Context-Aware Experience Sampling Method to Understand Human Behavior in a Smart City: a Case Study

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Published in:
Measuring Behavior 2018

Publication date:
2018

Context-Aware Experience Sampling Method to Understand Human Behavior in a Smart City: a Case Study

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The study of human behavior is inherently complex. A wide range of social-psychological behavior models identify external elements as one of the factors influencing human behavior. Consequently, researchers require methods to study behavior within its real-life environment, capturing external factors that influence the behavior. Today's new technologies and their large-scale deployment offer new opportunities to implement these methods. In this paper, context-aware experience sampling is presented as a method to study human behavior in its context and capture the influence of external factors. This method, part of a behavior change research methodology, is first explained and consequently demonstrated by means of a case study in a large-scale IoT living lab for smart city services in Antwerp (Belgium).

Introduction

Human behaviors are inherently complex and understanding them is one of the hardest challenges in social sciences. Numerous research disciplines study human behavior and from a social-psychological perspective different behavior models have been put forward identifying the underlying factors that influence human behavior [2]. We can distinguish internal, merely psychological and individual determinants and external determinants [6]. The latter could be for example social situations, institutional contexts or cultural norms [20, 22]. Conducting behavior research is challenged by the influence of external determinants such as time, location and social settings (other influences, see [20]). When studying human behavior, it is therefore necessary to take these external factors into account. The term context can be used as an overarching term to describe the external factors influencing behavior. Despite its acknowledged importance in the study of behavior, there are only a limited amount of methods that aim to understand human behavior on a large scale while incorporating the context. These methods either rely on objective measures of behavior (e.g. web log analysis) and thereby neglect the dimension of human experience and motivations; or they use self-reporting methods (e.g. diary-studies) that are context-independent and therefore more susceptible to biases (e.g. recall bias).

In this paper, we aim to contribute to the study of behavior by illustrating the potential of smart cities in behavioral research and more specifically in capturing the context of behavior. According to Townsend [25], "smart cities are places where information technology is combined with infrastructure, architecture, everyday objects and even our bodies to address social, economic and environmental problems". This increased digitalization could enable behavioral research by surpassing some boundaries of current methods such as limited resources and time. As argued in Spagnoli et al. [23], digital technologies make it possible to (1) capture data in real-life settings, (2) regain control over data by capturing the context of behavior, and (3) analyze large sets of information through continuous measurement. Moreover, the study of behavior is highly relevant in smart cities. Human behaviors play an important role in dealing with urban challenges [18, 19] and their interaction with technologies highly affects the smart city. Therefore, understanding human behavior is crucial in designing and implementing smart city services. In this paper, we present an explorative research design for behavior understanding that incorporates the context of behavior. More specifically, we describe a method, mainly relying on context-aware experience sampling, whose implementation can be improved and facilitated through the characteristics of a smart city. By describing a use case that applies this method to study human behavior in a smart city, we highlight the expansion of research opportunities that arise through smart cities. This results in a research design that extents current practices by (1) validating behavioral assumptions in a real-life context and (2) providing feedback loops to the user using their real-life data. In the remainder of this paper, we first present existing behavioral models and explain the concept of behavior understanding. Subsequently, we discuss the weakness of existing behavior understanding methods to capture context and position context-aware experience sampling as a viable solution. Finally, we illustrate this method by describing a case study within City of Things in Antwerp (Belgium), a large-scale Internet of Things (IoT) living lab and testbed for smart city services. In describing the case study, we mainly focus on the

R.A Grant et al. (Eds.): Measuring Behavior 2018, ISBN 978-1-910029-39-8
Manchester, UK, 5th-8th June 2018

methodology and how we put it into practice. The paper ends with our main learnings and some recommendations for future research.

Context in measuring behavior

Studying human behavior and its interaction within an urban environment requires a tailored approach that takes into account different contextual factors due to the many influences in a city. Hence, a framework for behavior analysis in a city context should capture a range of internal mechanisms (psychological and physical) and the external environment (physical and social environment). To this end, the Modular Behavioral Analysis Approach (MBAA), allows to conceptualize, implement and evaluate behavior change interventions in a smart city (see Figure 1) [7, 23]. Michie et al. [16] mention insufficient attention is generally given to the analysis and the understanding of behavior as a starting point of behavior change interventions. The MBAA, however, recognizes the importance of understanding (current) behavior in the broader context and foresees a specific step for mapping the current behavior and an identification of behavioral determinants, i.e. factors that influence the behavior. In this paper, we will focus on this activity of understanding behavior.

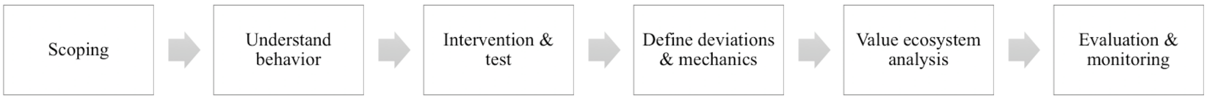

Figure 1. Modular Behavioral Analysis Approach (adapted from [23]).

The importance of context

To understand current practices of behavior understanding, we conducted a literature review consisting of 17 scientific studies published between 2014 and 2017. We observed that the majority of these studies rely on (semi-)structured interviews, which almost never took place during, or in the context of, the studied behavior. The latter might be a potential drawback of these studies because concerns have been raised which call into question the validity of this kind of self-reporting outside the context [27]. Research suggests that people are unable to accurately reconstruct their behavior and experiences [10]. Li [12] argues that there are two main sources for this inability: incomplete knowledge and biases. Additionally, contextual information supports people to become aware of factors that influence their behavior [13]. This insight is frequently being used in health research on physical activity or eating behaviors [4, 13, 24]. To achieve this contextual enrichment, these studies make use of different sensors capturing physiological parameters, often combined into a wearable. The use of these new technologies also provides the opportunity to accurately capture the actual behavior and therefore overcome recall bias. This approach is supported by literature on design for reflection, which describes different ways technology can support people to reflect on their own behavior [3]. First, technology can be used to record the behavior or experience itself in order to provide a record of events that can be looked at again. Second, it can augment this information by capturing data that otherwise might not be consciously observed. For example, exposing people to their physical activity (i.e. step count) helps them to reconstruct their daily activities [13]. Considered the importance of behavior to cities, the authors investigated other methodologies, facilitated by technologies in a smart city, that aim to improve current behavior understanding methodologies by including context.

Context-aware experience sampling method

A method that is often used to overcome the lack of context, is contextual inquiry. This is a user-centered design method that focuses on observing and interviewing people while they are carrying out a particular task in the appropriate context [5]. Due to its design, contextual inquiries are highly reliable and result in more detailed information compared to surveys [26]. However, in contrast to the advantage of surveys being scalable and relatively cheap, contextual inquiries are highly resource-intensive. A combination of the scalability of surveys and the contextual richness of contextual inquiries would provide researchers a method to obtain data with a higher external validity [21]. The experience sampling method (ESM) is an established method that combines these two advantages. The essence of ESM is studying experiences in the moment and thereby capture the experience in the context [29]. Originally, the method was designed to question people about their experience in random occasions and has been primarily used for time-use research [8, 10]. This has been implemented by the use of beepers and paper diaries, although more recently, technological advancements have made researchers use more often mobile devices as they have become a part of daily life [21]. Numerous studies using ESM throughout different domains acknowledge its value by being less susceptible to recall errors than other self-report methods [1, 10, 29]. Despite its strength to capture experiences in the context, ESM still lacks the ability to capture the context itself. To this end, the concept of a context-aware experience sampling method (CA-ESM) has emerged [8]. It improves ESM "by using sensing technologies to automatically detect events that can trigger sampling and thereby data collection" [17]. Intrinsically smart cities provide an optimal infrastructure to deploy CA-ESM since urban IoT platforms enable integrating a large number of heterogeneous context data streams originating from different end systems [28], such as weather data and traffic information. These data streams can be used to map and understand the context of behavior in a more thorough way, thereby reducing the recall basis and self-reporting weaknesses of current methodologies within behavioral understanding research. To include context when studying behavior in a city, we propose a research design that complements current practices by adding two additional research steps: (1) validate behavioral assumptions in a real-life context and (2) feedback loops to the users using their real-life data.

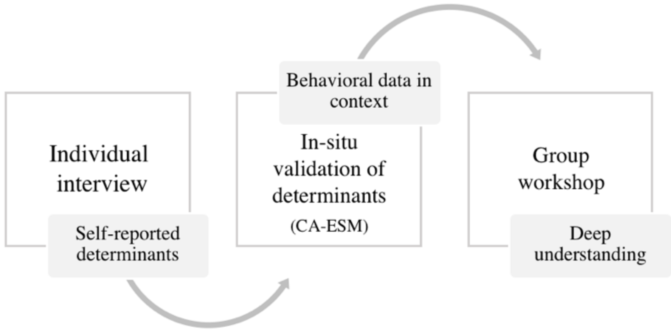

Figure 2. Proposed process to understand behavior.

The proposed research design consists of three steps (see Figure 2). First, we conduct individual interviews to elicit users' thoughts. In contrast to other studies, we use the interviews to discover *assumptions* about behavioral determinants. In the second step, we validate these assumptions (i.e. self-reported determinants) in a real-life context using CA-ESM. This consists of mapping people's actual behavior and studying the contextual influences. We focus on both the status of the determinant (e.g. "How is the weather?") and the influence of the determinant (e.g. "Did the weather influence your decision?"). The final step focuses on gathering a deep understanding of the determinants. This is accomplished during a group workshop where the participants are being confronted with their actual behavioral data, enriched with contextual information. According to the literature on context, providing this data would support the reflection on one's own behavior [12, 13].

Case study: understanding commuting behavior

To test and validate this use of CA-ESM, a pilot study was conducted. The scope of this pilot was to investigate how the method could be used to understand the behavioral determinants of people commuting to work. The pilot was conducted in October 2017 with five citizens from the city of Antwerp (Belgium). The researchers chose a small group because the goal was to get insights in the behavior understanding process, not to obtain an understanding of the behavior with statistical significance levels. During the next two months, the research steps as illustrated in Figure 2 were executed. Every participant signed an informed consent form by which they allowed the researchers to capture and use their personal data for the research purposes. Throughout the experiment, the participants could also contact a team of experts, in case they had any questions related to their participation. This project has been part of City of Things, a smart city living lab and testbed located in Antwerp (Belgium) [11].

Step 1: Self-reported determinants

The first step was conducted similarly to most of the research in behavior understanding: by means of individual semi-structured interviews. This initial interview was necessary to elicit the participants' assumptions about their current behavior that would be validated in the next step. The structure of the interview was based on the COM-B model, which is an existing model that is used to identify behavioral determinants [15,16]. The participants received a number of cards, each containing one abstract keyword representing a determinant from the COM-B model. Some examples: physical strength, self-confidence, time, location, money, identity, culture and belief. During the interview, the participants structurally went through the cards, explaining which cards had an impact on their commuting behavior. Specific attention was given to describing the meaning of the determinants. For

example, when the participant indicated that weather influenced his behavior, the researchers tried to clarify whether this meant either light rain, a thunderstorm or snow.
Finally, the participants were asked to rank their selected determinants (i.e. cards) from most important to less important. It was clear that this exercise was easy for external determinants (such as environmental and social factors). The participants considered those as rational determinants. The internal, more psychological determinants (e.g. self-confidence, beliefs) were perceived as more difficult to grasp. Some of the participants spontaneously placed these cards along the side to indicate that these determinants are always influencing their behavior in a slumbering way.

Step 2: Behavioral data in context

Following the individual interviews, a two-week during test was launched to validate the participants' assumptions, by means of CA-ESM. However, at the time of the pilot not all technological components were in place and therefore we used the Wizard of Oz method [9] to simulate the CA-ESM. To this end, the participants were asked to install an application (Life360 [14]) on their smartphone that allowed the researchers to track the location of the users in real-time during their commute and communicate with the participants. This research set-up allowed us to capture three types of data (see Figure 3): an objective measurement of (a) the participants' actual (commuting) behaviors and (b) the context in which these occurred. By means of the messaging function within the application, the researchers could obtain (c) additional feedback from the participants about what influenced their commuting behavior.

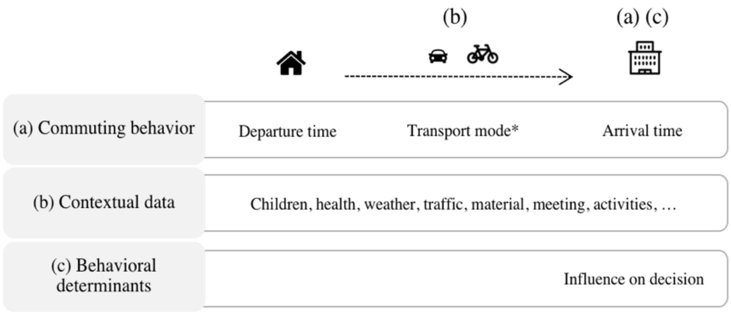

Figure 3. Data captured during in-situ validation of determinants.

(a) Commuting behavior: the participants' commuting behavior resulted in information about their departure and arrival time and the route they chose, as described in Figure 3(a). Ideally, the CA-ESM application would automatically track the transportation mode (bike, car, public transport, ...), but this was not possible with the given application* and the researchers had to collect this information through the participants. The application warned the researchers when one of the participants arrived at work. This event triggered the researchers to question this participant about his/her commute. In this way, the participants were questioned about their commute right after it happened in order to prevent recall bias. The set of questions the participants received upon arrival at work was based on the individual interviews, for example statements like "when it rains, I take the car". We wanted to investigate how contextual data can be captured and how behavioral determinants can be validated with CA-ESM. Therefore, two different types of questions were asked in week 1 and week 2.
(b) Contextual data: during the first week, we wanted to identify the added value of including contextual information (see Figure 3(b)). Ideally, the researchers would possess contextual information (e.g. weather, traffic, etc.) captured by sensors throughout the city. However, in this case, we were not able to access such data directly and consequently had to gather this information ourselves. Accordingly, upon arrival at work, each participant received a customized questionnaire containing questions related to the status of the determinants that were identified during the interview (e.g. "Did it rain when you left for work?").
(c) Behavioral determinants: the second week focused on the influence of the context on the behavior. Each participant received the same questionnaire which no longer questioned the status of the determinant, but the influence of the determinant on the behavior (e.g. "Did the weather influence your transport choice?"). In this second week, we used identical questionnaires because we wanted to investigate if it was possible to use a unified approach for all participants. Based upon the observations during the first interviews, the researchers decided not to include some of the underlying, more psychological determinants in the daily questionnaires. The assumption is that these determinants are less subject to change and do not determine behavior at a specific moment, but are

rather explanatory determinants, which promote a certain habit or a default behavior. For example, if a person beliefs biking is better for the environment, he will try to take the bike most of the time except if a contextual factor prevents him to perform the preferred behavior, e.g. if it rains. The CA-ESM approach is especially suited to provide insights on this kind of contextual influences.

Step 3: Deep understanding

After the two-week trial, a workshop with all the participants was organized. The goal of this workshop was to gain a better understanding of the captured data and how the context influenced the behavior. To this end, the participants were confronted with their actual behavior during the two-week test period. More specifically, they received an overview of their transport mode complemented with the contextual information they had provided through the daily questions. Based on this information, the participants got the opportunity to discuss their behavior and comment on how they had experienced the experiment. During the workshop, three out of the five participants concluded that their actual behavior deviates from their assumptions raised during the first interview. The behavior of these participants was influenced by a larger set of determinants compared to the remaining two participants. This demonstrates the difficulty of assessing the influence of a complex set of determinants. Being provided with information about their behavior and the context, clearly helped them to better understand and explain the influence of the determinants.

Lessons learned

The ESM-CA pilot study allows us to draw some learnings concerning the in-situ validation of the determinants. First of all, due to the short term of the study, the type of data from week 1 (the *status* of the determinant) was insufficient to discover patterns in the data (e.g. someone only cycles when it does not rain). It was therefore necessary to also question the *influence* of the determinant on the transport choice. However, solely questioning the influence of the determinant without knowing the status of the determinant turned out to result in incomplete knowledge as well. It is therefore recommended to combine data about the influence of a determinant with a continuous data stream of contextual parameters obtained from a smart city platform (such as weather conditions). By combining these data types, the method becomes more robust with regard to self-reporting biases, because the researcher can cross-check the answers from the participants with the objective contextual data. Secondly, the study showed that a uniform questionnaire was not sufficient to get a good understanding of people's behavior; working with personalized questionnaires or providing a field for free-text input is required. Finally, this trial also led to some practical concerns related to the CA-ESM tool. More specifically, when choosing the CA-ESM tool, one should pay specific attention to the following requirements: real-time accessible data, integration with contextual data, user-friendly content management system, pre-scripted triggering rules and question sets that can be send automatically and to each participant individually.

Conclusion and further research

Behavior studies often use various ways of self-reporting methods to acquire an understanding of factors influencing one's behavior. However, these methods raise some challenges as they are susceptible to biases and often inadequately capture the context of the behavior, resulting in incomplete information. Especially within an urban context, this challenge becomes even bigger as the set of influencing factors is not only much larger, but also more complex. In our pilot, we observed a difference between the initial self-reported behavior and the actual measured behavior of participants. When confronting them with this difference we were able to gather a set of new insights, which we would not have discovered by only relying on the (traditional) interview.

In order to understand human behavior within this urban context, it is necessary to able to capture the contextual elements throughout the research activities. In this paper, we presented a research design relying on the context-aware experience sampling method (CA-ESM) to deal with this challenge. The CA-ESM augments current practices of understanding behavior by validating behavioral assumptions in a real-life setting. Moreover, the CA-ESM provides additional value by combining the strengths of qualitative and quantitative research: a large number of participants can be questioned in real-life, while capturing additional contextual information to enrich the data. Today's technological possibilities make it easier to collect, integrate and analyze these different datasets. Additionally, they allow the CA-ESM to be implemented on a large scale by automatically asking the right questions to the right people based on contextual cues. In our pilot, we were able to interact with our different participants in a direct and individual way, based on the simulated CA-ESM tool.

According to the proposed research design, the CA-ESM has to be preceded by a process to elicit the behavioral assumptions. In our pilot, we used the COM-B model as a guidance to identify the behavioral determinants. This model has been very useful throughout the research. Nevertheless, we needed to grasp the proper meaning of the determinants as they were interpreted differently by each of the participants. Although these individual interviews are necessary, they limit the scalability of the research design and a purposeful sampling of the initial panel is required. However, in contrast to our pilot that had a small number of participants throughout the entire study, the second step of the research design could be easily up scaled by applying the CA-ESM to a large group of people. When applied to a larger sample, it is possible to assess the relevance of each of the determinants throughout the whole panel, enabling the development of user segments related to behavioral profiles.

Overall, the pilot demonstrates that the proposed approach offers a good framework to build an understanding of (current) human behaviors by capturing several contextual determinants. Since it is difficult for people to elicit these determinants adequately, the interaction with contextual data provides a more complete result that is less susceptible to biases compared to other approaches. Based on our experiences, we consider the CA-ESM as an instrument to collect data on behaviors and their context and should be applied within a broader research approach on measuring human behavior or behavior intervention design. Our approach can not only provide behavioral profiles, but also identify building blocks on which behavior interventions can be built on. Additionally, our approach would be suited to contribute to the validation of behavior interventions. Therefore, we argue for the use of CA-ESM during various phases of behavior research and especially in those steps where in-depth insights in the motivation and the context of the behavior is required.

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