Experience Sampling as Information Transmission: Perspective and Implications

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Abstract
We propose *Information Transmission* as a novel perspective on the mobile Experience Sampling Method (ESM) to frame a research agenda with a sharpened focus on increasing data quality in ESM studies. In this view, good experience sampling transmits valid, relevant, and "noise-free" information from users' in-situ experiences to remote researchers. We identify key transmission channels, which motivate combinations of objective and subjective data (i.e. device sensors and machine learning, *plus* asking users). We discuss opportunities and challenges, and give examples from our previous and ongoing work on ESM tools.

Author Keywords
Experience Sampling; Framework; Data Collection; Mobile Device; Sensing; Machine Learning

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction
Mobile devices such as smartphones have become ubiquitous everyday tools. People use them, for example, to communicate, navigate, and capture and access personal data, such as photos. This motivates users to keep these handy devices close to them throughout their day [2].

Thus, researchers in HCI and related fields have identified mobile devices as a prime opportunity to collect user- and context-specific data, for example to capture patterns of user behaviour, thoughts, and feelings beyond the lab [6].

There are two main approaches for collecting data in-situ: 1) with device sensors (e.g. GPS, accelerometer), or 2) by prompting users to provide self-reports (e.g. phone shows questions such as *"How are you feeling right now?"*). The latter is called *Experience Sampling Method (ESM)*. It is often used to assess subjective information, such as thoughts or mood (see survey [6]). Both methods have advantages and disadvantages: For example, self-reports may suffer from known biases of questionnaires, while passive sensing does not capture subjective experience.

The workshop call asked: *"How to increase data accuracy in mobile studies?"* In response, this note proposes *Information Transmission* (cf. [4]) as a novel perspective on experience sampling. This perspective provides a systematic framing for such concerns of accuracy as raised in the workshop call, and points towards opportunities for reflecting on and ultimately increasing the quality of ESM data. In particular, we highlight that both subjective and objective data can be combined to increase their usefulness overall.

Perspective: ESM as Information Transmission

We propose to view ESM as an approach to transmitting information on human experiences between two parties: 1) The "senders" are those people having the experience, while 2) the "receivers" are remote observers (e.g. researchers, developers, manufacturers). This view focuses on "channels" for transmitting information. In particular, we identify objective and subjective channels and motivate their *combination* (i.e. sensor logging and self-reporting).

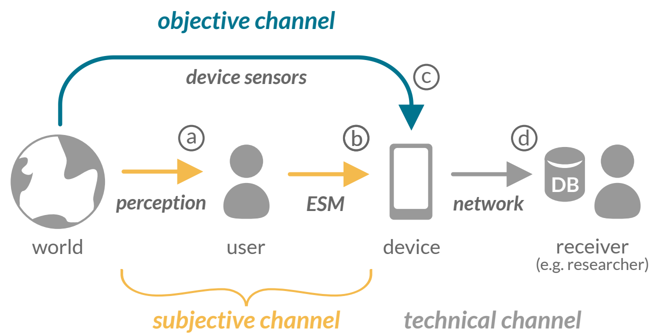

Figure 1: Information flow in mobile ESM studies. Our *Information Transmission* perspective frames ESM studies around two main information channels (subjective and objective) from users' experiences to remote researchers. Moreover, it frames various challenges for data quality in ESM studies in a unified view, that is, as "noise" along these channels. See text for further details.

Information Flow in ESM

One main aspect of our viewpoint is *information flow*. Figure 1 visualises this flow, which establishes channels from people's experiences and contexts to the remote researchers. We describe the individual parts next:

World-to-User (Figure 1a): Humans perceive the world and shape thoughts, feelings, etc. in their experiences. This is the prime *information source* to be assessed with ESM.

User-to-Device (Figure 1b): ESM tools allow humans to self-report experiences on mobile devices. Our view thus regards ESM as an *information channel* from human to device. Thus, the channel could be referred to as subjective.

World-to-Device (Figure 1c): This *information channel* links world to device via sensors (e.g. GPS, camera, microphone). It does not necessarily involve human experience directly and thus could be called objective. Indirect user influence still exists, e.g. (not) taking the device somewhere.

Device-to-Researchers (Figure 1d): Finally, information is transmitted to the remote party, for example researchers and their database, which act as the *receivers* in this view. This is a channel in the more technical sense, however there are also conceptual opportunities (see next section).

Note that one may consider *further information flows*, also beyond a study context: For instance, research results may inform the design of future devices, or produce knowledge that influences how people think about the world, thus contributing to future experiences.

Conceptual Background

A brief conceptual reflection puts our perspective into a broader HCI context. We combine aspects of two of the seven fundamental views on interaction extracted by Hornbæk and Oulasvirta [4]: 1) *Interaction as Experience* and 2) *Interaction as Information Transmission*. While these views traditionally differ in their notion of what (good) interaction is, here we employ one view (information transmission) to frame quality criteria of a *methodology* for fulfilling evaluation goals of the other one (human experience).

In a similar way, our novel perspective on ESM bridges two of the three paradigms of HCI described by Harrison et al. [3]: On the one hand, ESM presents a fitting methodology for the Third Paradigm's focus on human experience and meaning construction, since ESM assesses subjective experiences, feelings, and thoughts. On the other hand, by relating to information processing, our view on ESM follows Second Paradigm values: ESM ideally contributes to objective and generalised knowledge (and models) of human behaviour and its influencing factors.

By highlighting this aspiration, our view's combination of paradigms thus brings a fresh focus to ESM, including a focus on reliability and accuracy of the collected data.

Implications for Data Collection and Quality

We next outline and discuss implications of the proposed perspective, in particular with respect to the quality of the collected data. Note that we regard these aspects and ideas as starting points with first examples. They are motivated by our past and ongoing work and are not intended to present an exhaustive list of opportunities and challenges.

Channel Noise

Let us first point out the value of our proposed perspective for providing a unified treatment of the *challenges* related to ESM data quality (e.g. inaccurate data, biased answers, missed reports): In the proposed information transmission view, we frame such challenges as noise along the information channels. For example, obvious noise could be related to the sensors (e.g. GPS accuracy). However, one could also frame biases in human self-reflection as "noise" in the self-report ESM channel.

Is this more than a somewhat philosophical note? Yes – we argue that this view implies certain general solution principles: For instance, we can address such noise with accumulation of evidence over time (i.e. repeated sampling), with reasoning across both channels (e.g. combining GPS location and human annotation), and possibly also with reasoning across individual users (e.g. what have others reported at that GPS location?).

Similar ideas have been discussed by others (e.g. see the survey by van Berkel et al. [6]). Our information-centric view provides a systematic and unifying framing for such ideas. Technically, this unified take on addressing different kinds of noise with a combination and/or accumulation of evidence points towards *probabilistic reasoning* as an underlying solution principle. The following sections relate to different ideas on treating – or even utilising – such noise.

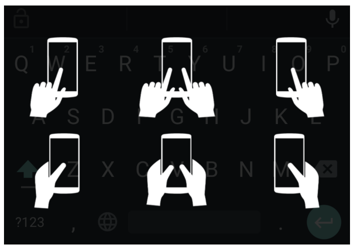

Figure 2: Our *ResearchIME* keyboard logging app [1] includes a keyboard overlay to assess information in the subjective channel, i.e. by asking users. In this example, the overlay asks users to indicate their current hand posture, but it could also assess data such as current mood or perceived stress. This can be used as a label for the collected objective data (e.g. touch events). For example, the combined dataset could then be used to train a keyboard model that infers the user's current hand posture or stress level based on typing touches.

Combining Subjective and Objective Information

As Figure 1 shows, our view on ESM includes both a subjective and objective channel. This implies an opportunity to combine the two, possibly in varying roles, to reduce noise.

We outline ideas for this based on our ongoing work on assessing personality with smartphones [5]. Here, it might be useful to have both a person's self-reflection (e.g. ESM showing a personality questionnaire), as well as the context of this self-reflection (e.g. at home vs in public) or the person's further behaviour patterns (e.g. in social situations). For instance, as the subjective channel may be biased, the objective channel could provide useful information to put self-reports into perspective.

This poses difficult technical challenges: For example, how might we infer social contexts from mobile device sensors? Rough approximations yield only limited information which is too inaccurate in many cases (e.g. assuming that number of bluetooth devices $\approx$ number of people nearby). We see an opportunity to employ Deep Learning here, for example to detect people and relevant objects in the camera stream, or to recognise conversations from audio. Such a system could run on the smartphone, and/or it could utilise other mobile devices, such as a lifelogging camera.

Roles of Information Channels: Main vs Side Channels

More generally, in some studies the objective channel may serve as a side-channel to contextualise self-reports (e.g. investigating mood during different activities). In other studies, the objective channel may be seen as the main one, while a subjective side-channel provides human-annotated labels (e.g. to collect labelled training data, see Figure 2).

In both cases, the goal could be not only to gain access to *more* information overall, but also to *improve* data quality by "cross-checking" both channels with each other and thus reducing noise. This might be rather straightforward in some cases (e.g. GPS says user is in a bar, but she self-reports that she was waiting outside), yet subtle and potentially ethically challenging in others (e.g. tracked data might indicate social acceptability biases in self-reports). Here, our view highlights that researchers need to carefully consider the implications of their reasoning systems on uncertain information (e.g. whom to trust more – users or sensors?).

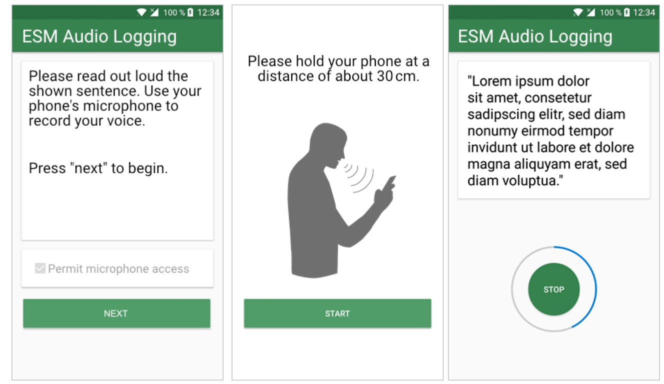

Figure 3: An audio logging module in our ESM app developed as a part of the *PhoneStudy* project [5]. This experience sampling task asks users to record audio (here: read a given sentence and record your voice). This is an example of triggering the collection of objective data (here: voice features) as part of an ESM task.

Conditional Information Channels

Another way of combining the two channels is to "open" one based on information provided by the other. This may reduce noise if one channel provides clearer labelling signals or indicators for "events of interest" than the other one.

In one direction, an ESM tool might trigger self-report questions based on context (cf. event contingency [6]). For example, an ESM app might ask the user about a social experience after it has detected the end of a conversation.

The other direction is also interesting: An ESM self-report question might motivate the user to establish an objective channel. For example, our interdisciplinary *PhoneStudy* project [5] now enables users to record audio as part of ESM questionnaires (Figure 3). In contrast to continuous automated tracking, this conditional channel results in more structured data (i.e. clear start and end points around events with human-provided labels). It may also better handle privacy concerns (i.e. user explicitly records audio).

Adding Noise as a Tradeoff between Privacy & Data Quality
Finally, our perspective implies another useful take on noise along the channels: Said noise may facilitate users' privacy. For example, our *ResearchIME* project [1] contributes a mobile keyboard application with a sub-sampling concept for filtering typing data (Figure 4). This enables researchers to record typing behaviour data in the wild without logging readable private messages of the users.

In the proposed view, this filter concept is framed as a "noisy" or "lossy" channel – only a small subset of the sent information (keystrokes) is recorded in full detail: For most keystrokes, our app does not store key labels and touch locations and thus avoids revealing readable text. However, this reduces data quality. For example, we could not measure error rates in our study, which used a random n-gram filter. See our *ResearchIME* paper for further discussions of the impact on possible analyses and related ideas [1].

Nevertheless, this approach presents an example in which channel noise may actually be *welcomed* by senders and receivers (i.e. users & researchers), since it facilitates privacy-respectful data collection for natural behaviour in the wild. Future work could investigate other scenarios with different kinds of noise and/or noise levels, which relate to different tradeoffs between data quality and privacy implications.

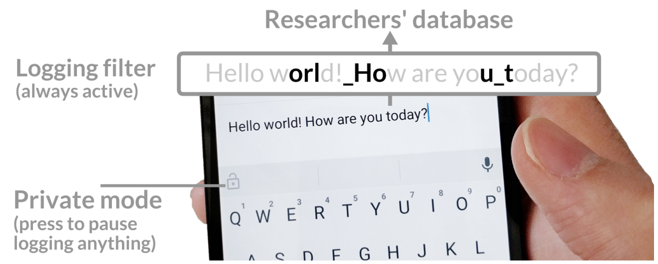

Figure 4: Our *ResearchIME* keyboard logging app [1] uses a logging filter that only transmits the full (i.e. text-revealing) information for short random subsequences of keystrokes. By adding "noise" to the channel in this way, the app avoids logging readable messages and thus better respects users' privacy.

Conclusion

We proposed *Information Transmission* as a new perspective on mobile experience sampling. Motivated by the workshop call, the goal of our view is to frame and conceptually support research on increasing data quality in ESM studies.

In particular, our viewpoint frames ESM studies around two information channels (subjective and objective). Moreover, it frames various challenges for data quality in ESM studies in a unified way, that is, as "noise" along these channels. In this information-centric perspective, good experience sampling transmits valid, relevant, and "noise-free" information from users' in-situ experiences to remote researchers.

We discussed key implications of this perspective, including the combination of subjective and objective channels, different roles of information channels in contextualising and labelling data, and conditional channels as a framing for systematically triggering self-reports as well as automated tracking. Finally, we pointed out the value of desirable noise for protecting users' privacy.

Some problems of experience sampling are likely to remain, despite combining objective and subjective channels: For example, people might be selective in their reporting (e.g. preference for taking pictures or recording audio only in certain situations). They might also try to influence measurements or simply forget to answer (e.g. missing an event-triggered questionnaire). Adequate UI and interaction design might help to address these issues and points towards future work in HCI and Psychology.

In conclusion, what work does this perspective do? Some of the outlined ideas have been proposed before (e.g. contingency sampling [6]), yet here we cast them in a novel light of information transmission. This helps to frame and highlight implications for improving data quality in ESM studies, and sparked a first discussion of ideas and solution principles for realising such improvements. In particular, we highlighted ideas for combining objective and subjective information channels. We illustrated these ideas with concrete examples from our previous and ongoing interdisciplinary research projects.

Overall, our view thus aims to provide an actionable framing and sharpened focus on combining different kinds of information for increasing data quality in ESM. Presenting this view, we hope to inspire fruitful discussions and practical projects at the workshop and beyond.

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