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HOW MUCH ELECTRICITY DO YOU USE AT HOME? AN INVESTIGATION INTO HOUSEHOLDERS' LITERACY FOR COMPREHENDING DOMESTIC ELECTRICITY DATA

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Abstract

This paper presents the results of a field study that investigated how users read and comprehended their own residential electricity usage data. Nine UK households were provided with a commercial electricity-tracking tool. We conducted a contextual inquiry and had participants think aloud while interpreting a graphical representation of their own domestic electricity consumption data. We were particularly interested if users would be able to understand this energy usage data in relation to their everyday household routines and behaviours. A second follow-up interview was conducted with the same participants three months later to find out whether users were still using the tool and if their understanding of how they use electricity in the home had changed. We found that energy literacy varied greatly within our sample of thirteen users. Across the sample, data comprehension for the graphic representation of the recorded electricity data was poor. The information feedback does not reflect everyday routines and therefore most users do not succeed in linking data patterns with performed actions in the household. The majority of our participants had stopped monitoring their consumption within the first few weeks or months. Those who kept monitoring did not report significant improvement in their understanding.

1. INTRODUCTION

Smart meters come with in-home displays (IHDs), which enable users to monitor their energy consumption. In addition to smart meters provided by utility companies, there are various tools on the market that come with mobile apps or websites that feed back energy usage information. Previous research has shown that eco-feedback can lead to changes in behaviour that result in domestic energy savings [1],[2],[3],[4]. Given this context, it is hoped that by monitoring domestic energy consumption with the newest technology, people will better understand their consumption and so learn to manage their usage better, save money, and reduce emissions.

The Smart Metering Equipment Technical Specifications (SMETS) state that the 'IHD shall be designed to enable the information displayed on it to be easily accessed and presented in a form that is clear and easy to understand [5]. However, concerns have been raised about how clear and easy to understand energy data is [6]. While most visualisations tend to represent energy data using either a line or bar graph, people may not be trained or might find it difficult to read graphs [7]. Interpreting energy displays takes a lot of cognitive work [8] and few studies have investigated people's ability to extract information from such representations [9].

Energy literacy in general is poor, creating a gap between what people know about their consumption and what they would need to know to comprehend energy data [10],[11],[12],[13],[14]. [15] write: 'Visualization of energy consumption is widely considered as an important means to assist the end-users and the energy managers in reducing energy consumption and bringing about sustainable behavior. However, there are no clear design requirements to develop the energy monitoring visualization.'

Independent of the visualisation aspect, various studies have looked into the effects of eco-feedback on behaviour change but few have addressed cognitive sense making processes and data comprehension [16]. The stages of integrating information and reflecting on it [17] are often not addressed, both in behaviour change models [18] as well as in field studies on eco-feedback and its effect on energy saving. Generally, people do not engage enough with energy monitoring technologies and therefore cannot tap the full potential that these technologies offer for savings [8],[19]. More work is required to thoroughly investigate how users deal with residential energy information and how they understand it.

In contextual inquiries, we observe how householders read, reflect on, and interpret their electricity data. Our main research question is whether people understand how everyday actions map to the presented data, that is, whether they are able to retrospectively explain their electricity usage curve, recognise appliances and actions, and identify possible opportunities for behaviour change. This mapping is crucial in eco-feedback, which needs to overcome the gap between theory and action, i.e. users have to be empowered to apply information and acquired knowledge to relevant use cases [20]. We expect that users will find it very difficult to spot this link, as many residential energy-metering tools only feed back total usage, but no appliance-wise information. It is assumed that disaggregated feedback would be more actionable for householders, but research has not yet delivered strong evidence to support this assumption [21],[22],[23].

2. METHOD

We conducted a field study with 13 participants from nine UK households (six female), with mean age of 40 years (SD = 15, range: 25-76). Education ranged from less than high school to Doctoral degrees. Five participants live in terraced houses, three in apartments, and two in semi-detached houses, three own their place. We provided each household in the study with a commercial electricity-monitoring device: the Loop energy saving kit, see https://www.your-loop.com.

Two weeks after the installation of the device, we conducted interviews, partly face-to-face, partly on Skype. Our aim was to determine whether people understand peak periods of electricity usage and explain what was contributing towards them, and also if they could deduct how they might go about reducing energy usage on the basis of this data.

First, we were interested in participants' energy literacy. We asked them which electrical devices in their household they believe consume most electricity and if they could quantify the consumption. Then we asked participants to make an intuitive sketch of their daily electricity usage. Participants were free to choose the type of graphic and metrics they wanted, and we stressed that drawing skills were not important. Like [13] we chose this approach because sketches are a rapid, accessible and expressive method which reveals what the sketcher has in mind; visuals and thinking are closely linked and sketches support the thinking process because they are an externalisation of internal thought [24],[25],[26],[27]. Also, sketches are being used in HCI to inform interface design [28].

Second, we did a contextual inquiry. Participants would log in to their Loop account online and we would direct them to the historic usage data. The task in the contextual inquiry was to verbalise what information they see in the graph and to explain which appliances or activities have led to the displayed data patterns.

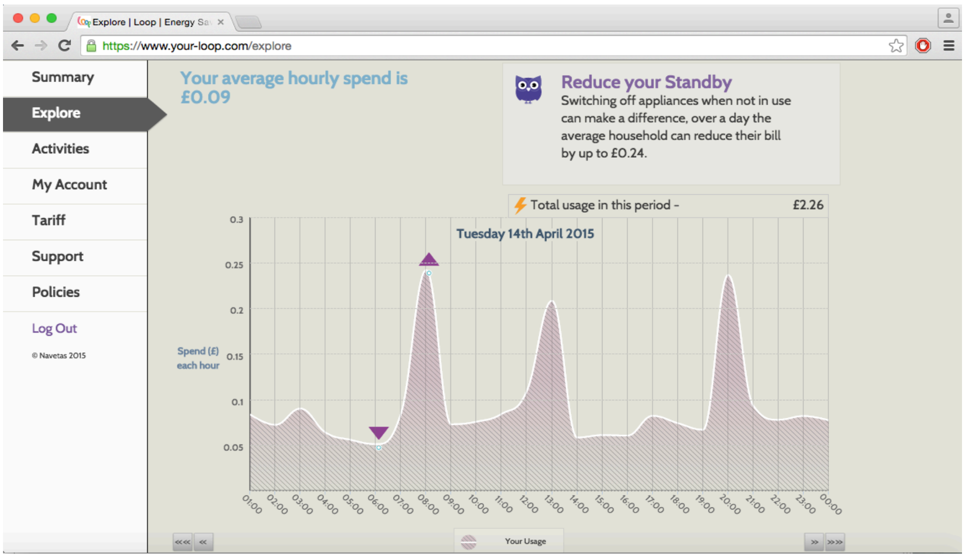


Figure 1. The historic data feedback of the Loop.

In addition, we also conducted a follow-up interview with 10 of the 13 participants three months after the initial interview. The aim of this follow-up interview was to find out if participants were still using the Loop electricity-monitoring tool and if they had improved their understanding of their domestic electricity usage. Furthermore, we asked participants to imagine that they could design the 'perfect' smart metering feedback to derive user requirements. We asked them to describe what would be important in terms of characteristics and functionality so that the feedback would be easy to understand.

All interviews were transcribed in the transcription software f5. The transcripts were then imported into the qualitative data analysis software Nvivo and analysed thematically [29],[30].

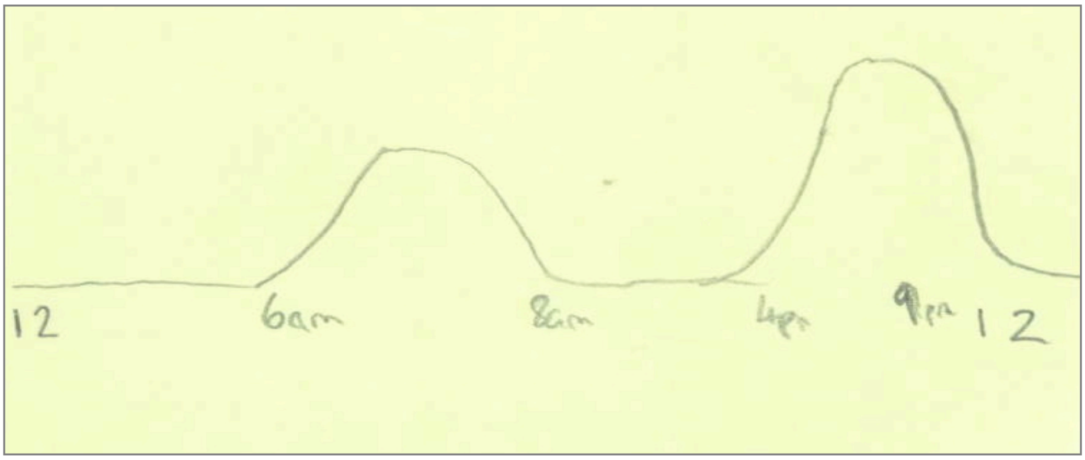
3. RESULTS

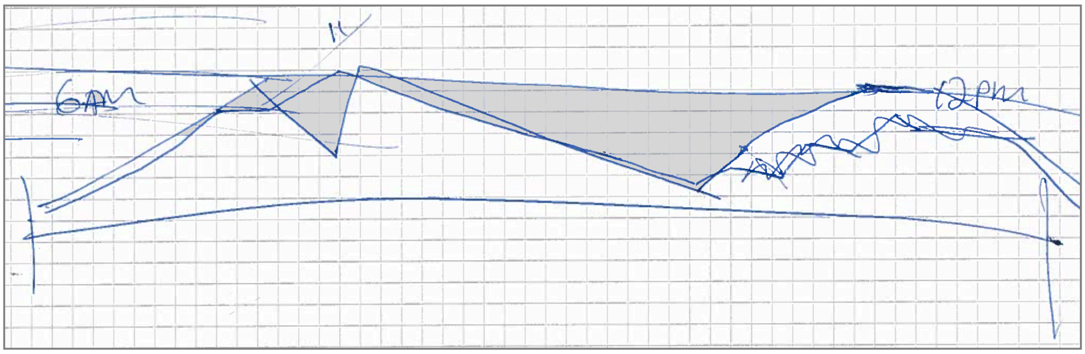
We divide the reporting of the results between the two activities used during the first round of interviews (assessment of energy literacy and contextual inquiry) and the two parts of the second interview (long-term usage and user requirements). See method for details.

3.1 Energy literacy

We found that energy literacy differed greatly between participants and was low for most interviewees. Participants were asked which electrical devices in their household they believe consume most electricity. The appliances named ranged from appropriate guesses such as the washing machine, over the fridge and the oven, to leaving the lights on or devices plugged in. A minority was confident about their guesses, two participants said they had no idea at all, most expressed uncertainty. More than half of the sample was unable to quantify the usage of any household appliance (*'I know what is kilowatts and watts, but that doesn't mean anything* *to me'*). Three participants named realistic estimates in Watts or Kilowatts. Two participants considered a monetary measure (*'I guess that it [oven] might cost 2 Pounds an hour?'*).

The sketches varied greatly in sophistication and detail. All participants drew a timeline on the horizontal axis. Some labelled accurately from midnight to midnight, using numerical scaling. Others started in the morning, coinciding with participants getting up. Some used verbal scaling such as *'Morning, Midday, Afternoon, Evening'* and yet others combined numerical and verbal labels. For the y-axis, some did not use labels whatsoever, others labelled *'consumption'* or *'more elec[tricity]'*. Two chose kW and kWh, and yet another two added numeric to the Kilowatts scaling. Three participants drew staircase-shaped graphs with square waveforms, while most others chose smooth line graphs with sine waveform, and one person drew triangle waveforms.





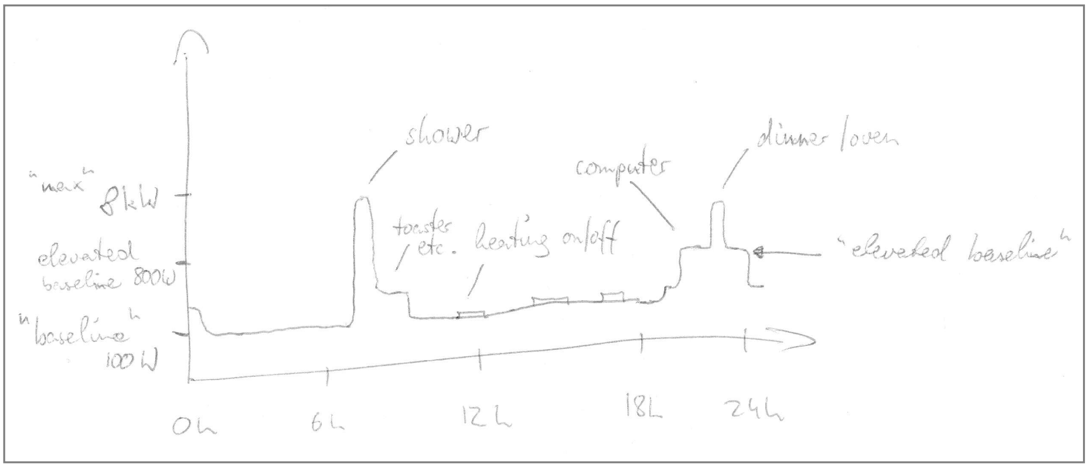


Figure 2. Participants' sketches of daily electricity consumption.
Top: timeline with sine waveform by P11. Middle: timeline with triangle waveform by P1. Bottom: most elaborate sketch by P13, depicting a square waveform and labels on both x-axis and y-axis.

The sketches were in accordance with participants’ daily routines, beginning with getting up, leaving the house, returning home, and taking up evening routines such as cooking and watching TV. When asked to elaborate on her sketch, Participant 1 explained: *‘that's not so much a measure of how much, but more kind of going up when we are here’*. Some participants would describe specific activities: e.g. using the electric shower in the morning and then the toaster for breakfast, or plugging the mobile to charge after returning home, making cups of tea, or switching the TV on. Such daily routines would be mentioned more often than appliances such as the washing machine, which does not run every day in most households and is less likely to have a fixed slot in the daily or weekly routine.

3.2 Contextual inquiry

Ideally, an energy monitoring tool is supposed to feed back relevant information that the user can decode when looking at their recorded data, thus gaining insights about their household consumption (bottom-up processing). However, when explaining their usage graph to us, participants heavily relied on cognitive top-down processes: they would draw from memory to interpret the displayed pattern. Typically, they would think about routines they perform at a time of day or week. The longer the day of question dated back, the less confident participants were about their interpretations. Two participants checked their calendars during the interview.

As a consequence of this routine-based reasoning, people would commit errors such as assigning peaks around lunchtime to cooking (even though their stove and oven operate on gas). Sometimes, there were data patterns that participants were unable to explain at all (‘*maybe my husband was at home yesterday. I don’t know*’). Overall, people found little information in the data that would help them derive sensible behaviour change resolutions (Participant 7: *‘It says what was your lowest day and then... what did you do differently that*

day? I suppose I did go to work (laughing)'; Participant 10: '*if I need to run my washing machine, I need to run my washing machine. So I can't do anything about it, right?'*).
We observed that the low temporal resolution of the graph limited sometimes concealed separate events that take place in immediate succession (for example the use of the electric shower and the hair dryer in the morning, which would blend into one peak in the graph and confuse users).

Participants articulated criticism concerning the quality of the feedback, thinking the tool is *'mostly a gimmick'* and leaving them '*frustrated. Not frustrated, too strong a word. But I would like more granular control'*'. Participants thought that the software should '*look at patterns and classify usage of different things*', asking for breakdowns of the information on the appliance level and graphs of activity. Yet, they considered it a *'timely thing to know, to get a lot of data, to have a lot of information'* and they appreciated having their usage recorded and being able to access this information: *'I think that's great it gives you access to information that you don't normally have and it gives you... the tools to actively try to become more aware and to either improve your behaviour or to just know what it is that you're doing where you're using energy'*. Participant 7 was convinced that *'Once you can actually see or personalise information about what you're doing - I think that goes for any behaviour - then you can start to think about what that means (...) Like with anything in life, we just go along, we pay the bills, we're busy, we're doing, you know, work and manage everything else and you just pay the bill at the end of the month, don't you, you don't think about it. So you wouldn't have any idea but once you got that information in front of you, you can start and start making it meaningful to your own life and your own kind of pattern of behaviour'*.

3.3. Long-term usage

In the follow-up interviews after three months, there were three participants who had never looked at the data again after the first interview. Participant 7 said she had been interested but had completely forgotten about it. Participant 2 did not see a benefit in it and Participant 1 found that the software didn't give her anything tangible. They wished for better explanations, for information that was easy to grasp and for a breakdown of the global usage.

Four participants had looked at their data again in the first weeks after the initial interview, but had quit by the time of the second interview. Participant 6 had looked again when being prompted by her children who wanted to know how they were doing, but she said any insights they have had were a *'one-off thing'*.

Finally, there were three participants who were still monitoring their electricity usage with the Loop, where one of them did not log in any more but read the weekly digest emails. Two of them stated they had been looking every two to three days at times. The consensus was weekly, especially for those who use the email digest, with a tendency to check more often when using the app. One participant had unsuccessfully tried to scrape the website for the full dataset. Even though these three households were still using the Loop regularly, they were not satisfied with the feedback and did not report significant progress in interpreting the information. At least, one person said that he could see from the data if things were left running, finding that the teenager in the household would waste a lot of electricity. Another participant had once used the Loop to check remotely whether his builders had done renovation work in his house. Equally, he was using it to find out whether his son would be home after school.

3.4 User requirements

When asked what would be important for the 'perfect' smart metering feedback, the function that was requested most often was appliance-wise data disaggregation to make the information more actionable. Implicitly, participants asked for interactivity in the system, which would help them explore their consumption. Many participants had the idea of a screen that would show a schematic flat or house or the actual property with its rooms. The display would then show the consumption per room, and per room they would be able to zoom in and obtain more details on the device level, such as their efficiency and how they could be improved. '*I'd like to know about (...) zonal areas where it actually shows you, kind of in a visualisation of your house, showing you heat maps of where (...) the usage is taking place so you can quickly zone in on these areas*'. One participant imagined a smart home system that would integrate information from the Internet and offer tailored advice; every plugged-in device would automatically communicate its specifications as well as its system status to the network, and thereupon the user could be sent useful notifications. Similarly, another participant suggested that whenever there is a new appliance, there could be a training phase for the system to learn to recognise all appliances.

4. DISCUSSION

4.1 Main findings

Participants' knowledge at the beginning of the interview varied, few have an idea how much electricity is used by individual appliances or actions. Our findings are in line with previous work, which shows that average energy literacy in the population is low [11],[12],[13],[14]. As expected, the participants' understanding of their electricity data was reflected in their sketches [27], thus we think that sketching is an appropriate way to assess a person's energy literacy. Investigating how people read and interpret the household's global usage data, we found that aggregated electricity feedback is far too general for users to map it to specific wasteful appliances or behaviours. Users are only able to reliably label very few peaks in their data patterns if they remember what they were doing, which is in line with previous findings [8]. Hence, it is questionable if users are able to make suitable inferences from residential energy feedback and build sustainable behaviour. We assume that exactly this mapping is crucial because users reason in terms of everyday actions and educational approaches should take relevant routines and situations into account [20]. Only three users who were quite energy literate from the start kept using the device. The majority of users typically abandon smart technologies within the first weeks or months [31],[32]. The action- or event-based nature of thinking about energy consumption is not mirrored in the data, so people fail to map data patterns to behaviour and to gain relevant insights. That also implies that the data can barely 'facilitate reflection and increase self-knowledge' [33]. Applied to the model of personal informatics [17], we encountered a comprehension barrier that prevents people from transitioning to the stages Reflection and Action.

4.2 Contribution of this study

Various studies have looked into the effects of eco-feedback on behaviour change. Few have addressed how people read, reflect on, and understand the data feedback. Actionable data feedback and comprehension of it are a precondition for sustainable behaviour change and energy saving. We believe feedback is 'actionable' when it addresses use cases that are relevant to the householder in their everyday lives.

4.3. Limitations and shortcomings of this study

Our sample is too small to allow for reliable generalisations to the population. More than that, we only used one particular tool as an example to explore how people read and make sense of residential electricity feedback. Our findings specifically address the characteristics of the Loop, such as the line graph and its resolution. Other tools or smart meters output the data in different, yet similar formats. While graph and resolution may vary, most systems feature aggregated feedback only. While we have investigated how people reason about usage data and possibly learn from it, we did not record actual behavioural measures. Our focus was not to explore if people would reduce their consumption by using the Loop. Although we can confirm that users ask for appliance-wise feedback, it remains to be investigated if they'd perform better with disaggregated data.

4.4. Future development of this work

There are two core questions for our further research, which concern disaggregation and energy data visualisation. First, it needs to be tested in how far disaggregated data is superior to global household consumption data. Second, we examine how disaggregated usage data is best processed and visualised for users to learn from it. The line graph with low temporal resolution did not provide sufficient detail to yield actionable insights. Judging from our participants' sketches, a line graph over time seems to be in line with users' mental models. However, we asked our participants to sketch their usage "over the course of a day" which might have biased them. Finding that total usage over the day does not yield sufficient learning, visualisations that depict each device's usage might be more useful. Also, interactivity could improve users' performance by allowing them to actively explore the data. Literature on graphic literacy and information visualisation suggests that representations enhance thinking [25],[34],[35]. If not chosen wisely, tough, comprehension is severely constrained [36],[37],[38]. Our on-going research focuses on different graphic visualisations of aggregated and disaggregated residential electricity data to inform future generations of smart home technology.

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