Ask, But Don't Interrupt: The Case for Interruptibility-Aware Mobile Experience Sampling

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Abstract
The mobile phone-based Experience Sampling Method (ESM) enables in situ recording of human behaviour and experience by querying users, via their smartphones, anywhere and anytime. Sampling can happen on a previously unimaginable scale, and across a diverse pool of participants. Therefore, mobile ESM is not limited to capturing users' manual responses, as the surrounding context can be automatically captured by mobile sensors. However, obtaining high quality data with ESM is challenging, as users may fail to respond honestly, or may even ignore the questionnaire prompts if they perceive the study as too burdensome. In this paper, we discuss the potential of using interruptibility prediction models to deliver mobile ESM questionnaires at opportune moments, and thus improve the effectiveness of a study. We examine context prediction and interruptibility inference, which are fundamental challenges that need we need to overcome in order to make mobile ESMs better aligned with a user's lifestyle, and consequently paint a truthful picture of a user's behaviour.

Author Keywords
Experience Sampling Method (ESM); User Surveys; Interruption; Context-aware Computing; Mobile Sensing.

ACM Classification Keywords

H.1.2 [User/Machine Systems]; D.2.2 [Design Tools and Techniques]; J.4 [Social and Behavioral Sciences]

Introduction

Today's mobile phones represent more than occasionally used communication devices. Equipped with sophisticated sensors and advanced computing hardware, mobile phones nowadays coexist with their users throughout the day. As such, the mobile phone has a potential to uncover a user's everyday behaviour in her natural setting, and become a revolutionary tool for social scientists.

The mobile phone is capable of *sensing* a user's physical and social context [17]. However, the automatic inference of a user's cognitive states, desires, motivations, intentions remains difficult. In order to obtain such information, a more traditional experience sampling method (ESM) is used. In ESM, mobile phone users are asked to provide the required information of interest to the study.

Given the pervasive penetration of smartphones, mobile phone based ESM allows for monitoring user's behaviour at any time and any place. However, the questionnaires via ESM might get triggered at inopportune moments (e.g., during a meeting). At the same time, these questionnaires are, unlike notifications from communication applications, "impersonal" and always present the same information to the user. Therefore, the user might dismiss or respond hastily to the questionnaires triggered at inopportune moments. These responses erode the quality of the collected data, potentially affecting the findings of the ESM study. Thus, it is critical that a mobile phone-based ESM triggers questionnaires at opportune moments, when a user is ready to provide a truthful answer to the questions posed.

In this paper, we present our vision of interruptibility-aware ESM that tailors the moments at which questionnaires are triggered according to the user's receptivity to such interruptions. Before triggering a questionnaire, the system predicts a suitable moment to interrupt the user. Based on the previous research on mobile interruptibility [8, 19, 16], we assume that these moments are indicated by the context, which can be sensed by smartphone sensors. To infer the user's interruptibility, we need two machine learning models. First, we need a model that learns how the receptivity of a questionnaire is connected with the sensed context, and second, we need an anticipatory model that explains the evolution of the context.

In the rest of the paper, we first provide an overview of the in-situ experience sampling techniques. We then show the effects of interrupting a user at inopportune moments and propose how these issues can be addressed. We discuss the key challenges in developing and deploying interruptibility-aware ESM, including interruptibility management, behaviour learning and context prediction. We conclude with an overview of related work and a discussion of a research agenda in this domain.

ESM for Social Science Studies

The most popular techniques concerned with the investigation of a user's behaviour in natural settings were diary keeping [2], direct photographic and video observation [21], and interviewing [3]. Diary and interview studies are subject to the so called *recall bias*, as users report their past, not necessarily accurately recalled experiences [23]. Photographic and video observations can provide very rich information, but are costly, time consuming to administer, and disruptive, thus remain impractical for the majority of studies.

In contrast with these techniques, the experience sampling method (ESM) asks the user to register the information in natural settings. Thus, ESM reduces the retrospective recall bias because the user feedback is collected immediately as experiences happen. ESM was proposed by Csikszentmihalyi and Larson [7] as a technique to query subjects, periodically or in specific situations, to provide the information (such as what people do, feel, and think while they perform daily activities) pertaining to a specific study in which they participate. The initial studies relied on manual, usually hand-written, data collection, and user querying via programmable beepers. The issue with this approach is that first, it requires a piece of specialised equipment (a beeper), limiting the scale of a study, and second, that it requires a significant amount of a user's time in order to manually input the data. The recent advances in mobile computing enabled the *mobile phone-based ESM* [11, 20]. Here, a user's existing device, e.g., a smartphone, can be used both as a means of signalling a user that a data is needed, as well as a means of inputting the data. Finally, equipped with an array of sensors, such as location, proximity, light, sound, etc., the smartphone *can automatically sense and report the user context*, thus alleviate a part of the data input burden from the participant.

Strategies for Triggering Questionnaires

Social scientists employ ESM to study users' everyday experience [1] or their experience at specific events [9]. However, in both scenarios different strategies are used to trigger questionnaires for the user.

- **Strategies for Studying Daily Experience.** In order to study the user's daily experience, the questionnaires are triggered periodically asking the user to answer the questionnaire and mapping the user response with the context in which the user is at that moment. The frequency of questionnaires can vary as it depends on requirements of the study. In case the user is not available, the questionnaire is triggered again after a specific time interval. Such a strategy has been employed to study the relationship between common events and mood factors [4].

- **Strategies for Studying Experience for an Event.** Studying the experience for a particular event is not as simple as studying the daily experience. In order to trigger questionnaires, the user context needs to be monitored to infer the moment at which event of interest occurs. Once this moment arrives, the questionnaire is triggered. In case the user is not available, the questionnaire is triggered on the next occurrence of the event of interest. This strategy has been employed to study users' existing transportation routines and willingness to move towards green transportation behaviour [5]. This type of experience sampling was virtually impossible with the traditional, non-mobile ESM technologies.

Effects of Triggering Questionnaires at Inopportune Moments

Due to the ubiquitous nature of mobile phones, the mobile phone-based ESM can be used to monitor user behaviour at all times, in a variety of different contexts that a user goes through in a day. At the same time, ESM still demands the user's attention, as a significant part of data still need to be reported manually – for example, information about user's emotions, thoughts, intentions, cannot be automatically sensed via her smartphone. To collect data at the right moment, mobile ESMs rely on *triggers*, notifications on a user's phone requesting the user to fill in a data query. Often, however, users are requested to provide information at inconvenient moments.

As indicated in several ESM-based studies data loss occurs when the users are asked to answer the questionnaire at inconvenient moments. For example, Froehlich et al. [10] and Consolvo et al. [6] report a completion rate of about 80%. As suggested by Scollon et al. [24], the intrusive nature an ESM might adversely impact a study by leading users to react in the following ways:

- **Answer Falsely:** Users might respond quickly to the questionnaires that arrive at inopportune moments. These responses would contain false or random answers which corrupt the dataset.
- **No Response:** Users could be engaged with an on-going task and may not want to divert their attention to another task. The questionnaires which are triggered at these moments could be directly dismissed (without any response) by the users. This would reduce the number of data samples collected which could impact the validity of the study.
- **Leave the Study:** Questionnaires that are triggered consistently at inopportune moments could cause serious disruption to users. In order to avoid being interrupted, users could decide to withdraw from the study. This will reduce the number of participants and more participants might be required to complete the study.

Interruptibility-aware ESM

We argue that mobile phone-based ESM can be made less disruptive and more efficient if delivered through interruptibility inference and context anticipation. We will refer to this new class of methods as *interruptibility-aware ESM*. In interruptibility-aware ESM, the moments at which questionnaires are triggered are tailored so that users are asked to answer questions mostly at opportune moments. Here, an opportune moment does not refer to the moment when the user clicks on a questionnaire notification. Instead it refers to the moment when a user provides a meaningful response to the questionnaire.

Therefore, before triggering a questionnaire, an interruptibility-aware ESM predicts the closest most appropriate moment where the user can provide a proper response and adapts the triggering moments accordingly. In order to detect such an opportune moment we should predict the user's interruptibility at the current context as well as at the next anticipated context. This would require two different models:

1. **Interruptibility Model:** a model of the user's interaction at different contexts to infer interruptibility at a given context;
2. **Context Transition Model:** a model of the user's transition from one context to another for anticipating the future context.

As shown in Figure 1, the process of predicting the best moment for interrupting a user with a questionnaire consists of two steps. In *Step-1*, the sensed context is provided to the interruptibility model for inferring the user's interruptibility in the current context. If the model predicts with a high probability that the user will provide a proper response, the questionnaire is triggered immediately. If this condition is not satisfied, the system executes *Step-2* in which the transition model uses the

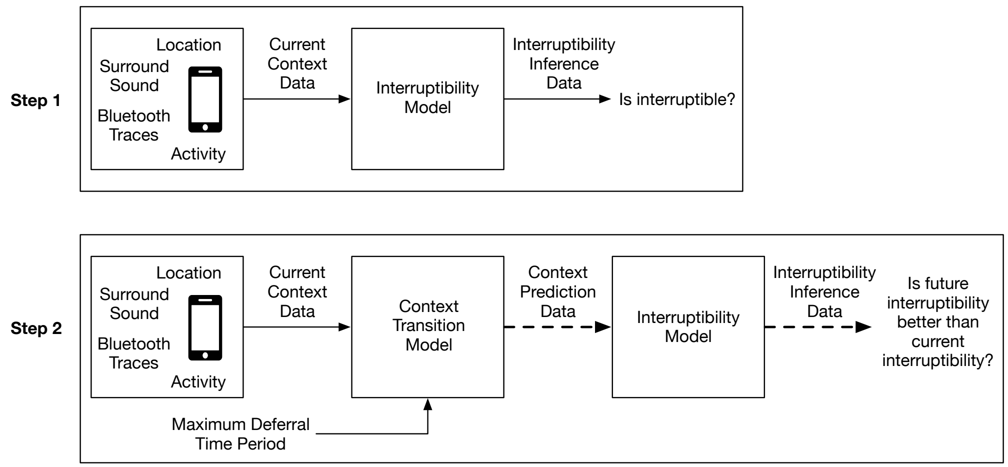

Figure 1: Process to predict the most opportune moment to interrupt the user by the ESM questionnaire. The process consists of two steps. Step-1 infers the user's interruptibility in the current context. Step-2 predicts the user's interruptibility in the future contexts and compare it with the current interruptibility to find the moment when the user is least interruptible. Note that Step-2 is executed only if the current context is inferred as an inopportune moment to interrupt.

sensed context to predict the user's future context transitions within the *maximum deferral time period*. Note that this time period is provided by the researcher in order to set the maximum time for which a specific questionnaire can be delayed by the system. Choosing the maximum deferral time period is in itself a challenging task and we discuss it later in the paper.

Once the user's future context transitions are predicted, the forecasted contexts are iteratively provided as input to the interruptibility model for predicting the user's future interruptibility. If the predicted interruptibility in any of the future contexts is better than the interruptibility in the current context, the triggering of the questionnaire is deferred to when that context arrives. Otherwise, the questionnaire is triggered immediately even though the user is not interruptible at this moment.

We could skip the *Step-2* by simply deferring the notification and waiting for the arrival of an opportune moment to trigger a questionnaire. But, we do not know if the future context will be more opportune to interrupt the user. It might be possible that the user will be busier in the future than in the present context. Thus, we should predict the future interruptibility and compare it with the currently inferred interruptibility in order to find the best moment to interrupt the user.

Open Research Challenges

In order to realise the proposed interruptibility-aware ESM, there are various challenges that need to be addressed. There are general implementation challenges, such as ensuring energy efficient sensing and reliable classification of the user's context. However, in this section, we concentrate on aspects that are unique to interruptibility-aware ESM.

Modelling Interruptibility

The interaction of a user with mobile notifications is indeed extremely complex and depends on numerous aspects. Past studies [8, 19] have used some of the sensed context and content information to infer opportune moments for interrupting users via notifications. However, ESM notifications asking to answer questionnaires are different, since they do not provide any information to the user but still demand the user's attention.

Moreover, unlike other notifications that are viewed or clicked if delivered at opportune moments, an ESM notification should be be triggered at an opportune moment only if the user provides a quick and meaningful response. In order to build an interruptibility model for ESM notifications, we should infer the quality of information provided by the users by using existing techniques, such as adding a trap question, or checking the response time [18]. While the previous interruptibility studies considered time-to-reply as a metric of interruptibility, we instead propose a machine learning interruptibility model that builds a relationship between *the quality of user responses* and the context in which the questionnaire was triggered.

As shown in Figure 2, the user response is analysed by the *Response Analyser* to infer the quality of information. Note that the Response Analyser can be built by using the methods mentioned earlier to infer the quality of information. The response quality data is coupled with the context in which the questionnaire was triggered. Finally, this information is used by a machine learning (ML) component in order to construct an interruptibility model of the user.

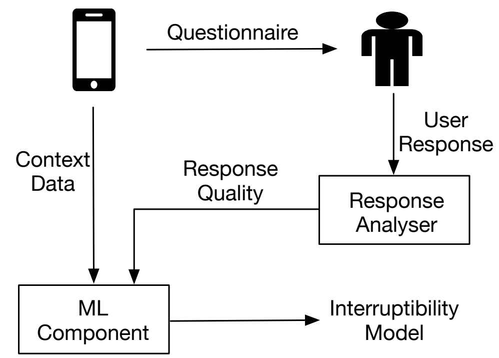

Figure 2: Using context data and the user's response to questionnaires to construct an interruptibility model.

It is worth noting that in some cases the users provide proper responses, but the interruptions adversely affect their cognitive state. For example they might lead to anxiety and increased cognitive load. However, users can be asked to register their emotional state at the time of responding to a questionnaire. Their responses could be used to learn moments in which they are responding to questionnaires without feeling annoyed.Nevertheless, this would likely incur a contextual bias [15] that can yield faulty conclusions for the original study because ESM studies are often geared towards sampling users' emotions and we would not collect samples of moments when people are annoyed. Therefore, in our opinion, *annoyance* should not be used as a feature to infer interruptibility.

Anticipating Future Context
Highly personal everyday use of the mobile phone allows us to identify the inherent patterns of human behaviour from the sensed context data. Machine learning models of human behaviour can be built by using the context information to predict the future context. Certain modalities, such as location, tend to be more suitable for prediction than others because people follow circadian rhythms, such as commuting to work during weekdays and relax during weekends [22].

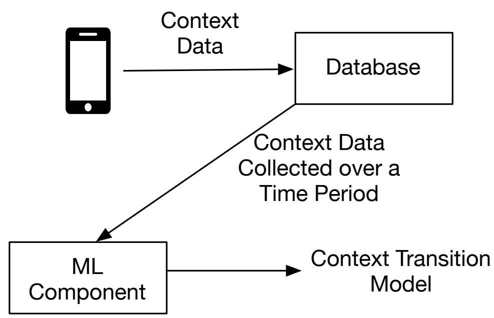

Figure 3: Constructing and maintaining a context prediction model by using the context data collected for a time period.

As shown in Figure 3, the user context is sensed periodically and stored in the database. The ML component then uses the newly available data to construct or update a context transition model. Since, we are interested in anticipating the future transitions of the user context, we would need a ML component that is capable of constructing a model which can predict the future contexts in which the user will switch to within a certain time period (i.e., maximum deferral time period).

In order to build such a model, we can employ the approach similar to that used in NextPlace [22]. In NextPlace, Scellato et al. demonstrated how their approach can predict the time and place of the future location based on non-linear time series analysis of the arrival and residence times of users in significant locations. A similar approach can be used to predict all the contexts in which the user will transit to within a given time period. However, the key issue is that in order to infer the user's interruptibility at future context, we need to anticipate not just a single context modality but multiple modalities (for example, the user's location, activity, engagement in a task, and the social environment). Hence, predicting the future value of multiple context modalities would be very difficult as compared to predicting a single context modality. Moreover, the inaccurate context predictions would also impact the accuracy of predicting interruptibility in the future.

Minimising Interruptions While Maintaining Relevance
Interruptibility-aware ESM must maintain a balance between minimising interruptions and obtaining relevant data specific to the user's current situation. While we strive to find the most appropriate moment to trigger a questionnaire by comparing the user's interruptibility in the current context to their interruptibility in future contexts, it might not always be possible to wait for a moment when the user is interruptible. Some ESM questions might be susceptible to recall bias or become irrelevant if postponed for too long.

A potential solution to this problem is to define the maximum deferral time period that refers to a duration in which a particular questionnaire is valid. However, it can be difficult to exactly determine the duration of this time period. For example, consider a questionnaire that asks users why they visited a certain place. A user might visit a place of interest but the questionnaire might be postponed because the system predicted that it would be best not to interrupt the user during that time. When this questionnaire is eventually triggered (e.g., after 30 minutes), the user may have already left the place and visited another one, which could result in recall bias. Therefore, determining the maximum deferral time period to balance interruptibility and ESM data quality remains an open challenge.

In addition to timeouts for questions, it is possible to define other types of constraints for ESM questions (e.g., location, physical activity) or combine these with time-based constraints (e.g., the question is valid for an hour as long as the user stays within a 500 m radius of the location trigger). A potential alternative approach is to contextualise the content of ESM questionnaires. A postponed question could remind the user of the context when the question was initially triggered. For instance, a location-specific question could include location names or show the user which location it is referring to on a map.

Related Work

Mobile-based ESM makes it possible for social scientists to study users in their natural environment. The advances in mobile sensing helped ESM to collect data about users' situation and ask them to provide information when the events of interest are happening (known as event-based ESM [9]). Nowadays mobile-based ESM is employed in different domains including the investigation of daily events and moods [4], and the investigation of behaviours related to sustainable transportation choices [5].

A major challenge in the ESM studies is to maximise the quality and quantity of the data samples by reducing interruptions to the participants. A handful of previous studies have proposed strategies to optimise data collection and reduce interruptions [12, 14]. Hsieh et al. [12] propose an approach, named as *experience sampling with feedback*, which provides visual feedback to users. They suggests that the feedback mechanisms make the information personally relevant and interesting to the users. They show that their approach can reduce the time and attention demanded by ESM studies, and increase the value of the study. Khan et al. [14] proposed *Reconexp* – an ESM tool that uses the Day Reconstruction Method (DRM) in order to compensate the data loss. DRM is a method that allows a user to report the most impactful experiences at a later time [13]. In Reconexp, users are prompted on their PDAs to answer questionnaires. When the questionnaires are triggered at inconvenient moments and users are unable to respond, they may answer at a later time (on the same or the next day) via website-based DRM. In this case, users might not remember all the events, but they can provide information about important events that they are still able to recollect. Moreover, Reconexp enables the users to review data they have provided during the day through the ESM running on a handheld device and supply extra comments to improve the already given answers.

These studies suggest different approaches to improve the quality of data by enhancing ways of data entry. Unlike the approaches suggested by these studies, we propose a solution that adapts the trigger timing according to the user's interruptibility so that questionnaires are prompted mostly at opportune moments.

Summary and Future Work

Advances in mobile computing lead to mobile phone-based ESM, which enables social scientists to understand behaviour at an unprecedented scale and granularity. However, eliciting timely, high-quality data from study participants remains a problem. Users provide false information or leave the study when the study questionnaires are clashing with their everyday lives and habits. In this paper, we have advocated the usage of mobile sensing in order to design mobile phone-based ESMs that are better aligned with the users' lifestyles. The studies can be made less disruptive and annoying and result in higher quality data if the user's interruptibility is taken into account. In order to model the user's receptivity to questionnaires we should not just consider the sensed context in which the user replies to the questionnaires but also the quality of response in different contexts. The user's interruptibility should be predicted in both current and near future contexts, and a questionnaire should be triggered immediately or after some delay according to the moment at which the user is predicted to provide a meaningful response.

Our proposed mechanism combines both anticipatory computing and interruptibility management. In the future, we will build a framework that will allow mobile-based ESM applications to easily include this mechanism. As a first step, we plan to build a framework that can predict the user's receptivity to ESM questionnaires by using the quality of response. Such a framework would need to collect some additional context data (such as the user's activity, mental load at the moment of interruption, and whether their senses can register an alert), which might raise some privacy preserving challenges. Therefore, we plan to identify sensing modalities that are most informative when it comes to inferring users' receptivity to questionnaires. Additionally, we will work on predicting the future values that these modalities will take.

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