Enhancing Personal Informatics Through Social Sensemaking

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ABSTRACT
Personal informatics practices are increasingly common, with a range of consumer technologies available to support, largely individual, interactions with data (e.g., performance measurement and activity/health monitoring). In this paper, we explore the concept of *social sensemaking*. In contrast to high-level statistics, we posit that social networking and reciprocal sharing of *fine-grained* self-tracker data can provide valuable context for individuals in making sense of their data. We present the design of an online platform called Citizense Makers (CM), which facilitates group sharing, annotating and discussion of self-tracker data. In a field trial of CM, we explore design issues around willingness to share data reciprocally; the importance of familiarity between individuals; and understandings of common activities in contextualising one's own data.

Author Keywords
Personal Informatics; data sharing; social sensemaking.

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

INTRODUCTION
With the increase of available tools (e.g. Fitbit, Strava, MyFitnessPal) for recording one's activities, self-tracking has become increasingly popular [8,20]. Motivations for self-tracking vary [13,28], and applications include a wide range of domains and activities that come with their own opportunities for design [2]. Despite the popularity of activity trackers, they suffer from temporary lapses in practices of recording data [18] and high abandonment rates due to range of factors [10,15,22]. Although self-tracking is for the most part an individual activity [24,25], in some cases it is a social and shared activity [13,19,28], and reflection on collected data is influenced and often shaped by social interactions [4]. For example, collaboration takes place in Quantified Self [38] meetings where self-trackers share practices and learn from others, but generally does not involve sensemaking [21] of individuals' data. Most of the tracker applications available [40,41] limit collaboration to only sharing high-level statistics or achievements in order to get extra encouragement or peer support [17,26,29] for behavioural change [11,12,27]. And, a lack of context can make data difficult to interpret, as Slovak et al. [30] found in relation to the sharing of heart rate among couples, for example. Collaborations with personal informatics data has also been studied in chronic self-care applications [1,3,9,31,35,39]. While in some cases the analysis of data can be a joint effort in this domain [1,9], in contrast to our approach here the sharing (and importantly, making sense of) data is still unidirectional. Epstein et al. [14] used Value Sensitive Design to explore models of sharing fine-grained data. Building on this prior work, a key challenge that we take up in this paper is understanding appropriate ways of reciprocal sharing and presenting data in context, so that it can be *meaningfully related to activities and everyday life* for all parties involved [2].

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Our contributions are, first, the design and implementation of CM interactive visual tool for social sensemaking of personal tracker data. This entails sharing and comparing temporal traces of personal tracker data, and facilitating dialogue that is programmatically related to parts of the collective datasets, i.e., making subjective statements and asking questions of each other's data based on these comparisons. Secondly, in a field trial of CM we explore sharing models in practice to understand how social context of data contributes to sensemaking, and to investigate what is the real value in exploring other's data and how is this value distributed? How much context is needed to make sense of data? Is there value in reflecting on our own activities and daily lives in the context of other's data? What mechanisms would be required for us to be able to make sense of another's datasets and how might technology mediate this value exchange?

DESIGN OF CITIZENSE MAKERS
Our design-led approach consisted of preliminary focus groups to understand data sharing and sensemaking practices with conventional tracker interfaces, and the design and evaluation of CM. We recruited an opportunistic sample of

participants (n=20) from a parallel research study where 4 offices were provided with Fitbits to monitor their heart rate in response to weekly changes in their office environment. Fitbits were used for data collection and participants were not given any other instructions for using them. Over the course of a 12-week study we ran weekly focus groups where we asked questions about practices of sharing and exploring data that emerged. We transcribed and thematically analysed these [6], with key themes emerging around engaging with data, lack of controls for sharing, additional measures for comparison, and meaningful social functionalities. We show how these themes informed the design of CM.

Data Driven Narratives

People were interested in seeing patterns in different datasets that the Fitbit was recording. They often got confused as they clicked between different datasets to do the comparison. For example, one participant tried to find correlations between sleep and heart rate: *'I couldn't find any [correlations], like if I sleep more does it make your heart slower, and if I sleep less does it make it higher? But I'm not very good at numbers so I can't figure it out'* (Susan).

Design: To make this task manageable, we chunked the data into sections based on the time of day (e.g. 'morning'). Once a day is selected, the platform automatically constructs a 'data story' from it. Our approach to data interaction is based on data driven stories or interactive storytelling [32–34]. We adopted a scroll-based interaction to navigate through data. This method requires less effort from the people and it is almost always preferred over clicking as a way to make content visible [5]. Adding additional context to the data creates new opportunities for interpretation, which can be further enhanced by interactive visual tools [7,23] and the storytelling approach. Unlike Fitbit, CM does not provide aggregated statistics. Instead, it lets people explore and look for interesting patterns in the fine-grained data.

Levels of Sharing, Privacy and Control Over Data

When we spoke to participants about control over data and privacy, they recounted that they were happy to share their data with their friends and co-workers, but were less comfortable sharing data beyond this circle. It was also evident that the sharing was affected by type of data. One participant stated: *'We've looked into the privacy settings in Fitbit and I generally set everything - I'll share anything as long as we're friends. I don't want to share it beyond that. I think that's a bit strange sharing your heartbeat with the world'* (Tim). Also, people were conscious that their activities are recorded and made available for others to see. This fear of surveillance was uncomfortable and sometimes even made them change their behaviour: *'I started feeling […] like, "Big Brother is watching me" sort of thing. "I'd better not do that. It will record somewhere"'* (James). Participants thought that their privacy was intruded on when colleagues questioned them about the activities they did in their spare time: *'I find it creepy when somebody tells me what I have been doing at the weekend […]. Personally I think it is right on the borderline of being a little bit too much information [shared]'* (Ryan).

Design: We designed CM so that people could set individual rights for each person they wanted to share data with. From Epstein et al.'s [14] design considerations and our study findings, we arrived at two shareable transformations of fine-grained data – Detailed Single-Day View and Limited Hours View. We modified the Single-Day approach to enable people to choose weekdays and/or weekends to share data. In addition, the Limited Hours allowed people to set limits to the range of hours they want to share. By default, data sharing was turned off.

Meaningful comparison

One of the participants drew our attention to the utility of social context for sensemaking: *'If each other's heart rate was plotted on a graph with a section of a day where we were all kind of in this situation just inactive, sitting at a desk, then it will be interesting to see how who's doing what. And, you know, if something happened in the office that affected everyone, doesn't everyone kind of spike?'* (Tim). Sharing data and knowing that it is constantly recorded made people quite competitive. Participants were constantly checking Fitbit leader boards and even engaged in challenges. One of the participants felt that the numeric representation of steps does not give them a good comparison: *'The frustrating thing for me is there's really only the steps metric that's a comparison, whereas if you like look at active minutes or cardio exercise or other elements of the data, then there will be more [better comparisons]'* (Jake).

Design: We implemented functionality to allow people to visualise their own data alongside other peoples' for a specific timeframe, in order to explore the role of social context in improving the sensemaking process (Figure 1). Being able to explore and compare fine-grained data in the context of others might lead to better understandings through visible connections between real life events and interactions with others.

Social Sensemaking

In addition to having competitions (using Fitbit's interface) and comparing step counts with each other, participants also had conversations in person around these numbers. When asking participants if they talked about the data, they said that *'we've all swapped stories'* (Dan) and *'we've sort of compared notes'* (Frank). These discussions about the data provided additional context to make sense of it and to compare it to their own data.

Design: To facilitate this discussion and to link it to the data, we built an annotation system into CM. This allows people to mark a specific section of the data using *brushing* (i.e., selecting a subset of the data with an input device), and add textual annotations. These short comments or stories are then stored in a database linking to the specific data that was commented on. We distinguished two types of comments: private comments and public comments. Private comments

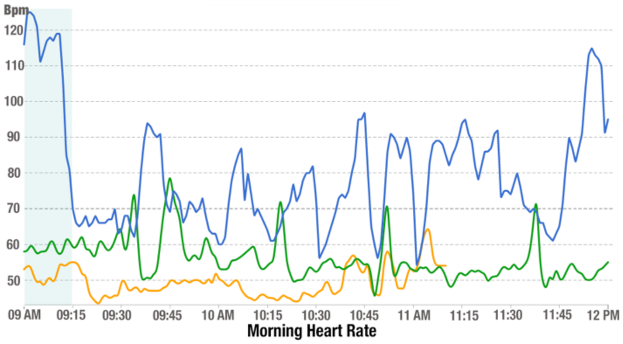

Figure 1. View from CM of multiple individuals' morning heart rates on the same timeline with brushed section.

are for personal reflection and only visible to the individual who enters them. Public comments are visible to all the people who are selected and whose data is displayed on the graph, when brushing occurs.

DEPLOYMENT AND EVALUATION

For the deployment of CM we recruited 18 participants (4 female) using purposive sampling. Seven participants from the formative study took part. Additional participants were recruited by snowball sampling via university mailing lists. Over the course of 2-weeks, we asked people to wear their Fitbits and use CM in their own time to share and explore their data. We sent them a link to CM, accompanied by a 5-minute video of how to use it. Participants received a £15 voucher for taking part. We subsequently interviewed (15-20 mins. semi-structured) 14 participants to understand their experiences with CM. In total, 4 hours of audio were recorded, transcribed and thematically analysed [6].

Willingness to share

Participants' willingness to share depended on the type of data in question: *'I was happy to share all my steps and stuff. Maybe if I had heart rate [data] I might not share that as much'* (Tom). They discussed clear sharing boundaries that distinguish self–use from sharing with others in the office, sharing with others in the study, and sharing with everyone, including other institutions. All the participants said that they chose to share data with people they knew personally or who they were *'aware of already'*. This was not so much a privacy issue: rather, it was mainly because they felt that strangers would not benefit from looking at their data. Although participants said that they would be more encouraged to share their data if it were anonymised, they did not see the usefulness of sharing it without context, i.e., who the person is or what their routines were. Referring back to the benefits of sharing, people were unsure whether sharing would be reciprocal: *'I didn't really want to share my data with other people who I didn't know. Especially when I wasn't sure that I wasn't going to see their data in return'* (Fin). However, if somebody they did not know already shared data with them then they were more likely to share their data in return, pointing to the reciprocal nature of sharing. Hence, joint-sharing between people who did not know each other often depended on one pe taking the first step: *'…another two names popped up and I was just like, "Oh, if people are happy to do it then I'll…" and I clicked everyone. Just shared it with everyone after that'* (Leo).

The utility of other people's data

Participants compared individual data to other people's as a way of baselining for normative comparison of health and exercise. They also shared with groups to compare common activities and for competition. People were interested in comparing their data with others as a way of contextualising it: *'It helps you get more grounded in different metrics, because you compare them to different people'* (Andrew), and *'to be able to drill down further than you can with Fitbit'* (Jane). People noted that although it gives you a way to compare and see where you fit in the grand scheme of things, it is a more useful tool when they share common activities and experiences that can provide a basis for comparison: *'If you're not having the experience at the same time as somebody else, it's a bit arbitrary […] shared experiences, how the same thing affected people differently is kind of interesting as well'* (Jane).

Although the interface allowed people to explore their data and search for interesting new patterns, they often focused on specific, known activities. For example, one group of participants played 5-a-side football with each other and they were curious to see whether they could identify and compare data from that: *'If you had some kind of a macro view for football, just call it "Football View". It would be brilliant to see that as a breakdown and annotate things'* (Robert). For the people who were more interested in the competitive aspect of self-tracking, it gave new dimensions for comparing performance. It revealed the rich dynamics of the experience or performance that would otherwise be hidden in a daily step count. Importantly, the value in this relied on an understanding of the activity, either through having participated in it (as was the case for the football) or through concrete knowledge of its structure (e.g., an hour-long game with average heart rate and step count).

Discussing data

People working in the same office were already used to informally discussing their own data with others, but with CM, they could start discussing other people's data as well. Overall, 60 comments were entered to the system over the 2-week deployment. People often used discussion board for informal jokes, and this led to surprising realisations about what could be inferred from their data. One of the participants had a realisation after receiving a comment on his data: *'I was saying, "You guys look super active," and someone turned around and was like, "Yes, I think you were in bed then." […] after that comment, I was like, "People are looking at my data!"'* (Robert).

In another example, a participant received a comment that was he *'kicking around a football'* at the time he was supposed to be working. This highlights the importance of people always having control over how their data is shared. The social element of discussions was appealing to people.

However, as with visualising and comparing data, people found that discussions were more useful in contextualising their data when they had engaged in mutual activities. *'For the group discussion, I mostly used it where I already knew that there was a group activity'* (Jeremy). This was one of the reasons why people did not want to initiate discussions with strangers on the platform. If they did not know the person and did not share common activities, they felt '*kind of weird'* and *'Big Brotherly'* adding comments to their data.

DISCUSSION

Our study illustrates the value of socially contextual data exploration, as well has highlighting challenges around people's willingness to share data reciprocally, and engaging in meaningful interactions with such data. Here, we outline future design considerations for CM, as well as understandings of people's perceptions and current practices around collective sensemaking [21].

Significance of everyday activities

A common theme in our findings is the significance of everyday activities as abstractions for exploring and understanding data. Our participants got more value out of seeing data about specific events or activities that they engaged in with others. Prior work points to ways of supporting this abstraction with pre-processing and visualisation, where subsets of data from meaningful events, locations and activities are presented to people as 'cuts' [16]. While this work placed an emphasis on individuals and their personal goals, it is evident from our findings that the concept of a 'cut' is highly relevant for reciprocal sharing and collaborative exploration of data. But how might these be best represented for social sensemaking, and what implications might they have for sharing and collaboration?

In one sense, interactions with cuts might support the development of 'mental models' of the relationships between physiological indicators and behavioural and environmental factors. This was an issue that arose from people's attempts of trying to make sense of their own data, and is further increased in interactions with the data of others. Some examples might be people looking for traces of work related stress from their heart rate data or trying to understand what meaningful levels of heart rate might be for physical activities, and how these change. Related work by Wang et al. [37] investigated how sensor data reveals effects of increased workload on students' health, mental well-being and academic performance. Behavioural trends clearly impact on physiological indicators and cuts can provide useful units for analysing and monitoring these longer-term correlations, and better understanding them by sharing, discussing and collaborating with others.

Extended sharing preferences

Our findings have shown that the use of temporal semantics for specifying sharing preferences, and the possibilities of sharing with strangers, sometimes led to anxieties related to the open-endedness around who could see what. A promising role for cuts in sharing data is to limit the scope of what is shared to manageable and meaningful units. For example, consider activities like the 5-a-side football match: some people who engaged in this collaborative data collection activity might not wish to share their data outside of this particular event. They might only want share and compare this specific activity instead of a specific day or time interval [14]. In Epstein et al.'s [16] study, people pointed out that they are more likely to share cuts as summaries, instead of raw daily lifelogs which can be overwhelming to understand and might reveal too much [14]. In a sense, some of our participants already marked and annotated cuts in the data by highlighting segments linked to comments or discussion.

Participants expressed an interest in extending this feature to support additional functionality such as automatic tagging of events and highlighting of interesting relations in data, both on an individual level and in relation to others. Tsubouchi et al. [36] have attempted to detect social relationships using machine learning on Fitbit fine-grained sensor data. By adding this to CM we could present people with some of the cuts and social context automatically detected in the data, using these as our basic units for sharing and discussing data with others. While participants could do this themselves, the automated detection of individual and shared experiences might provide a more effective model for sustaining engagement with the platform and data. Importantly, this might also be applied to alleviate concerns about how others might see their data (e.g., using pattern recognition to suggest potentially sensitive cuts prior to sharing). While cuts serve as sensible units for sharing and indexing data, they must be integrated into CM in a coherent way, alongside the data narratives and chunks that were beneficial to participants. Key challenge for design is balancing tensions of providing freedom to share, explore, and customise the flow of data, while also providing engaging routes into interactions with the data and alleviating anxieties around willingness to share.

CONCLUSION

We investigated the concept of social sensemaking with the Citizen Makers platform, which allows individuals to share and explore their fine-grained fitness tracker data in relation to others. Our study demonstrates that with this type of data, privacy concerns might be alleviated using abstractions of the data and the mutual benefits of sharing these. However, the value is foremost when people share a common activity, interest or goal.

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