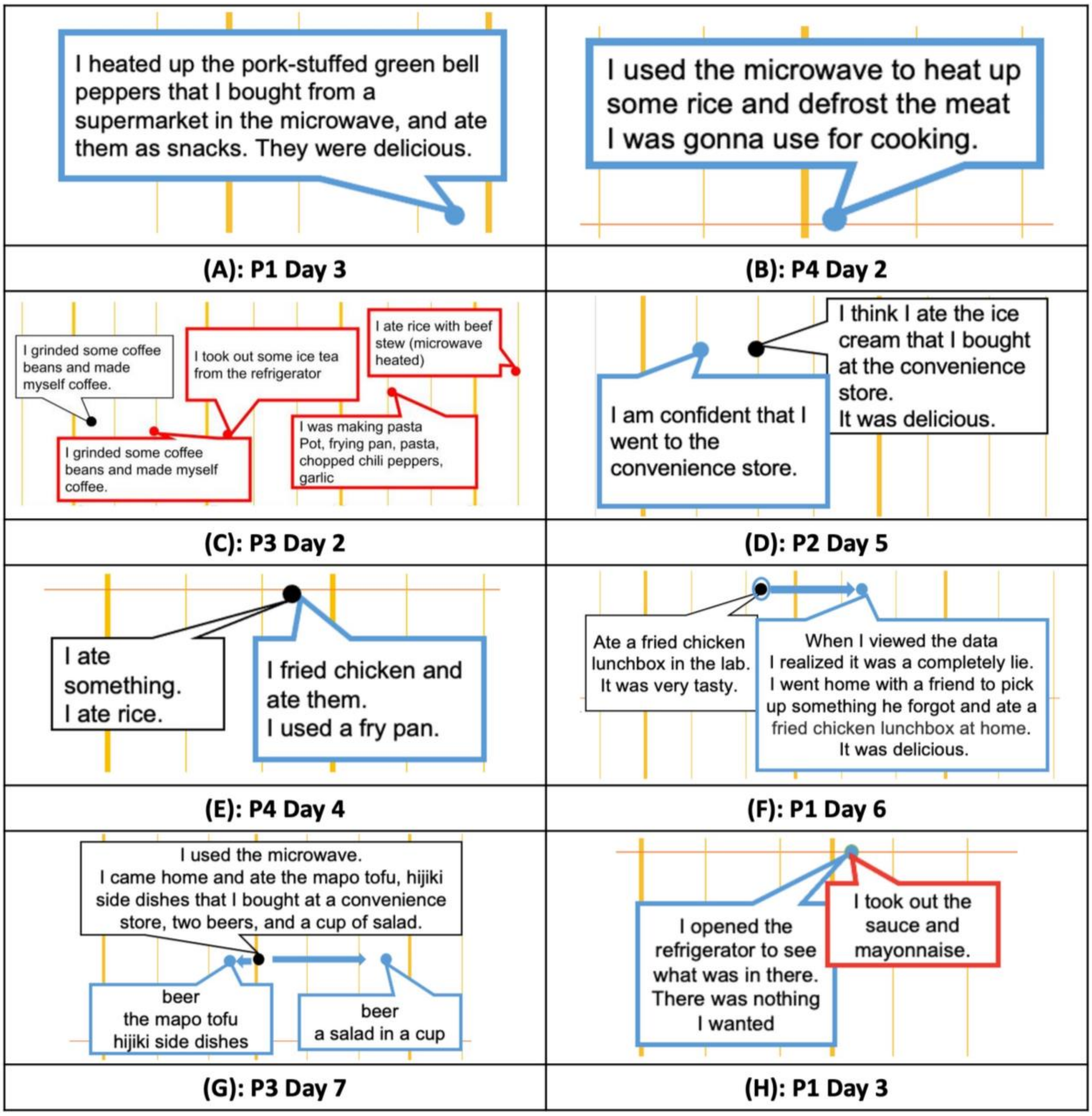

Figure 4. Examples of the UJM shifts (Participant number, Date of UJMs)

3.2.2. Recalled emotions in relation to recalled behaviours

Table 4 shows three participants reported that they could recall more memories of emotions due to the sensor data while the score was not as high as the questions regarding their behaviour. In drawing DataJM, although the participants could recall emotion along with the newly recalled behaviours, they could not additionally recall their memory on the behaviours which they had wrote down in MemoryJM. None of the participants reported that the sensor data helped them to recall their emotions at the time more clearly, as shown in the following quote.

> *I can't really recall what I was thinking at each point in time (when sensors were activated). I can vaguely recall what I was feeling that day. [P3]*

3.3. How participants recalled episodes by the sensor data

From the post-experimental interviews, P1, P2, and P3 indicated that they could recall their lives more easily after viewing the data.

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Now that I knew the timeline of a day, I could link it to my behaviour and recall. [P1]

it is easier to recall episodes if I have access to data that can trigger my memory[P3]

The sensor data triggered recalling the memory in two different ways. First, the data of basic behaviours helped the participants to understand the flow of their lives, such as time spent at home and at bedtime. As a means of understanding the rough flow of their lives, P1 used the kitchen presence data which detected whenever he went out or to the bathroom. P2 used the refrigerator data which was frequently used during spending time at home. P3 and P4 used other data that were not collected by the proposed method: P3 used the schedule application, and P4 used the history of a text chat application.

Second, the sensor data made it easier to recall some activities. This made it possible for participants to recall other memories related to the activities already recalled, and it helped recall the entire day.

It was easy to recall many behaviours after viewing the traces of using appliances. [P2]

Since I recalled more from looking at the sensor data, I was able to construct a story of what happened on that day. [P3]

Some participants mentioned that the usage data of less-frequency used kitchen appliances such as microwave and rice cooker were good triggers to recall activities than refrigerators which were used frequently for a variety of purposes.

I think the memory I recalled from the rice cooker and microwave was vivid. Memories based on data having less frequency or purpose are more accurate. Because there is a lot of usage data of the kitchen, it is difficult to sort out the behaviours. [P1]

By observing how users recall their lives through the sensor data, the designers could also learn users' unique routine of using kitchen appliances from which sensors collected data. The information could be elicited because the participants use their unique routine of using the appliances to recall their lives. For example, the unique meaning of coffee machine was elicited from P3.

I have a desire to drink coffee at around 3:00, so if the usage data of the coffee machine is later than 3:00, I can tell that the day is not going well. [P3]

4. Discussion

4.1. The potential of using sensors data for users to recall their memory

The experiment showed that the sensor data embedded at the participants' homes could let the participants recall their lives. The participants could recall more episodes in more detail with higher accuracy with sensor data than with their own memory. We observed that the participants needed less burden with sensor data than they did with video recordings because the sensor data can be glanced at. Arvola et al. (2017) reported that video recording could recall participants memory while it was heavy burdens for the users due to the required time for recalling their episodes. Sensor data has less privacy issues than video recordings because sensor data does not accumulate information that is not the subject of investigation. It suggests that sensor data can be a good alternative trigger of recalling their memories.

While the sensor has the potential to collect user data without interfering with users lives, the result identified two issues which prevented users from spending their time as always. The results of the interview revealed what made the participants aware of the presence of the sensor during data collection. Eliminating the cause, i.e., LED blinks of the sensors and manually pushing buttons, can make user research with sensors be conducted without interfering with the users. In other words, the sensors installed visible position may not a problem when the participants do not interact with the sensors by pushing it or by seeing it blinking. The experiment revealed another concern that one of the participants thought it was better to use appliances with sensors more often than he usually did. The participant's perception might be a result of their desire to act desired by the designers. A similar bias is reported in user interviews, which is interviewees intentionally and unintentionally giving responses which designers wish (Baxter et al., 2015). In design practice, it is necessary for designers to make sure the participants understand that there is no desired behaviour during the research.

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4.2. What kind of data is likely to evoke the user's memory

Overall, the memory of the recalled behaviour was increased, and participants could recall their lives easily due to viewing the sensor data. However, the results showed that there was a gradation in the effect of the data depending on the number of days from behaviours to be recalled and the type of data.

The results showed VideoJM had more information than DataJM when the participants recalled behaviours after four days from data collection. However, DataJM and VideoJM were almost identical when participants reflected their behaviour within three days after data collection. It suggests that the viewing sensor data allows users to recall memories at a level closer to watching videos of their lives only when reflection is done within a few days after activities happen.

The types of sensor data influenced differently to the participants for recalling their behaviours. Sensor data of high frequently used kitchen appliances rarely support the participants to recall relevant episodes as much as low frequent kitchen appliances but support to construct an overview of a day. It helped the participants to identify which day of the week it was because the data could provide how long the participants spent time at home. On the other hand, sensor data of appliances that were used less frequently were effective. We speculated that those sensor data limited the participants' memories regarding the experiences with the appliances, which made it easier to recall. For example, the use of the microwave added the constraint that the participants had heated something at home, which made it easy to choose the right memory from their meal experiences because he does not have many memories of heating something up during the data collection. This effect may be similar to the effect when memorizing a poem, where external constraints, such as the rhythm associated with the poem, make it easier to recall the poem. The external constraint narrows down the number of words you can think of in your mind when recalling the poem (Norman, 2013). As it was found that the effect depends on the type of data, it is possible to make it more effective while reducing the reflecting burden on the user by paying attention to the difference when collecting and presenting the data.

4.3. Future Perspective

Duration of data collection may influence data collection strategy and participants' awareness of data collection. The longer the data collection becomes, the fewer participants may gain awareness of the presence of sensors at home. When this method is used continuously for a long-time, this method may be able to make rich and accurate memories of users and reduce the frequency and burden of reflection compared to ESM. Long-term reflection by accumulating data is also valuable because it allows users to understand their behaviour patterns and trends they have not known. (Li et al., 2010). Data visualization may influence users' reflection when showing accumulated data because data representations impact the perception and understanding of data. (Oh and Lee, 2015). The interaction with designers may also influence the amount of information that can be elicited from the users. In this study, UJM was used to measure users' memories which users had to recall by themselves. Users might not have written down all the details they could recall because they thought they had already written down enough information. Interviewing with the participants based on data enables designers to ask questions which have roots in their real and specific behaviours. As such questions are easier for users to understand what is being asked, which lets users respond in detail (Portigal, 2013), designers may get richer information regarding users' lives and contexts. In this study, the emotions at that time were not recalled by the sensor data. It suggests that data on the use of kitchen appliances and data on behaviour are useful to recall behaviours not emotions. The emotional aspects of users might be able to be recalled by collecting qualitative emotional data using wearable devices, as it is done by Arvola (2017). Methods of combining sensor data to collect behaviour and wearable data to collect emotions deserve to be evaluated in future research. It is also of interest to investigate privacy aspect of sensor data collection for future study. We note that the number of participants was small and the participants' situation was specific. The participants profile might have influenced on the degree to which sensor data recalled behaviours. While it is necessary to experiment with a larger number of participants under different circumstances to generalize the findings, this preliminary study suggest that the sensor data can be a way of user research.

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5. Conclusion

This study developed and verified a sensor-enabled method for user research. The method's effectiveness was evaluated with the experiment where sensor data were collected at the participants' homes. The results showed that sensor data helped the participants to recall their behaviour, and sensors in users' environment had the potential for users to spend their time naturally during data collection. In particular, sensor data could evoke as rich and accurate memory as video recordings while the effectiveness of sensor data decreased time passes from data collection. This method could be more effective than video in terms of user privacy and reflection burden. In addition, sensor data may help to understand users' lives trends through data accumulation and improve the quality of questions in interviews with users. One of the future directions is including methods of collecting users' emotions. Considering technological advancement and the use of IoT and wearable devices in society, this study contributes by demonstrating the potentials of IoT sensors data for user research.

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