Imagining the Future of Longitudinal HCI Studies: Sensor-Embedded Everyday Objects as Subjective Data Collection Tools

Armağan Karahanoğlu and Geke Ludden

Abstract Automated data collection has a significant role in collecting reliable longitudinal data in human–computer interaction (HCI) studies that involve human participants. While objective data collection can be obtained by and mediated through personal informatics, subjective data is mostly collected through labour-intensive tools. The potential of sensor-embedded everyday objects as subjective data collection tools is underexplored. Hence, in this chapter, we investigate the use of such products for subjective data collection purposes in longitudinal studies. First, we demonstrate current practices on subjective data collection tools and examine the aforementioned research gap. Following that, we discuss the results of three discussion sessions in which we collected insights from six expert researchers on the enablers and barriers of using sensor-embedded everyday objects as subjective data collection tools. We present our insights with use-case scenarios to communicate what possible roles sensor-embedded everyday objects could have in collecting subjective data in future longitudinal HCI studies and discuss how they could be further developed within the field.

Keywords Subjective data collection · User research · Everyday objects · Sensor-embedded objects · Longitudinal data

1 Introduction

The HCI community has studied the impact of interactive systems on people's daily lives for decades [1, 2]. While a focus on user experience after first time use has been dominant for a long time, since the earliest call for more experience-focused longitudinal studies [3], long-term user experience of interactive systems has been

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examined by various scholars [4–7]. In one of the earlier studies, Kujala et al. [4] propose "UX Curve" that aims to support people in recalling the details of their experience and draw a free-hand curve to describe it. In another example, Karapanos et. al. [7] propose "iScale", an online survey tool with a similar purpose, in which participants are asked to recall and sketch their most impactful experiences with a product. Both studies address the necessity of developing tools to explore and evaluate long-term user experience.

Scholars agree that to reliably study experience over time, as well as processes and effects of change, we need longitudinal studies that investigate user experience beyond the first time use [8]. An observable characteristic of longitudinal studies is that a minimum of three repeated observations on a construct of interest is carried out [9] that provides data in a series of time points [10]. In order to arrive at actionable data sets, most studies involving human participants, rely on two types measurements: objective (i.e. number of steps taken) and subjective (i.e. the perceived effort or confidence of the user).

Advances in personal informatics tools offer sensor-based, almost effortless objective data collection practices. These tools equip both the users of such tools, as well as researchers interested in their data, with an immense number of possibilities. Today, personal informatics help people to automatically track the number of steps they take, or the quality of their sleep [11]. It also supports people to arrive at meaningful information about their health status [12]; and supports decision-making on actions to take to improve their health [13]. For researchers, the same sensors bring new possibilities to collect and study objective data about the behaviour of large populations. One of the most well-known examples of this approach is probably the use of physical activity trackers to unobtrusively collect physical activity behaviours [14, 15]. Because tracking physical activity is now a practice that is available to almost every individual, the data gathered could even be used to study how the lockdowns due to the COVID-19 pandemic in 2020 affected physical activity of populations at country and city level [16]. While regular personal informatics tools are usually embedded in smartphones and smart watches, researchers have recently also started using different types of everyday objects as data collection tools. For instance, Bogers et al. used a sensor-embedded baby bottle to collect the baby-feeding behaviour of mothers [17].

These developments manifest effort-free, reliable objective data collection possibilities. The challenge here is no longer to collect data, but to make sense of the collected data. Although personal informatics provide researchers with easy to use tools to collect objective data, this does not always mean that the data collected gives them all the answers they are looking for. There are things that these sensors cannot capture automatically, such as the subjective experience of participants. For example, how did a person's mood or emotion affect their physical activity? Did the low quality of sleep affect feeding behaviour? How did that person experience their recent walk or run? These are all questions where sensors cannot provide a full and decisive answer and that require subjective measurement tools.

For subjective longitudinal data collection (SLDC) purposes, HCI studies involving human participants borrow various methods from different disciplines in the social sciences. Most commonly, studies use paper artefacts (such as questionnaires or diaries) or digital data collection tools (such as ecological momentary assessment applications). For instance, ecological momentary assessment (EMA) is usually implemented as an electronic diary on a smartphone or on a separate device. The goal of EMA is to obtain subjective, ecologically valid, real-life data [18]. Next to these tools that were specifically developed for research purposes, people have started to devise and use self-tracking tools for mood and emotion. For instance, Ayobi et al. [19] found that people are willing to use bullet-journaling to track their habits and mood. In another study, Sarzotti [20] found that people are interested in tracking their emotions especially when the way of tracking is combined with wearable trackers, such as a bracelet, a necklace or a smart watch. These are interesting findings which show that people are also interested in collecting data about their own subjective experiences. However, there still is no automatic way of collecting this type of data.

Collecting data in-the-wild requires participants' active and conscious involvement to collect reliable subjective data about their experience [21]. While researchers may applaud involvement of participants in their studies, it also places a burden on participation that may cause boredom or frustration with the participants, which eventually may limit the quality of the data collection. Therefore, in this chapter, we will explore how sensor-embedded everyday products can play a role in smarter subjective data collection and overcome the challenges that current subjective data collection tools face.

We propose that sensor-embedded everyday objects can be employed for collecting reliable subjective data purposes. To support this proposal, in the following section, we first analyse available tools and put forward the challenges of collecting subjective data in longitudinal HCI studies. Following that, we provide the results of three discussion sessions that we conducted with six design researchers. In these sessions, we aimed to discover the broader potential of sensor-embedded everyday objects as alternative means of collecting subjective data in longitudinal HCI studies. Accompanied with visualizations made by five industrial design engineering students, we refine and present the emerging subjective data collection possibilities for different contextual data collection case. We discuss how the ideas presented can contribute to the future of data collection in the HCI community.

2 Subjective Data Collection Tools in Longitudinal Studies

Commonly used retrospective and real-time data collection methods and tools in HCI have their origins in social science domains such as psychology and anthropology. The use of self-reports is widespread both for collecting subjective data about one time use and for collecting longitudinal data. Schwarz [22] suggests that a combination of open-ended questions (such as asking the participant "what did you do today?"), closed formats (such as a list of activities from which the participant can pick) and rating scales (such as questionnaires) can help the participants to better

Table 1 Overview of retrospective subjective data collection tools

Tools	Forms of data collection	Advantages	Challenges
Diary studies	Participants' own insights and narratives	Powerful in collecting real-life insights	Depends on participants' memory Decreased response rate Individual biases
Experience sampling method (ESM)	Combines objective data with ecologically valid assessments	More ecologically valid data than diary studies	
Ambulatory assessments (AA)	Combines self-reports with observational, physiological and behavioural methods	Reduce retrospective biases	Fatigue in responding
Ecological momentary assessment (EMA)	Mostly used in collecting behavioural assessment which the researcher may not reach easily	Mobile and less labour intensive	Require strong infrastructure

clarify on their experiences. Often, self-reports have been criticized to be less reliable, because the method highly relies on the memory of the subjects in reporting their recalled experience [23]: the participants might self-select what to report [24]. On the other hand, research shows that when planned carefully, self-reports can turn into powerful self-tracking tools for HCI researchers [19]. To come to a good understanding of the current practices in subjective data collection, we provide an overview of and discuss commonly used tools for retrospective data collection (see Table 1).

Diaries are the most frequently used tools for self-report studies [e.g. 25], that provide researchers with participants' own insights and narratives [26]. The diaries can be both paper-and-pencil and digital formats. Green et al. [27] compared the compliance of participants in these two designs by employing them in the same study. They found that regardless of the format, the compliance of the participants changed when a very narrow time window was applied. Therefore, the time window must be carefully defined depending on the research question.

A more structured and less time-consuming version of self-reports is experience sampling method (ESM), which originally focuses more on sampling of experience at random times [28]. It usually combines objective indices and contents [29] and grants "ecologically valid" assessments of human behaviour [30]. With an aim of minimizing the retrospective biases, ambulatory assessments (AA) compound self-reports with observational, physiological and behavioural methods and study people in their natural environment [31]. The common trait of these tools is that all can easily be applied both in physical and digital forms.

Recently, technological advancements have enabled researchers to develop easy to use and more advanced digital tools for self-report [32, 33]. For instance, ecological momentary assessment (EMA) [34] is an effective tool used to collect people's experiences, behaviours and moods in real-time and in real-world settings [35]. The emphasis in EMA is in collecting people's current state, that aims to avoid the biases of other subjective data collection tools [34]. Asking closed questions, this form of assessment corroborates to reliably collect momentary behavioural data of (i.e.) physical activity [36], dietary intake [37] or smoking cessation [38] very well. Nevertheless, especially the longer EMA studies require participant compliance [39] and strong infrastructure when it comes to collection of data flow and monitoring of the assessment completion [35].

Although self-reports can reveal insights about participant's experience over time, there are several drawbacks of self-reports. The report rate of the participants can decrease considerably over time, in correlation with the formulation (i.e. having too many questions asking for text input) [40] and length of the questions in self-reports (i.e. having too long questions) [41], resulting in fatigue effect (such as getting tired of answering the same questions over time) [42] and individual biases. Still, data collection in-the-wild can result in unexpected technical issues [21], such as interruptions in sensor recording [43] and variations in sensor placement in mobile devices [44].

One of the issues that emerge from these findings is that the forms of longitudinal subjective data collection can be perceived as labour-intensive by both the participants and the researchers. Most of the tools still rely on text-based input. We see that development of these tools has stayed very close to the original practices in the social sciences. However, there are other ways to express our experiences than using text that technology is able to capture. In addressing especially the report rate, which creates reliability problems for most commonly used methods, we find it promising to investigate alternative ways of subjective data collection. Considering the above-mentioned challenges, we propose that sensor-embedded everyday objects that participants wish to interact with can be utilized as a tool for SLDC purposes. The potential use of these objects as subjective data collection tool in longitudinal studies is still open to exploration, as advances in technology do not yet provide a definitive solution for capturing subjective experiences. In the next section, we discuss how our ideas can have broad implications in designing and developing the future of subjective data collection tools.

3 Imagining the Future of SLDC Tools

Considering the capabilities of HCI researchers, we argue that HCI research has the competencies to overcome the presented challenges (see: Table 1) of SLDC methods. To imagine the future of SLDC tools, we studied the enablers and barriers of using everyday objects to collect subjective data in longitudinal studies. For this purpose, we conducted three video conference sessions with duos of experienced researchers. In the following parts, we explain the details of these discussion sessions. The outcomes of the discussion sessions were input for imagined scenarios presenting alternative means for subjective data collection that can help overcome current challenges in this field.

Participants

To select the participants, we set the following criteria: the researcher must have been involved in at least one longitudinal study that involved human participants in HCI or adjacent fields as a hands-on researcher. One of our goals was to reach out to researchers with diverse research interests in terms of both research methodologies and application fields. With these criteria we scanned our network and preselected 13 researchers. We reached out to these researchers, informed them about the goals of our research and invited them to participate in an online discussion session. Six researchers responded positively. The other invitees, despite their interest in the topic, were not able to participate due to time limitations.

Of the participants, two were pursuing a Ph.D. degree, while four were working as post-doctoral faculty members in three different universities. The background and research interest of each researcher is presented in Table 2. The researchers had 3–7 years of experience in research involving human participants. The methods the researchers are familiar with are also listed in the below table. In the end, we were

Table 2 Participants of the discussion sessions

Session	# Researcher	Researcher background	Academic position	Research interest	Experience in research methods
1	R1	Computer science	Assistant professor	Physical activity behaviour change	Automatic (sensor) data collection and reflective interviews
	R2	Psychology	Ph.D. researcher	Well-being technologies in forensic mental health care	Questionnaires
2	R3	Design engineer	Assistant professor	Research methodologies in the process of design	Paper-based self-reports
	R4	Interaction design	Ph.D. researcher	The effect of nature on mental well-being of hospital patients	Paper-based self-reports, observations
3	R5	Industrial design	Post-doctoral researcher	User experience of emerging and future technologies	Self-reports, diary studies and reflective interviews
	R6	Industrial design	Assistant professor	Integration of user experience research methods in design process	Paper-based and online diary studies

able to include researchers with different backgrounds who are all working in diverse application fields and active in HCI research.

Flow of the Discussion Sessions

We prepared a 15 slides' PowerPoint presentation to facilitate the discussion sessions. The slide stack consisted of three parts. The first part was for welcoming the participants, introductions and explaining the aim of the session. The second part was for presenting an overview of existing subjective data collection tools and challenges of employing those in longitudinal HCI studies. The third part was explicitly for illustrative and discussion facilitation purposes. This part is built up on two slightly challenging subjective data collection scenarios. Those scenarios highlighted possible needs of future researchers to effortlessly and reliably apply subjective data collection tools in longitudinal HCI studies. The first scenario was urging the need of collecting participants' *perceived effort* in an exertion activity. For this scenario, we illustrated a runner from whom future researchers would collect *perceived increase in effort* data during a high-intensity workout. The challenge of the scenario is that due to the intensity of the workout, the runner is not able to speak, nor stop to provide feedback. In the second scenario, we illustrated an elderly person, from whom future researchers would collect *satisfaction* data in a home context. We raised the challenge of this scenario as the incapability of the elderly person in using emergent technologies. While preparing these scenarios, we put forward several aspects of connected everyday objects as enablers of subjective data collection. These were exemplified as "having physical affordances, material properties and spatio-temporal relationships" as suggested by [45].

The online sessions started with presenting the first part of the presentation and getting acquainted with each other. For this part, first author shared her screen with the researchers. After the first three slides, screen sharing was disabled, and each participant was invited to tell more about their prior experience in participant research, and the connection they see between their research and the subject of the current research. Afterwards, the first author reshared her screen and presented second and third parts of the presentation.

Researchers were informed that after the presentation, the discussions were envisioned to evolve around the two illustrated scenarios. We also invited the participants to feel free to ask any questions that came up during the presentation. Where necessary, to clarify what we mean by sensor-embedded everyday objects, we gave existing examples such as smart watches or the previously mentioned Phillips Baby Bottle [17]. In the end of the third part, the screen share was disabled again and the discussion started. The discussions were formed around our two goals: (1) collecting inspiring ideas for using everyday objects as data collection tools in the scenarios proposed and (2) discovering potentials of using everyday objects as subjective data collection tools for researchers' own research projects.

4 Results

After each discussion session, we transcribed the voice recordings into Word documents. We analysed researchers' experiences of current subjective data collection separately. The rest of the data was thematically analysed. These themes were then discussed among the authors who ultimately arrived at four themes, that were covering the separate discussions completely and exclusively.

We recognized two directions in the results: (1) capturing subjective experiences through objective measures; (2) discussions around new directions for subjective data collection. We also found promising suggestions made by the researchers. To better conceptualize the results, we asked five second year industrial design students to visualize the results. We present our findings next to these visualizations in the following parts.

4.1 Capturing Subjective Experiences Through Objective Measures

During the sessions, researchers discussed important differences, benefits and drawbacks of collecting both objective and subjective data. Moreover, they discussed how they could be combined. We briefly present this discussion here before moving on to new SLDC tools.

It was suggested that automatically captured data could transform into a powerful subjective data collection tool. Over the three discussion sessions, we observed consensus among the researchers on this. Researchers described three stages in this type of data collection. First, objective data on research-significant moments would be captured by sensors. Collecting research-significant data was indicated to be important in order to eliminate the burden of analysing non-tagged research data. Second, this data would be shared with the people. Finally, the people would be asked to reflect on what the collected data means for them. This way, subjective data collection could be less repetitive and less boring for participants because they are only asked to reflect on relevant use-episodes. As an example, R1 explained a previous study of measuring perceived fatigue over multiple running trainings. In that specific study, the researchers wanted to reliably capture "perceived effort" by using repeated measures of several sensors. Following, the researchers asked the participants to reflect on their own data and report their perceived effort during and in between several workouts. While this provides a way to combine objective with subjective data, this type of research setting might lead participants to overinterpret the data because they feel pressured to make sense of it.

R6 suggested that using a method similar to the one explained above, fluctuations in heart rate measurements collected by smart sensors could be shown to runners to gather their subjective reflections after a running workout. Combining objective data with self-reflections collection is not completely new. For instance, in an explorative study, Gouveia and Karapanos [24] investigated the effectiveness of camera-captured memory cues during diary studies. They found that visual cues, such as pictures from the context of experience, is the most effective memory trigger in recalling activity tracking experiences. However, this way of capturing data does not eliminate the retrospective challenges of longitudinal HCI studies completely. Retrospective investigation still has the pitfall that the reports of the participants about the moment they are reflecting on are influenced by their present feelings.

The participants in our study stated that emotions, as a subjective measurement outcome, are interesting, yet challenging to reliably capture. R2 shared her knowledge in validated studies of emotion capturing by technology. A large body of work on emotion recognition by technology has been studying how to reliably capture people's emotional states through their tone of voice [e.g. 46]. R5 suggested to make use of the knowledge available in this field by using vocal interaction with smart objects as a natural way of objective data collection over subjective experiences. She suggested that in the near future, products like Alexa or Google Home could be programmed to understand the feelings of participants in home context (Fig. 1, left image). This was found to be a pleasant way of collecting emotional states, especially for people who have problems with sight or using hands. However, R1 and R3 criticized these and similar attempts to use technology to capture emotions. These researchers recommended refraining from automatic capturing of emotions, not only because it is hard to reliably capture emotions, but also because it may be more important to understand how a person actually looks back on and memorizes a certain experience.

Alternatively, R5 recommended that people could be asked to interact with a smart object (a lamp in this case, Fig. 1, right image) to select a colour that best expresses their emotional states, at certain moments of the experiment. Achieving this could lead to a labour-free way of reflecting on participants' mood or emotional state. Although this was not specifically mentioned in the discussion with participants, we believe that the body of work on the relation between colours and emotions [i.e. 47] could be used to build future studies on.

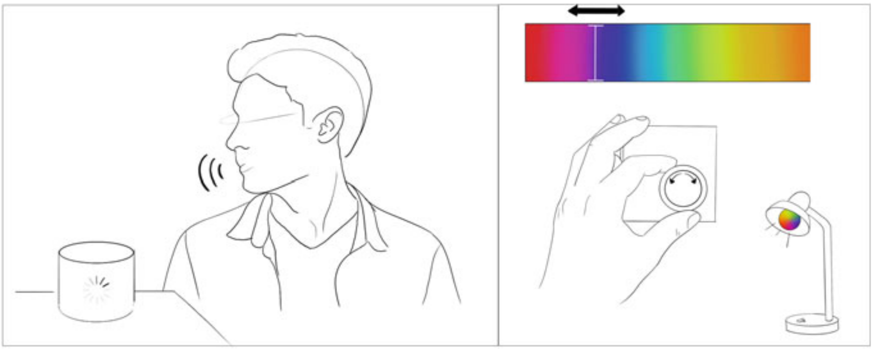

Fig. 1 Examples for "selecting" and "vocal interaction"

Researchers also agreed that the HCI domain can benefit from the capabilities of the field to create “fun” (R2, R4) and “interactive” (R1, R5, R6) ways of subjective data collection. Designers could also assist HCI researchers in developing more “user-friendly” (R3), “intuitive” (R5) and “engaging” (R3, R5, R6) subjective data collection tools. Researchers pointed out the importance of understandable, intuitive interactions in collecting reliable subjective data collection through everyday objects. These exemplify simple ways of interacting, such as touching. A domain of HCI that has recently been developed, affective haptics, deals with the skills of smart surfaces to identify the characteristics of touch (such as an angry touch or a comforting touch) [48]. This possibility could be further elaborated on for subjective data collection purposes as we will also see in the examples proposed in Sect. 2.

We noticed that the importance of SLDC was acknowledged by the researchers. The topic was found to be “timely” (R3) and “significant” (R1 and R5) for the HCI domain. These researchers agreed that the existing subjective data collection tools could be extended with or merged into artefacts that human participants could more easily use to express their experience. R3 and R6 indicated that sensor-embedded everyday objects could be “promising” and “effective” next-generation subjective data collection tools. As an example, R4 expressed her experience of patient-research in hospital setting. Her biggest challenge was that the participants were not comfortable in speaking about their feelings, while it was easier for them to communicate those when family members came to visit. This researcher stated that, even though it is fundamentally different from interacting with people, interacting with everyday objects could well be utilized as subjective data collection tools. She imagined that the patients could use the sensor-embedded everyday object for story telling purposes throughout the day. R4 did not provide any further insight about how a patient would interact with everyday objects or what they should look like but others did offer such ideas as we shall discuss in the next section.

4.2 Discussions Around New Directions for Subjective Data Collection

We observed several recurring ideas in the results. We categorized these ideas under the categories that we asked during the video discussion sessions: “physical affordances, material properties and spatio-temporal relationships” [45] of everyday objects. We combine the emergent ideas with scenarios to come to a more clear image of potential scenarios for using the sensor-embedded everyday objects as subjective data collection tools.

Sen and Sener [45] discuss above-mentioned three dimensions as the sources of sensorial enrichment in product interactions. Gibson explains affordances as all the possible actions that physical capabilities of products supported [49, 50]. Physical affordance covers the physical qualities of interactive products such as the physical alterations in size, weight, colour as well as the position of the interactive controls on the products [45]. Material properties are as the descriptive properties of the materials, such as rigidity, elasticity of the materials, which are inherent to the materials and can naturally enhance the physical affordances [45]. The difference between physical affordances and material properties is that physical affordances is all about what type of interaction products afford, material properties is about how we can interact with the materials [e.g. 51]. Spatio-temporal relationships of interactive products are about the change of places, proximity between the controls and speed and repetition of physical manipulations [45].

Physical Affordances

In two of the video sessions, it was suggested that physical properties of everyday objects could be a labour-free way of data collection for participants. In all three discussion sessions, researchers suggested multiple ways of using the physical properties of objects as a way of collecting subjective data from people. Tactile interactions with objects such as pressing, tapping, touching or stroking could be used, where the amount of "pressing", "tapping" "touching" or "stroking" or the mere presence of one type of interaction over the other would inform the researchers about the subjective patterns in an experience. For instance, R6 suggested using photo frames as a subjective data collection tool. A smart photo frame could display a range of images and, in a research context, "touching" or "hugging" a photo frame could be natural way to express varying "emotions" towards pictures presented in smart photo frames where hugging would for example communicate love for the image on display and mere touching would indicate interest (Fig. 2).

It was suggested that subjective data collection through using physical affordances of everyday objects could also be implemented into sensor-embedded clothes. For

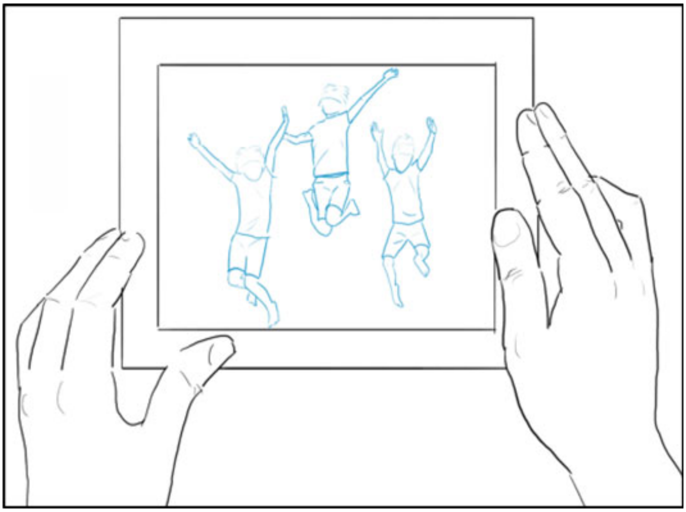

Fig. 2 Touching smart photo frame as a subjective data collection method

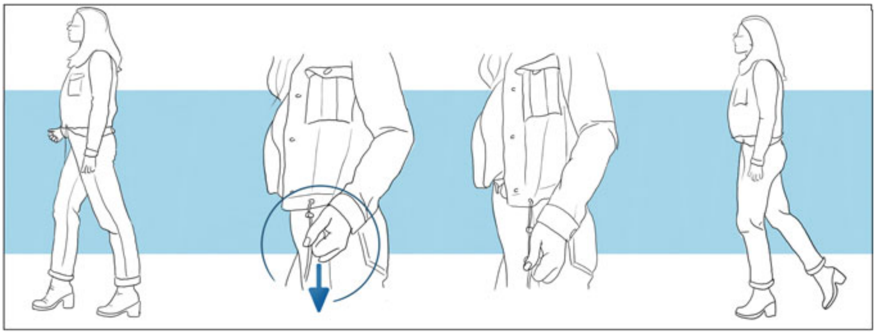

Fig. 3 Pulling buckle of jacket for subjective data collection

instance, R5 suggested that a "pulling" function could be implemented into a certain garment of a participant, and the person wearing the garment could be requested to provide subjective data by interacting with the embedded sensors. In the same discussion session, R6 suggested that this idea could be applied to different scenarios. R5 and R6 built up a scenario in which this function was implemented. In this scenario, it was assumed that the goal of the research is to explore how often participants experience pleasant moments during city walks over time, participants could be asked to report those moments by interacting an accessory of a sensor-embedded jacked. Aligned with their suggestion, in the example, we illustrated below, the participant can pull the buckle of their jacket to the right to report positive experiences while pulling the buckle to the left can be used for reporting negative experiences (Fig. 3).

This way of data collection can also be an alternative for real-life data collection tools. Relevant initiatives are coming to market, such as Levi's commuter trucker jacket [52], that uses touch-sensitive, copper-core threads, woven directly into the fabric. This example alone shows that similar types of interaction could soon be implemented into research contexts as well.

Material Properties

Ideas for using material properties in subjective data collection arose as a possibility for measuring certain feelings (Fig. 4). For instance, R2 articulated that referring to the flexibility of certain materials, some type of "stress ball" could be an unobtrusive way of measuring "stress" experience of people. R2 suggested that participants could squeeze the ball in case of feeling stressed, and the fluctuations in data could provide frequency and length of feeling stress. In this type of research setting, data about the length and the strength of squeezing could be used to compare within person subjective data. This type of interaction is already accessible in physical and occupational therapy studies [53] and could be employed for subjective data collection purposes as well.

Another possibility would be using elasticity of the materials. For instance, stretching the fabric of clothes would be a way of providing data about feelings at a certain moment. This idea emerged while R5 was talking about measuring the

Fig. 4 Using material qualities for subjective data collection

tiredness level of runners. Especially in the studies where performance athletes such as runners or cyclists, are the participants, material properties of clothes could be used for subjective data collection purposes (Fig. 5). In this use case, athletes could be asked to provide subjective feedback about the level of exertion they feel during the workout, by stretching the fabric of the t-shirt they wear. R5 suggested that using the elasticity of the fabric, the type of data that is challenging to collect during the activity can be collected by using the material properties of clothes.

While we see the potential of expanding the research with material properties of objects, we acknowledge, that especially in this example, material properties and the physical affordances of sensor-embedded everyday objects can be complementary and intertwined: the elasticity of the material of the object could be combined with the physical affordances (the degree of elasticity).

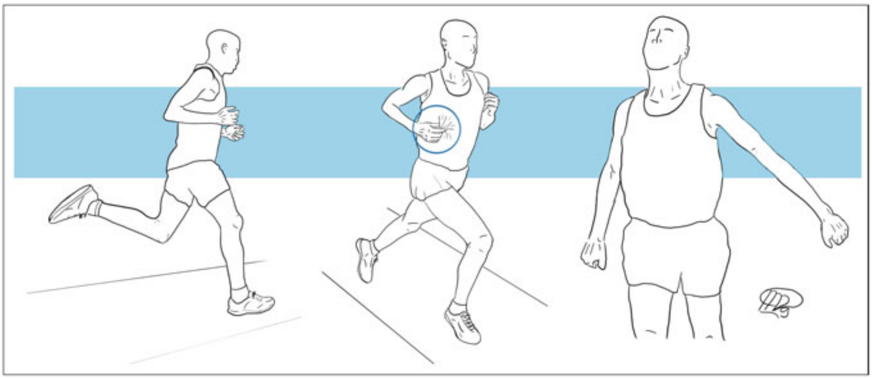

Fig. 5 Smart t-shirt as data collection tool

Spatio-temporal Relationships

Another possibility of using sensor-embedded everyday objects in subjective data collection is to reappraise the spatio-temporal relations of objects with their use contexts. R6 stated that moving (Fig. 6) a simple and data-related object from one place to another could be used for collecting subjective data This idea emerged during the discussions about collecting subjective data in a home context. R5 and R6, emphasizing their experience of longitudinal studies, especially in kitchen and home contexts, suggested that the objects that people use frequently at home could be transformed into subjective data collection tools. Considering the diversity of people they interviewed within the longitudinal studies, they argued that especially in home contexts, people should feel comfortable about using (products) and should not be forced to use tools they might not be familiar with. For example, in a study on the experience and effectiveness of a virtual coach for lifestyle change, participants might be asked to place a sensor-embedded bottle on a kitchen cabinet if they did not like the particular coaching message they were given and on the kitchen counter if they did like the message.

In our final example, we discuss a scenario that shows how collecting subjective data could be implemented into studies that require the input of older adults. During the session with R5 and R6, it was suggested that garments or accessories that participants carry could be used to collect subjective data outside the home contexts. To clarify their proposition, these researchers developed an idea in which subjective data from older adults was collected through a sensor-embedded everyday object such as a scarf (Fig. 7). It must be noted that these researchers suggest "scarf" as an example, rather than a "must-use" product like a coat, allowing the person the freedom not to use the sensor-embedded garment. The test objects could also be things like an umbrella or a hat. R5 and R6 emphasized that the data collection objects must be selected from the range of products that participants are familiar with. These objects must also make sense in the context of data collection.

In the scenario that was developed in session 3, that we visualize below, wearing the scarf could be taken as an indication that the elderly person is willing to provide subjective data. The researchers portrayed a research set-up in which older adults

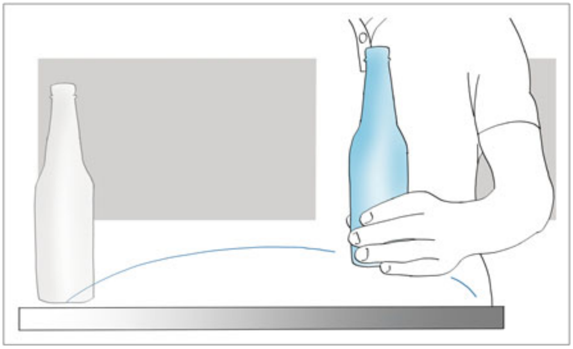

Fig. 6 Example "spatio-temporal relations"

Fig. 7 Scarf as a subjective data collection tool

are encouraged to take more steps while the researchers monitor their fatigue level. In such a set-up, older adults could be asked to interact with the scarf to provide subjective data (fatigue during physical activity). The data collection moments could be emerged by detecting the most research-significant moments such as when the person sits on a bank in a park to take a rest. In such a scenario, the data collection tool, a scarf in this case, must be dedicated only for the data collection purposes, in order to avoid conflicts of use.

5 Discussions and Conclusion

In this chapter, we presented sensor-embedded everyday objects as promising future subjective data collection tools in longitudinal HCI studies. Since the beginning of the last decade, understanding user experiences has been interesting for HCI researchers to be able to design interactive systems that fulfil users' needs [4, 7]. Recognizing the necessity of capturing experiences over a period of time, HCI researchers were challenged with finding ways to explore people's experiences in-the-wild [21]. While collecting objective data is relatively smooth with very well developed personal informatics tools, collecting subjective data is still a considerable challenge in longitudinal HCI studies.

For subjective data collection purposes, the HCI field adopted various methods and tools from social science research domains such as psychology and anthropology. As we explained in Sect. 2, these tools include several forms of self-reports, such as diaries, experience sampling method, ambulatory assessment and ecological momentary assessment. We portrayed one of the main challenges of these methods as increasing participants' fatigue in responding over time, and therefore decreasing the reliability of the studies. Besides this, for digital data collection tools, technical problems in sensor recording may result in interruptions of data collection. Overcoming the infrastructure hurdles is something that can eventually be solved, while the other challenges need all the creativity the HCI community has to offer. We argue that going beyond adopting existing tools in other research domains, HCI researchers can design their own research tools for subjective data collection purposes.

The findings presented in this paper highlighted several new directions for subjective data collection in longitudinal studies. Some of the directions we propose have similarities with exiting studies that use everyday objects as data collection tools such as the work of Giaccardi et al. [54]. In their work, they suggest using things as data collection tools and using sensor-embedded objects as data collection. However, the difference is that we ask for active participation of people for subjective data collection, but in a more intuitive and automatic way.

We see the opportunity that the directions presented in Sect. 4.2 could alleviate some of the mental burden that research set-ups put on people. In current practices of subjective data collection methods, the participants are asked to fill in text-based questionnaires by using smartphones or paper-based data collection tools. Conversely, we propose that data collection tools can be selected from everyday objects that make sense in the context of data collection and that the people are familiar with. One way to employ this method is familiarity with objects (e.g. a scarf), and the other is meaning attributed to the interaction (e.g. hugging or mere touching). People's familiarity with data collection objects (similar to the example of scarf) as well as the connotations that these tools elicit in use context (such as wearing the scarf while going for a walk) can help researchers to reduce the mental burden that longitudinal studies can induce on people. With this approach, using sensor-embedded objects as a data collection tools may partly overcome lower response rates and biases due to the formulation of the questions that traditional data collection tools impose [31–33].

We believe that sensor-embedded everyday objects have the potential to be developed into a new category of data collection tools. We have presented a number of interactions with subjective collection tools that are the first to think of, when considering the use of this type of objects in daily life. To come to smart solutions for interactions, the field may make a link with shape-changing interfaces [55]. This type of interfaces has so far mostly been used to provide status feedback, but they could also be interfaces for subjective feedback.

Despite the need and opportunity for sensor-embedded everyday objects in longitudinal HCI studies, we see some weaker points. In order to successfully implement these objects in research studies, we invite researchers to consider the following points carefully. These points are especially important in order not to overwhelm people with the ambitions of the researchers' goals, but rather engage the people with the longitudinal studies.

1. *Reduce participant effort*: The perceived effort of the participant influences the participants' responsiveness in repetitive measures studies. In the case of using everyday objects for subjective data collection purposes, it is essential to make the participants comfortable about the demanded time and cognitive effort for participating. This connects to points 2 and 3.
2. *Collect one type of data at one time*: Researchers should prioritize the importance of subjective data being collected from participants. After all, with the type of

interactions that we propose in the scenarios, only one question can be answered with one object. If there is an interest of collecting multiple data, using multiple sensor-embedded everyday objects could be considered or perhaps the object could be designed in a way that it allows for response on two variables. However, researchers should be very cautious not to complicate the use of the objects for data collection.

3. *Find friendly ways of using sensor-embedded everyday objects*: Not every form of everyday object might be suitable for subjective data collection. The researchers should review the objects that participants use within the context of experience (such as a t-shirt during a running experience). The researchers should find the most relevant everyday object that is meaningful for the experience to embed sensors in.
4. *Consider user privacy*: Using sensor-embedded objects pose the danger of easily violating the privacy of individuals. Therefore, the ethics of using these objects in data collection should be well elaborated. Researchers should think carefully about the perceptions of participants and other individuals within the context of data collection, to avoid giving the impression of "big brother is watching us".
5. *Consider frequency of data collection moments*: It is still probable that the set-up of the research results in participants dropping outs. In that sense, the research should be flexible enough so that the frequency of data collection moments could be adapted. For instance, when it becomes clear that at a certain phase of the research the participants become idle, a clear reframing of data collection moment could be planned to reduce the burden on participants. This obviously demands flexibility of the studies in the way everyday objects are used for subjective data collection purposes.

One limitation of the present study is that the set-up of our video sessions with researchers might have affected the outcomes, as we had presented predefined roots and scenarios. On the other hand, our findings showed that the participants already had experience and knowledge about the directions we proposed and did not feel restricted to only those scenarios.

We believe that the directions we proposed in this chapter are promising, yet still might be difficult to develop. The proposed subjective data collection directions require extensive work for developing reliable sensors and strong infrastructures. While reducing the burden on the participants, those tools have the danger to increase the time investment of researchers on tackling the technical challenges of proposed subjective data collection tools. In that respect, the ideas might still align with the challenges of EMA [34]. Future research can explore ways to overcome these challenges, by collaboration of multiple HCI researchers and sharing their experiences in a platform that the tools developed for subjective data collection purposes are showcased.

The ideas presented in this chapter should be considered as envisioned possibilities for future studies, rather than reliable and valid subjective data collection tools. We hope that these ideas will inspire the HCI researchers to discover new opportunities of collecting subjective data in longitudinal HCI studies.

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