



# Probing IoT-based consumer services: ‘insights’ from the connected shower

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## Abstract

This paper presents findings from the deployment of a technology probe—the connected shower—and implications for the development of ‘living services’ or autonomous context-aware consumer-oriented IoT services that exploit sensing to gain consumer ‘insight’ and drive personalised service innovation. It contributes to the literature on water sustainability and the potential role and barriers to the adoption of smart showers in domestic life. It also contributes to our understanding of context, which enables user activity to be discriminated and elaborated thereby furnishing the ‘insight’ living services require for their successful operation. Problematically, however, our study shows that context is not a property of sensor data. Rather than provide contextual insights into showering, the sensor data requires contextualisation to discriminate and elaborate user activity. Thus, in addition to examining the potential of the connected shower in everyday life, we consider how sensor data is contextualised through the doing of data work and the relevance of its interactional accomplishment and organisation to the design of living services.

**Keywords** Internet of things · Connected shower · Technology probe · Sustainability · Context · Data work

## 1 Introduction

A burgeoning array of Internet of Things (IoT) devices or connected appliances and products are now commercially available and finding their way into domestic life (see [42] for a wide range of examples). A key factor driving commercial uptake of the IoT is the potential it offers for enhanced consumer ‘insight’ and with it, personalisation. As Raferty [43] puts it,

With hundreds of millions of interconnected devices ... the IoT offers the opportunity to tap into new data sources and glean new insights. IoT-based insights can help you communicate more effectively with customers, better understand their needs or desires, and make

personalised offers that quell frustration and reward loyalty.

Personalisation is a key driver of widespread commercialisation of the IoT [37]. The potential insights afforded by the IoT make possible what some market analysts have called ‘living services’ [19] or services that exploit smart objects to learn consumer habits and to predict and react to consumers’ changing needs and circumstances. Living services are designed to be responsive to individuals, rather than provide generic services for mass consumption. They are autonomous and ‘contextually aware’ (ibid.), reacting in real time to changes in the environment and/or the consumer’s behaviour.

This enterprise view of the IoT may be questionable, but it is widespread and played a formative role in the design of the connected shower reported in this paper through the involvement of an industry partner who was and is interested in garnering insights into the use of personal cleaning products for commercial reasons and how they are implicated in and impact water use. In exploring the relationship between products and water use, the connected shower was thus construed of as a probe that might inform the manufacturer’s reasoning about sustainability and indeed make a contribution to the design literature in this area. Showers are a major source of water

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consumption in the western world at least [27]. In the UK, for example, over 90% of homes have showers, and there has been a sharp rise in ‘power showers’, which have a relatively high water usage rate, and the trend is only expected to increase [2]. Design researchers have sought to engage with showering from a sustainability perspective to enable water conservation through the design of eco-feedback systems, in-home displays and the use of ‘persuasive’ technology to motivate behaviour change [e.g., 3, 16, 21, 33, 34]. The connected shower complements this body of work by exploring the potential of consumer-oriented IoT services to enable sustainable water use.

The second contribution of this paper concerns the assumption and even the assertion that consumer-oriented services built on the back of the IoT are contextually aware. As IoT developers themselves note, ‘sensor data is meaningless without context’ [32]. Context, as Dourish [15] reminds us, is required to ‘discriminate or elaborate the meaning of the user’s activity’. It is, as Perera et al. [39] point out, ‘one of the main challenges’ that confronts the IoT. The ‘collection, modelling, reasoning, and distribution of context’ is therefore seen as ‘critical’ to understanding sensor data (ibid.). However, as Dourish [15] observes, the idea that context can be readily captured and modelled is problematic as it assumes a ‘positivist’ view that treats context as something that effectively *surrounds* human activity. Dourish argues that this container viewpoint is incompatible with the ways in which context is manifested in and as a dynamic feature of human interaction. The upshot being that if autonomous consumer-oriented IoT services are to deliver the insight into human activity they promise—if they are to become context-aware—then they will need to do more than collect, model, reason about, and distribute ‘features of the environment’ (ibid.); sensing is embedded within.

Our contributions are twofold then. First we explore the potential of consumer-oriented IoT services to enable sustainable water use through the construction and deployment of the connected shower. Key findings indicate that service propositions which have the potential to reduce costs, of either water or personal cleaning products, may be well received. However, their uptake turns on key concerns over data transactions, transparency, end-user control, and security being addressed. We then turn to consider context, which our study shows is not something that can be ‘read off’ the sensor data but rather is brought to be bear and elaborated by participants in discriminating and elaborating user activity when examining sensor data. Our results were and are shot through with different orders of situated reasoning invoked by participants to account for, articulate and ultimately contextualise the sensor data produced by the connected shower. So in addition to explicating the orders of reasoning implicated in contextualising the data, which speak to sustainability concerns in one way or another, we also attend to the ways in

which those orders of reasoning were reflexively elicited so that we might understand something of the *interactional accomplishment of context* and its relevance to the design of autonomous consumer-oriented IoT services. Of particular note here is the ‘data work’ [18] occasioned by the exit interviews with users of the connected shower and the methodological ways in which the doing of that work is ordered and accomplished to furnish insights into the social and material circumstances of the sensor data’s production. These insights elaborate the contextual relationship between local household routines, individual showering routines, seasonal variations, moral and economic considerations, and impact of domestic infrastructure on the temporal patterns of showering and water consumption detected by the connected shower.

## 2 The connected shower

The connected shower is a custom-built IoT device. It consists of (1) an in-line sensor placed between the shower controls and shower head to monitor flow rate, water consumption, and water temperature over time; (2) a shower head that combines an accelerometer and gyroscope to map shower head movement; and (3) a bespoke set of scales that logs the weight of personal cleaning products (shower gel, shampoo, conditioner, etc.) to provide insight into product usage during showering. Data from these sensors is sent via BLE in real time to a local hub: a Raspberry Pi running Debian, an SQLite database, a low-power RF chip for connecting the sensors, and a monitor for visualising data produced by them (see Fig. 1). The hub is not connected to the Internet and did not transmit any data outside the home during deployment. This was a conscious design decision taken to ensure study participants’ privacy and to provide control (they could disconnect the device at any time, though we note none did). The data was made available to a field worker during exit interviews via a WiFi connection to the hub. Given the potential hazards of mixing water and electricity, not to mention the building regulations that govern such situations, the connected shower’s sensor-based components were designed to operate on low-power batteries. They were also designed to be watertight and to mount to standard water pipes and fittings found in UK bathrooms. The Raspberry Pi is mains powered and situated outside the bathroom area.

The design of the connected shower was framed by two envisioning workshops involving project partners, including researchers from the Dyson School of Design Engineering and researchers active in the field of human-computer interaction. In all, 20 people attended the workshops and together shaped three related design scenarios which they thought might motivate adoption of IoT-based showering services:

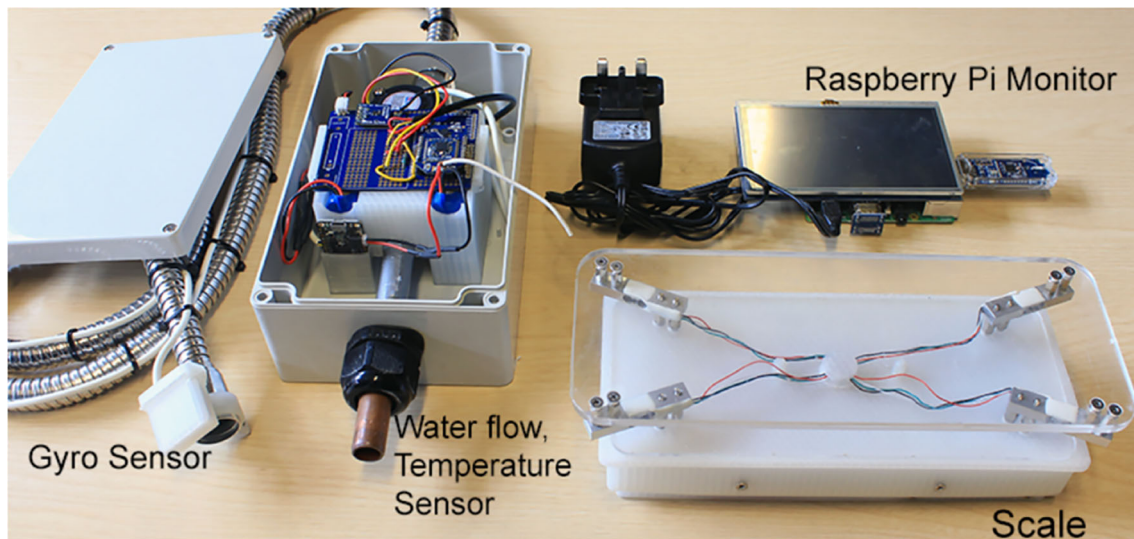


Fig. 1 The connected shower components

- *Personalised product offers.* The first scenario posits an IoT service that sends data from the connected shower to the manufacturers of an individual’s favourite personal cleaning products. The data provides consumers insight that allows manufacturers to better understand how their products are used, and in return, consumers receive reminders when products run low and special offers for personal cleaning products, which may be delivered directly to the consumer.
- *Water conservation.* The second scenario posits an IoT service that monitors water consumption in the home. The connected shower provides consumer insight into the household’s use of water, with the data being used by the water company to reward responsible use through lower charging or to increase charging if water use is deemed excessive.
- *Smart shower scheduling.* The third scenario trades on the second and posits an IoT service that helps the household coordinate showers to minimise water use. The service learns to predict how much time each household member spends in the shower and how this affects the household’s daily return. It also sends individuals a reminder to take a shower at the optimum time to avoid anyone running late and has the added benefit of helping household members avoid domestic conflicts occasioned by competing demands for shower use.

The scenarios were not conjured out of thin air but, as Reeves [45] observes in examining the origins of ubiquitous computing, the technological projections or envisionments encapsulated in our scenarios are grounded in a ‘milieu of existing and developing socio-technical infrastructures and innovations, drawing upon developments in diverse technologies’. Thus, the scenarios were created through, and reflect

our understandings as a research team of, current technological and engineering possibilities and how they might enable us to *probe* the IoT in ways that reflect our research interests and which allow us to explore those interests with potential end-users.

## 2.1 Probing the IoT

It is important to recognise what the connected shower is and what it is not. While the scenarios may convey a sense that the connected shower is a product or at least an exploration of a potential product delivering a selection of contextualised shower services, it is actually a ‘technology probe’. The term was coined by Hilary Hutchinson and colleagues in 2003. In explaining what it means, the authors note,

A well-designed technology probe ... is not a prototype or early version of a technology ... Rather, it is a method to help us and our ... design partners determine which kinds of technologies would be interesting to pursue. [30]

The ‘design partners’ Hutchinson et al. speak of are not only professional designers but also potential end-users as well. Seen and understood as a technology probe, the connected shower is not a product then—not even a prototype or early version of a new technology—but a *participatory research method* that allows us (a set of designers and human-computer interaction (HCI) researchers with industry partners) to explore with potential end-users (a set of people skilled in the mundane business of showering) the prima facie viability of exploiting the IoT to deliver bespoke contextualised shower services and of understanding the real-world, real-time challenges involved.

Technology probes combine three fundamental elements: engineering, design, and social science. The engineering element is concerned with field-testing novel technology or technological configurations; design is concerned to engage design practitioners and potential end-users in a process of technology development that clearly addresses end-user needs and desires; and the social science element is concerned to collect information about the users and use of new technology in real-world contexts. A well-balanced technology probe reflects each of these concerns. Thus, and for example, the connected shower addresses the engineering goal of field-testing a novel technological configuration, the design goal of engaging potential end-users with potential IoT-based showering services, and the social science goal of understanding technology in context through the showers' deployment in potential end-users' homes.

'Technology probes' is one of several probe-based approaches in HCI. 'Cultural probes' was the first to emerge in the late 1990s. It was developed by artists who sought to foster a 'design as research' agenda and rejected what they viewed as precise analyses or carefully controlled methodologies in favour of more playful or 'ludic pursuits' and opening up new cultural spaces for design [25]. Cultural probes are 'packages of ... materials [bespoke maps, postcards, cameras, photo albums, media diaries, etc.] ... designed to provoke inspirational responses from ... people in diverse communities (ibid.)'. Cultural probes were seen as a novel source of insight and were widely adopted in HCI, where they were intentionally adapted into 'informational probes' [7], thus cutting the tie to the artistic and cultural foundations of the probe-based approach. Informational probes instead tie the approach to social science research methods, and ethnography in particular, exploiting bespoke probe packs to elicit information from study participants and complement field observations.

What is common to all three probe variants is the *collection of data* [26]. Cultural and informational probes create physical probe packs that invite participants to inscribe and record their viewpoints on particular topics of interest and thereby provide material/data for inspection/analysis by the design team. Technology probes exploit the logging functions of computers to create digital records that detail user interactions. This digital data is typically combined with social science data to understand and unpack the real-world, real-time uses of novel technology and attendant challenges. After their deployment technology probes are typically 'thrown away' [30]; their value lies in the insights they furnish during field trials rather than in the technology itself. Technology probes are commonplace in HCI. Some recent examples include office heating controls [10], the Carolan guitar [4], automated domestic laundry [1], energy advisory services [17], and household grocery ordering [22]. The approach has become a core HCI research method advanced in its foundational pedagogical texts [14].

Before we move on to consider probe deployment, it was suggested in the discussion of this paper that our project appears 'a bit rushed' as we 'did not study the context of [showering] practice before' designing the connected shower. This of course not only confuses the approach we have taken for one that a reader might instead prefer but also ignores our methodological gambit. As noted above, those who champion the use of the IoT to deliver personalised services assume and indeed assert the IoT furnishes contextual insight. The connected shower allows us to *probe that very proposition*. It is not the case, then, that we were a bit rushed and missed some vital methodological step that would see us do some kind of contextual inquiry (e.g., ethnography) prior to designing the connected shower. Rather, we intentionally adopted a technology probe approach as it allows us to explore key assumptions *about the technology* and to understand what *it* can actually deliver in practice.

## 2.2 Deploying the probe

Deployment of the connected shower was approved by our ethics committee, and we subsequently hired a local recruitment agency to find participants. We asked the agency to look for households who would agree to have shower-sensing technology installed in their shower for a week and to explain that this would involve measuring things like flow rate and temperature, product use via a scale, and shower head movements. Participating households must have a non-electric shower so that the connected shower could be installed by our researchers. Participants were also informed that they would be required to take part in an hour-long interview at the beginning and end of the study and that they would be reimbursed £50 per household. We instructed the agency to forward the information sheet approved by the ethics committee to the participants, which explained the study in detail. Due to ethical reasons, we excluded households with children using the same shower. The agency subsequently recruited six households, all consisting of adult female-male couples; one household also had a 1-year-old baby who did not use the shower and so was not excluded from participation. Our participants were not early adopters of technology, though most were concerned with water consumption: 5 out of 6 households had water meters and pay for the amount of water they use (1 was unmetered and instead pays a standard yearly fee regardless of the amount used based on the rateable value of their property). An overview of our participants is provided in Table 1; we use the NRS social grade [38] to classify participant demographics.

We make no claim as to the representativeness of this sample and merely note, as we have explained in detail elsewhere [e.g., 11–13], that having a representative sample is not the only means of obtaining valid and indeed generalisable results. The original technology probes deployed by



**Table 1** Participant demographics

| Household | Gender | Age | NRS social grade            |
|-----------|--------|-----|-----------------------------|
| #1        | Female | 25  | Junior managerial (C1)      |
|           | Male   | 28  | Skilled manual (C2)         |
| #2        | Female | 63  | Retired (C1)                |
|           | Male   | 68  | Retired (C1)                |
| #3        | Female | 32  | Skilled manual (C2)         |
|           | Male   | 36  | Skilled manual (C2)         |
| #4        | Female | 59  | Retired (B)                 |
|           | Male   | 58  | Intermediate managerial (B) |
| #5        | Female | 51  | Skilled manual (C2)         |
|           | Male   | 53  | Skilled manual (C2)         |
| #6        | Female | 53  | Junior managerial (C1)      |
|           | Male   | 57  | Skilled manual (C2)         |

Hutchinson et al. [30] were only deployed in five homes, yet this did not undermine confidence in or uptake of the approach. We thus set aside a concern with the logic of quantitative science and statistics in favour of experiential insights gained in deploying a ‘throw-away’ technology probe.

In this respect, the first thing that struck us was the practical challenge of deploying the connected shower; for despite the use of low-power batteries and standard fittings, each of our participants’ homes had different showers, which impacted installation of the shower components, and different layouts, which impacted communication between the shower components and local hub and required the careful mapping of wireless signal strengths to find the right location to place the hub. Each connected shower deployment was thus a bespoke installation configured around the particular physical and material aspects of each participating home. Each installation was documented, and it was explained to the participants just how the components of the connected shower work, where the data was stored, and that they could disable logging at any time by simply powering off the Raspberry Pi. A field worker and the participants then worked through ethics documentation and informed consent forms, and the connected shower was left for them to live with for a period of 1 week. Figure 2 provides an example of what the connected shower looks like in situ, with the in-line sensor connected to the shower outlet, the gyro sensor connected to the shower head, and a selection of products placed on the scales. On the eighth day, the field worker returned to remove the connected shower and conduct exit interviews with the participants.

### 2.3 The exit interviews

The exit interviews lasted between 40 min and 1 h, were recorded on video, and yielded approximately 4 h of data. The interviews were oriented to examination and discussion of the data generated by the connected shower, which the field

worker accessed via a laptop connected to the Raspberry Pi and an interactive calendar-based visualisation (Fig. 3). The interview began by examining and discussing an aggregated view of showers taken over the last week, which showed the *total* and *average* duration of showering and the amount of water used (see Fig. 3, item 1). Individual showers, including time, date, duration, and amount of water used, were then examined and discussed (see Fig. 3, item 2). The interview also included consideration of the data from individual sensors. Time series graphs of water flow, water temperature, movement of the shower head, and the weight of products on the scales (Fig. 4) enabled the field worker and participants to drill down into the connected shower data. Participants found the water flow, temperature, and product use graphs legible but the shower head graph said little about the nature of movement to the untrained eye.

The exit interviews also examined and discussed the three future IoT service scenarios and participants’ reactions to them. On completing the interviews, each was transcribed and then analysed according to the study of sensor data conducted by Tolmie et al. [54]:

Below we look at the ways in which the data gathered by the sensors could be seen as revealing certain orderly characteristics of the household and how both the participants in the study and the researchers working with them sought to arrive at accounts of the data in these terms. A critical point here is the apparent gap between what is captured by the sensors and what is necessary to render the data locally and socially meaningful.

Thus, in turning to consider our findings, we explicate the cooperative work that is required to contextualise the data and discriminate or elaborate the meaning of connected shower users’ activity. The doing of this ‘data work’ [18] recognises the gap Tolmie et al. speak about is a gap between what sensors sense and what people do. In bridging this gap through the doing of data work, the field worker and participants produce insight into mundane showering activities and practices and the future potential of shower-oriented IoT services. Furthermore, as a reflexive feature of that accomplishment, they elaborate what is involved in contextualising sensor data to provide insight into the everyday life of the ‘consumer’. However, before turning to our findings, the question was raised in the discussion of this paper as to why we did not start the exit interviews by exploring how participants understood their showering activities prior to showing them the data? The answer again lies in our methodological gambit—i.e., in our aim to explore key assumptions about IoT-based services and their ability to elaborate context. From the off, it is perspicuous, as we will see, that this assumption is deeply problematic.



Fig. 2 The connected shower in situ

### 3 Findings

The analytic orientation Tolmie et al. take towards understanding sensor data in terms of ‘orderly characteristics of the household’ is a distinct social science analytic rooted in a branch of sociology called ‘ethnomethodology’ [23]. Ethnomethodology has played a prominent role in the development of digital technology since the approach was adopted by Xerox PARC in the 1970s [51]. Its studies elaborate the methodological character of practical action and practical reasoning [6]. Of particular relevance here are the *different orders* of practical reasoning that were drawn upon in the doing of data

work to make sense of and attribute meaning to the sensor data furnished by the connected shower or at least to representations of it. In this section, we group our findings in terms of the discrete orders of practical reasoning drawn on to contextualise the sensor data and elaborate human activity and practice. We thus unpack (a) how the sensor data was accounted for in terms of participants’ reasoning about their *showering activities*, *product use*, *water use*, and the impact of *domestic infrastructure*. We also consider (b) how participants’ responded to the future IoT service scenarios posited by the design team, before moving on in Section 4 to (c) unpack the methodological ways in which the sensor

| H1 SHOWER  |                                     | Shower Graphs →   |                                    |                                    |                                    |                                    |
|--|-------------------------------------|---|------------------------------------|------------------------------------|------------------------------------|------------------------------------|
| <b>Total</b><br>Showered for 3 hours<br>Used 2,318 litres of water |                                     | <b>Average</b><br>Showered for 10 minutes<br>Used 145 litres of water |                                    | 1                                  |                                    |                                    |
|  |                                     | Tue<br>11 July  | Wed<br>12 July                     | Thur<br>13 July                    | Fri<br>14 July                     | Sat<br>15 July                     |
|  | 2                                   | Shower 20:35<br>4 min, 45 litres                                      | Shower 07:14<br>15 min, 226 litres | Shower 07:06<br>5 min, 63 litres   | Shower 07:04<br>5 min, 66 litres   | Shower 07:54<br>17 min, 253 litres |
|  |                                     | Shower 20:44<br>9 min, 138 litres                                     | Shower 07:50<br>4 min, 60 litres   | Shower 07:15<br>15 min, 224 litres | Shower 07:16<br>18 min, 269 litres | Shower: 08:47<br>5 min, 69 litres  |
|  |                                     |   |                                    |                                    |                                    | Shower 18:04<br>6 min, 86 litres   |
| Sun<br>16 July   | Mon<br>17 July                      | Tue<br>18 July  |                                    |                                    |                                    |                                    |
| Shower 11:26<br>4 min, 53 litres                                   | Shower: 07:05<br>18 min, 261 litres | Shower 07:19<br>21 min, 299 litres                                    |                                    |                                    |                                    |                                    |
| Shower 11:35<br>10 min, 153 litres                                 | Shower 07:23<br>4 min, 53 litres    |   |                                    |                                    |                                    |                                    |

Fig. 3 Overview of showers across the week

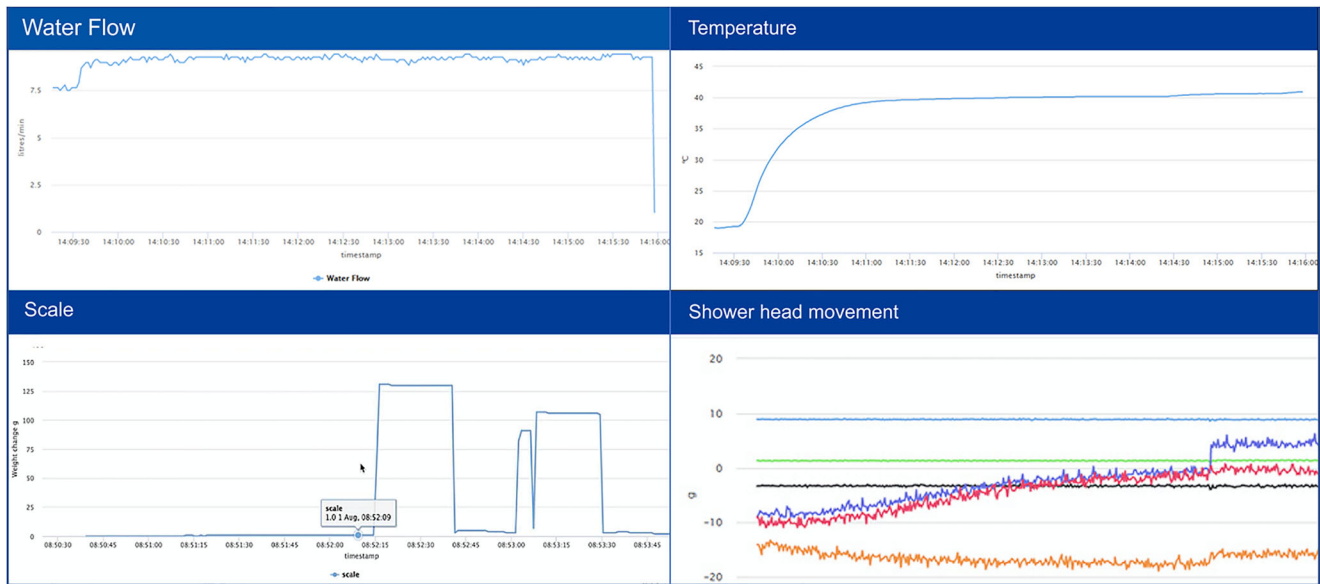


Fig. 4 Individual sensor graphs

data was *reflexively contextualised in interaction* in the course of addressing both of the above considerations. Understanding the methodological ways in which the sensor data was reflexively contextualised is particularly relevant to understanding the interactional accomplishment or production of context and the kinds of mechanisms that need to be *designed into the IoT* if it is to deliver on the promise of personalised context-aware services, a point we pick up in Section 5. First, however, we begin at the beginning with the observation that before anything else could happen, the field worker and our participants had to discriminate *just who* the data was about. If we look again at Fig. 3, we can see it provides insight into the total and average durations of showers and amount of water used in a household and even breaks this aggregate information down into specific instances of showering occurring on specific days at specific times using specific amounts of water, but it does not tell us specifically who generated the data. Let us start then by considering how participants discriminated who the data was about. The names in the edited interview extracts below are not the participant's real ones.

### 3.1 Reasoning about showering activities

The following conversational extract makes visible the how participants drew on their understanding of showering activities to make sense of the data and discriminate *who* it was about.

Field worker: So, you've already started looking at this overview ...

John: Yeah a little bit.

Field worker: what makes sense to you in looking at this initially?

John: It's quite obvious whose shower is whose, because mine is about the third of the time of yours (looks at partner) if not a quarter.

Field worker: So you can begin to tell whose is whose here?

John: Easy.

Sarah: Yes, easy.

Field worker: How can you do that?

Sarah: My time.

John: Because Sarah takes longer. The only [odd] one is Saturday. Then I can still tell those two are me, because I went to the gym on Saturday and had a shower afterwards whereas Sarah was at work all day, so she's just had her morning shower.

Field worker: So is there something about the order of this as well?

John: You can tell who's got up first in the morning.

Field worker: So is that part of the routine?

Sarah: We sort of talk before going to bed who (looks at partner) ...

John: Yeah, because my job starts at different times, so our routine will change.

The 'obviousness' of 'whose shower is whose' is for participants plain to see in the sensor data. However, it is notable that it is not at all obvious to the field worker, nor we suspect to other external parties, as discriminating who the data is about turns upon local knowledge of showering activities and what constitutes 'the routine' in 'this' house, which is nowhere encoded in the sensor data. It may be tempting to see the

sensor data as surfacing and documenting the routine, e.g., in terms of a temporal order of showers, but this is misleading. The sensor data does not elaborate the routine but is rather accountable to it. Thus, we find that our participants are readily able to discriminate ‘whose shower is whose’ because they know who gets up first in the morning, how long they usually take to have a shower, and even what they do before getting into the shower. Some participants go straight from bed to shower, for example, whereas others first eat breakfast. It is the local activities and practices in which showering is embedded that constitute ‘the routine’, not the temporal order of showering itself (i.e., when showering occurs), and it is with reference to these local activities and practices that the data is held accountable. One participant continued with his routine of showering before his evening meal as he had done when serving in the Navy, for example, despite the fact that he retired from service over 40 years ago.

We find then in looking at the sensor data that in addition to discriminating who gets up and does what first, participants make the data accountable to routine features of everyday life such as eating an evening meal, going to the gym on Saturday, or going to work. Work was drawn on by many participants to reason about shower duration as this was constrained by time, the distance they had to travel on any particular occasion, and whether or not their partner had to satisfy similar demands. With regard to this latter point, it becomes visible that just when showering takes place and for just how long is a negotiated (and even contested) matter done with respect to other members of the home and their needs. It might thus be said that ‘the routine’ is also dynamic, a point underscored by Sarah and John who ‘talk before going to bed’ about use of the shower as Jon’s job routinely ‘starts at different times’. The dynamic and negotiated character of ‘the routine’ is further reflected in irregular temporal patterns of showering, which were made accountable in terms of part-time working, weekends, leisure activities, cleaning the bathroom, looking after the baby, or the grandchildren during school holidays. Showering is not only embedded in and accountable to an array of dynamic and negotiated local practices that constitute ‘the routine’ in ‘this’ house then; ‘the routine’ is also temporally variable and temporally distributed. This means that whatever constitutes ‘the routine’ in any home does not necessarily happen at the same time or even roughly the same time every day or every week. Indeed, as with looking after the grandchildren during school holidays, it may only happen a handful of times a year. Nevertheless, garnering insight into everyday life demonstrably turns on understanding ‘the routine’. Problematically, however, ‘the routine’ is *not* a property of sensor data *nor* is it elaborated by it. Indeed, the converse holds true: ‘the routine’ demonstrably elaborates sensor data.

### 3.2 Reasoning about product use

While the time series graphs clearly ‘tell’ us that something has happened—that the shower has been turned on or off, the head moved around, or that personal cleaning products have been removed from or returned to the scales—they do not ‘say’ *what* has been done. Discriminating this also requires the doing of data work as can be seen in the following extract where scale data is being examined.

Field worker: So does this relate to your usual routine?

Elaine: Yes, shampoo conditioner and shower gel, which I took off because I couldn’t reach for it all the time so I just put it back at the end.

Field worker: OK. Can you go into more detail about what exactly is going on in the time between the products coming off the shelf and ...

Elaine: So shampoo, you wash your hair, rinse it out, then conditioner. Conditioner is something that you have to keep in your hair for a longer time. So usually I put conditioner on and then do the rest of my shower routine. So something that uses shower gel, for example, or shaving or just, I brush my teeth in that time as well ...

Field worker: Cool.

Elaine: because its something that – hair conditioner, the longer you leave it, the longer it stays in, the nicer your hair is.

This extract makes it visible that while the smart shelf graph displays three products going on and off it, and that two items were taken off for a short time and a third for much longer, there is no way of telling by looking at the graph alone what the products are or what is being done with them. To understand that, we have to appeal to members’ personal showering practices, which again are nowhere documented in the data, and how they use particular products. When we do so, we find that product use is embedded in ‘shower routines’, such as leaving conditioner in while one gets on with other things in the bathroom. Showering routines are highly personal and individual. How and when one person uses shower gel, shampoo, or conditioner, for example, is different to how and when another uses them, if they use them at all (e.g., a balding participant only uses shower gel) and their use combines with other activities and products in the bathroom. As one participant described their showering routine, ‘I like do everything in the shower, I even brush my teeth in the shower!’ Nonetheless, and despite enormous variation in individual showering routines, participants often described an orderliness to product use (e.g., wash hair, add



conditioner and leave, wash body, do teeth, and remove conditioner), and this includes the orderly placement of products for ease of use during showering as Elaine describes for example above.

Product use is also and obviously tied to the use of showering equipment. However, the relationship between product and equipment is not visible in the data. It is not as simple as shower on, shampoo on, rinse, and shower off, for example. That the shower had been turned on and the shower head moved did not necessarily mean people had gotten into the shower and begun their ablutions. Participants might have to wait for the water to reach the desired temperature, and they often adjusted the shower head to suit their personal preference and the activities they were engaged in (e.g., washing their hair or not). By the same token, if the shower had been turned off, it did not necessarily mean that an individual had gotten out but, as part of their showering activity, they might be washing while saving water before turning the shower back on to rinse. Some of our participant's even 'potted about' outside the shower for several minutes (e.g., brushing their teeth while conditioning the hair) before getting back in to finish showering. It is also the case that the use of products was embedded in broader domestic routines. Participants with long hair, for example, only washed it on certain days of the week when they had time to treat it properly. Thus, discriminating what has been done during showering turns on understanding personal showering practices and shower routines, implicating the highly individualised and orderly uses of products and their in-use relationship to bathroom equipment and the broader round of domestic routines that enable participants to discriminate who the data is about in the first place.

### 3.3 Reasoning about water use

Particular showering routines and the broader domestic routines in which they are embedded were also invoked to account for water use and to reason about *why* the data had the shape that it has, which was often quite 'surprising' to participants at first glance.

Helen: It surprised me how many litres ...

Tom: Yeah you don't want to see litres do you.

Helen: I mean 300 litres of water (pointing at the Tuesday on the screen).

Tom: Shhh, don't say it out loud!

Field worker: That is a lot considering ...

Helen: I took a shower for two today didn't I?

Tom: 21 minutes. I mean, I don't think it's a lot necessarily – I think it's in line, isn't it? (Pointing to his partner's other showers on the shower overview).

Tom: I mean (points at Friday) 18 minutes is 269 litres, 21 minutes is 299. Its in line, its just a bit longer that's all.

Despite the initial reaction to how much water was used in the course of showering, as Tom makes perspicuous, water use was quickly made accountable to the norm, that is, the local norm, the norm for you or me 'in this house', not some general norm (e.g., 45 l for a 5 min shower in the UK). Our participants rendered what at first appeared to be 'a lot' of water into an amount that is 'in line' with normal usage by comparing particular instances of showering with one another. Nonetheless, anomalies, such as taking a noticeably longer or shorter shower, became accountable matters that prompted explanation (e.g., having a stressful day or being in a rush).

In articulating the reasons for their data's appearance, our participants also invoked the weather as a determining factor in their choice of temperature on any occasion of showering. If the weather was warm, which at the time of the study it was, the shower temperature was generally cooler than it would be in winter. Water use was also accounted for by one participant in terms of environmental considerations and what they perceived as a moral responsibility to reduce water consumption. Our other participants were also concerned with reducing the amount of water they used. However, for them, it was on the grounds of cost. As noted above, out of the 6 households participating in the study, 5 had water meters and pay for the amount of water they use. Most were concerned to manage their water consumption then, and one even went so far as to 'gamify' showering with her friends, using an egg timer to keep her showers under 4 min. So seasonal variations in temperature and moral and economic concerns all shape the data and are built into 'the routine', though again these matters are *absent* from the sensor data.

### 3.4 Reasoning about domestic infrastructure

One final issue was frequently invoked to account for *how* the data comes to have the shape that it has. When discussing the graphs, household members would bring to account various physical features of their showers. One of the first topics that came into question was the amount of pressure their shower produces and its impact on the water flow graph.

Paul: I would like more pressure but unfortunately we can't achieve that.

Field worker: Is that down to the boiler?

Paul: No, its down to the builders of the house putting in 15 millimetre pipe and not 22 millimetre pipe.

While some participants revealed that their shower systems were quite powerful and required adjustment to a comfortable setting, others, like Paul, revealed that theirs did not go any

more powerful than the reading displayed. Readings were defined by the limits of what pressure could be provided as opposed to any preference these particular users may have had. Graph readings were also recognised as being impacted by other systems in the house that used water, an example being a dip in the graph line which was recognised as the toilet being flushed, as opposed to the sink or washing machine being used. It thus became apparent that the domestic infrastructure connected to the water supply underpinned participants' accounts of the water flow graphs and their features.

This was also the case for the temperature graphs, where the time it took for the water to warm up on just this occasion that the graph displayed turned upon knowledge of their heating system. The efficiency of the boiler was frequently invoked to explain the shape of the curvature on the graph. Understanding routine adjustments to the boiler itself was also brought into account as a feature of temperature management, where, for some households, this provided the most effective means of making the shower hotter or cooler. Other infrastructural features that our cohort stressed as important was understanding what temperature the water was going to be at when it initially comes out of the shower head. They revealed to us that temperature readings were bound to routine temperature adjustment and caution was exercised if, for example, a central heating system was known to make the temperature of the water in the pipes initially warm but was subsequently followed by cold water. In other cases, whether a member had gone in the shower just before them was seen as a feature of the graph in that the pipes, on these occasions, had already been warmed up. Knowing how the domestic infrastructure affected the temperature of the water was key to understanding the graphs. Even the energy efficiency of the house was called on to account for temperature settings. Thus, in houses deemed 'cold' by participants, hot showers were routinely had 'to warm up'. Again, *none* of this 'insight' is to be found in or is provided by the sensor data.

### 3.5 Responding to the service scenarios

Having reflected on their shower data, our participants were also asked to consider the three future scenarios that might motivate consumer adoption of connected shower services. One of these focused on the local use of sensor data to enable shower scheduling. The other two focused on transacting data with external parties in exchange for services that on the one hand enabled differential charging based on water consumption rates to promote water conservation and on the other provided personalised product offers. The scheduling service was dismissed as irrelevant by all of our participants. Not only did participants know and work around each other's showering patterns, there was also the sense, as one participant put it, that scheduling showers 'seems

sort of controlling, a bit military' and thus inappropriate to the mundane order of showering in domestic life. Differential charging received a more mixed reception. Some participants thought such a service might be useful if they received a default reduction in charges for installing a connected shower regardless of the amount of water used, whereas others were concerned that water companies might exploit their data to make more money through 'time of day' charging. The product offer scenario was similarly received. While participants could see that product offers might 'save you money', a core part of the underlying service model was seen as unviable.

Field worker: They sell you something as a service, so you have shampoo as a service, it's a bit like having a milkman right? He comes around once a week when he knows your running low or whenever, drops the bottles off. You get the same sort of thing with your bathroom products.

Stuart: That will never work.

Field worker: Why do you reckon it wouldn't work?

Stuart: I didn't work for the milkman.

Participants were also wary that such personalised services might impact personal autonomy and freedom of choice, with product manufacturers leveraging the data to exercise 'control' over consumer purchasing behaviour.

Cutting across these considerations was common concern about transacting personal data in the first place, regardless of the service being offered. Participants were concerned about their showering activities being 'readable all the time', both locally by fellow household members, and the consequences this might have in making what goes in the bathroom accountable to others (a general concern that attaches to data sharing as highlighted by Tolmie et al. [54] and Tolmie and Crabtree [53]) and with respect to the consequences of making the data available to external parties. Participants were particularly concerned that their data would be open to reinterpretation by external parties and that it could have horizons of use that may be incongruent with their own. One participant suggested, for example, that governmental agencies could garner insight into how many people lived in a property by way of seeing how many showers were had each day. Participants were also concerned that their shower data might be combined with other data, e.g., from supermarket loyalty cards or other smart home systems, and be used to profile their homes and target them in some way. One participant invoked her Hive thermostat by way of example and how after installing it she started to receive emails comparing the heating of her house to other houses on her street.

Elaine: That was eye opener, because I thought it was just a thermostat that I was going to control but you get all this guff about your neighbours that are also using Hive and that your house is one degree hotter than theirs!

Participants were concerned by the ‘lack of control’ over what is done with their data by external parties and also the potential for the data to be ‘leaked’ or ‘hacked’. As one participant put it, ‘the more information you put out there, the more information can get away.’ Overall, considerable risks were attached to transacting data in exchange for personalised services, which speaks to the broader need to build transparency and control into autonomous consumer-oriented IoT services if they are to be widely adopted [36].

## 4 Contextualising sensor data

A key plank of this paper is that it is also necessary to build context into autonomous consumer-oriented IoT services if they deliver the ‘insight’ needed to drive the delivery of personalised services. Our findings make it perspicuous that far from elaborating the context of showering, the data from connected devices needs to *be contextualised* in order to discriminate or elaborate the meaning of the data and understand user activity. It is not sufficient to know when showering occurred then, or how much water was consumed, or what products were used during showering. If the meaning of these temporal patterns is to be discriminated and personal insight garnered, then it is also necessary to understand who produced them and the social and material circumstances of their production, which might otherwise be glossed as the what, the why, and the how of the matter. Given the inherent ‘indexicality’ of sensor data to the social and material circumstances of its production [17], there is need, as Tolmie et al. [54] point out, to build articulation mechanisms into sensing-based systems to enable people to make the data accountable to the local order and thus render the data meaningful and ‘insightful’. It is hard to see how autonomous consumer-oriented IoT services can be ‘context-aware’ if they have no sense of the different orders of practical reasoning that enable the meaning of sensor data to be discriminated and elaborated. Yet these stand *outside* of the data, hence the need for articulation. In articulating the who, the what, the why, and the how of the data’s social and material production—in making it an accountable feature of everyday life ‘here’ in ‘this’ house, for example—the parties to its articulation contextualise the data and make it possible to discriminate or elaborate the meaning of the user’s activity.

We achieved the articulation and thus contextualised the data through ‘interviewing’, which is a gloss on the situated and occasioned doing of data work in this instance. ‘We’ is an

important qualifier; it refers to the field worker *and* the participants, to the collaborative, interactional doing of data work. Now we are not suggesting that autonomous consumer-oriented IoT services should be predicated on doing ‘interviews’ with consumers. As Tolmie et al. (*ibid.*) note,

no one is going to want to account for every moment of their day ... the design challenge ... is not one of enabling all sensor data to be articulated but of figuring out **just what** needs to be accounted for in building and using networked sensing systems and the services that will be delivered through them.

Nonetheless, we are suggesting that much might be learnt by understanding context as an interactional achievement, rather than as a container. While we could imagine a future in which more and more sensing is built into the environment (e.g., via smart products [9]) and married to data from other devices (e.g., location from smart phones) in a bid to further contextualise connected shower data, this will still result in a situation where the data produced is but a trace of what was done that is inevitably indexical to the social and material circumstances of its production. It would appear, then, that it is necessary to provide *articulation mechanisms* that enable the users of autonomous consumer-oriented IoT services to contextualise sensor data. It is towards consideration of what might be involved in enabling this that we turn next.

### 4.1 The interactional accomplishment of context

As noted above, we articulated and contextualised the sensor data from the connected shower in interacting with participants through interview. Understanding how the interview works is central then to understanding how context is interactionally accomplished. Interviewing is the most common means of engaging with people in systems research and understanding their viewpoints and experiences; it also dominates social science inquiries. In either case, interviews are typically treated as a resource reflecting interviewees’ viewpoints on topics of interest to the interviewer. This often leads to methodological considerations that put the interviewer at the centre of a research practice that provides for the ‘proper conduct of interviews in compliance with a set of pre-formulated “correct principles”’ [28]. However, in elaborating the interactional accomplishment of context, we set such methodological considerations aside and instead focus on the interview as the joint accomplishment of interviewer and respondents.

As Suchman and Jordan [52] note, the interview is essentially an interactional event, which means that respondents’ accounts cannot simply be read as ‘reality reports’ [29]. Rather, the accounts provided by respondents to contextualise the sensor data are a product of situated interaction between

them and the interviewer (the field worker in our case). This does not mean that there is no reality to what our participants told us about showering in order to make the data meaningful and discriminate user activity. It is to say that the reality reports furnished by our inquiries into the connected shower are collaborative products of the interactional work between participants and field worker. This interactional work was not accomplished by conducting, or trying to conduct, the interviews in compliance with a set of pre-formulated ‘correct principles’. This is not because we eschew correct principles on analytic grounds but rather, as Rapley [44] emphasizes, because whatever analytic stance is adopted, one ‘cannot escape’ the interactional nature of interviews, which inevitably turns on methods that people employ ‘in doing everyday life’ [8]. These methods are not to be found in social science textbooks on interviewing. They are members’ methods [23] drawn on and used locally to *order* the actual conduct of the interview, and they enable the sensor data to be contextualised.

At its most basic, it might be said that these methods consist of asking and answering questions. As Rapley [44] nonetheless points out, there is a mundane ‘art’ to the matter, one that turns on ‘vernacular competencies’ [35]. In the first instance, questions are *recipient designed* [52], which is to say that they are sensitive in their construction to the history of the current interactional event and seek to accommodate the particular respondents involved in the interview. Take the following extract of talk, by way of example.

Field worker: So, you’ve already started looking at this overview ...

John: Yeah a little bit.

Field worker: what makes sense to you in looking at this initially?

John: It’s quite obvious whose shower is whose, because mine is about the third of the time of yours (looks at partner) if not a quarter.

Field worker: So you can begin to tell whose is whose here?

John: Easy.

Sarah: Yes, easy.

Field worker: How can you do that?

Sarah: My time.

John: Because Sarah takes longer. The only [odd] one is Saturday. Then I can still tell those two are me, because I went to the gym on Saturday and had a shower afterwards whereas Sarah was at work all day, so she’s just had her morning shower.

The questioning of the respondents is not done in a general manner then; the respondents are not asked if they can take a look at the data and make sense of it, for example. Rather, the question is sensitive to the local history of the interview and

the actions that have already occurred (e.g., that the respondents have ‘already started looking at this overview’) and seeks to accommodate their particular views on the data (‘what makes sense to you in looking at this initially?’).

The example makes a second ubiquitous feature of open-ended or semi-open-ended interviews perspicuous, namely that the questioning turns upon *formulation work* [24], which is to say that the parties to the interview draw on scenic features of the interview to formulate questions and responses. Thus, the field worker draws on the respondents’ ‘looking at this overview’ to formulate the question ‘what makes sense in looking at this initially?’, and the respondents draw on the formulated question and the overview to formulate the response that ‘it’s quite obvious whose shower is whose ...’. As Hester and Francis [28] point out, formulating work is manifested in two basic types in the course of open-ended or semi-open-ended interviews: pre-formulations and post-formulations. Pre-formulations are prospective in nature and thus preface the elaboration of upcoming detail; they formulate what upcoming details will amount to (e.g., ‘so you can begin to tell whose is whose here?’). Post-formulations are retrospective in nature and they clarify and/or elaborate what has been said (e.g., ‘it’s quite obvious because mine is about the third of the time of yours ... Sarah takes longer ... those two are me ...’).

A third distinctive feature of interviewing and constitutive feature of formulating work is that it is done through asking and answering different *types* of question [44]. The field worker’s question ‘what makes sense in looking at this initially?’ is a topic-initiating type of question, introducing a topic of talk (e.g., what in the data makes sense to you?). The subsequent questions asked by the field worker in the above extract—‘so you can begin to tell whose is whose here?’ and ‘how can you do that?’—are follow-up questions. Follow-up questions are contingent on some part of a respondent’s answer to topic-initiating questions, in this case, on John and Sarah finding it ‘quite obvious’ and ‘easy’ to tell whose shower is whose. Follow-up questions are not preconfigured or scripted but formulated in reaction to the here-and-now talk. They seek to unpack and elaborate ‘mentionables’ (such as it being quite obvious and easy to tell whose shower is whose). As Rapley (*ibid.*) puts it,

This combination of producing a topic-initiating question and following up the interviewee’s answer with a follow-up question is **the** central way in which (semi-)open-ended interviews come off. The methodological rationale of (semi-)open-ended interviews – that they allow a rich, deep and textured picture – is locally produced in and through the ‘simple’ method of producing topic-initiating and follow-up questions. [The] large numbers of ‘mentionables’ produced through this method then become **resources** for the research project.



Thus, we find, for example, that the connected shower data is contextualised in local details of household routines, individual showering routines, seasonal variations, moral and economic considerations, and domestic infrastructure.

The ‘topic-contingent ordering’ of the interview, achieved through recipient-designed formulating work and the ‘simple’ method of asking and answering topic-initiating and follow-up questions, is also complemented by what Hester and Francis [28] call an ‘assemblage-contingent ordering’. This is to say that the parties to the interview (the field worker and the participants) are not just talking. Their talk is oriented to and about ‘case materials’—i.e., the sensor data graphs—which constitute the *focus* of the interview. The ‘case materials’ are assembled on a laptop that is situated on table in front of the interviewer and interviewees, and it is and through their interaction with these materials that the questioning is organised and topics emerge for consideration. Importantly, as the moniker indicates the topicalising is not only contingent on participant’s responses to topic-initiating questions but on the material assembled for consideration. As Hester and Francis (*ibid.*) put it, ‘the accountable features of the particular case material under consideration establish a topical theme for selection and discussion’. Take the following extract by way of example.

Fieldworker: So I mean, the times that they [the showers] start [points at overview graph], does that say something about work routines as well?

Jane: Well we’re retired, so we don’t work.

Fieldworker: OK.

Jane: So (laughs) it’s not like, the crack of dawn, get up and have a shower. We tend to potter around a bit before, water the plants, have a coffee, that sort of thing and then go into the shower.

Phil: We don’t have much of a routine, well not at the moment.

Jane: It’s school holidays. We normally do childcare. One of the parents is a teacher, so he’s off looking after his children. So we’re not, we haven’t got a routine have we?

Phil: No.

Jane: But when its not school holidays we take care of the children first thing in the morning, so there is more of a routine then isn’t there?

Phil: Yes, yes, yeah.

Jane: But now its holiday time.

Fieldworker: I see.

In this, we can see that the accountable features of the overview graph are not to do with work but other mentionables—‘pottering around’, ‘watering the plants’, ‘having a coffee before showering’, ‘that sort of thing’. And we can see that the topicalising is ‘assemblage-contingent’,

i.e., contingent on what the parties to the interview *can* say about the material to hand, which in turn provides for the selection of relevant topics that contextualise a temporal order of showering that is not ‘normal’ but occasioned by their grandchildren being on ‘school holidays’. Thus, the assemblage-contingent ordering of the interview *transforms* the interview from a ‘simple’ topic-contingent interactional event into an event occupied with the local repair and elaboration of the indexical nature of sensor data representations through the collaborative doing of data work. There is, then, an incarnate or ‘endogenous’ reflexivity [40] to the doing of data work that provides as a matter of method for the contextualisation of sensor data through the *assemblage-and-topic-contingent* asking and answering of questions. To borrow again from Hester and Francis, it might otherwise be said that the sense the data has—it’s meaning and with it the discrimination of user activity—is produced in, and is inseparable from, the ‘ordering work’ which comprises the interview’s talk.

## 5 So what?

Why does it matter how the interview works? Why should designers care about the mundane art, ordinary methods, and vernacular competencies involved in asking and answering questions? What possible relevance is the ‘ordering work’ of the interview to the development of autonomous, consumer-oriented, IoT-based services? After all, it might be argued, it’s not as if these services are going to rely on this ordering work; it is just an artefact of a micro study incidental to large-scale technical implementations. However, as noted in introducing this paper, it is broadly recognised by the developers of IoT-based services that data from sensor-based devices is *meaningless* and must be *contextualised* if ‘insight’ is to be garnered into consumer behaviours and leveraged to deliver personalised services. Context cannot be had from adding more environmental information as that information is also *indexical* to the social and material circumstances of its production, which are demonstrably drawn upon in interaction to contextualise the data. So, there has to be some means and some mechanisms, whereby infinite regress can be terminated and context be *articulated*. Tolmie et al. [54] were the first to elaborate the necessity of articulation to the contextualisation of sensor data. Their study of the deployment of wireless sensing devices monitoring electricity use, temperature, humidity, light, and motion in the home revealed that fine-grain understandings of human activity cannot be simply be read off sensor data. Rather it takes work to make the data intelligible and to make it ‘speak about’ human activities and practices. Tolmie et al. showed that this work demonstrably implicates various orders of practical reasoning implicated in the local ordering of domestic activities, reasoning that makes

the data generated by sensors accountable. Furthermore, as Tolmie et al. underscore, the work of making sensor data accountable, of articulating what it is about, ‘is a methodological matter’ that turns upon the occasioned, mutually constitutive, recipient-designed construction of accounts that elaborate the local social and moral ordering of domestic life.

Fischer et al. further elaborate methodological ways in which sensor data is articulated and contextualised in the doing of ‘data work’. Their studies of the deployment of wireless sensing devices monitoring electricity use, indoor and outdoor temperature, humidity, light, and CO<sub>2</sub> to support the delivery of energy advice to households afflicted by fuel poverty elaborate the indexical and opaque relationship of sensor data to the social and material circumstances of its production and a range of ‘members’ methods’ for introducing and situating IoT devices in the home and subsequently unpacking the data’s indexicality to enable situated action (e.g., the giving of situationally appropriate advice) [17]. Reflecting on the general insights furnished by their studies, Fischer et al. [18] note,

The essential indexicality of sensor data occasions the need to build people whose behaviour is sensed into the loop, at least insofar as systems are designed to respond to their conduct. System-supported dialogues might enable this ... There is a need then to actively involve data producers in a dialogue a) to understand the action that generates data and the reasoning implicated in it, and b) where remedial actions are required, to formulate viable alternatives.

The connected shower complements and extends our understanding of the mundane methodologies involved in contextualising sensor data. In this respect, the unique contribution of this paper lies in the elaboration of the ‘ordering work’ of interviewing. This not only provides for the situated accomplishment of data work and discrimination of user activity. It also provides a resource for the design of autonomous consumer-oriented IoT services, providing further insight and instruction into *how* ‘system-supported dialogues’ can enable the contextualisation of sensor data and deliver on the promise of bespoke ‘living’ services.

The *how* of the matter becomes particularly relevant if we consider an imminent future in which human agents are replaced by computational agents, as autonomous systems inevitably envisage [31]. So understanding how the interview works and data work gets done tells us something about what autonomous services that rely on sensor data will need to do to enable contextualisation at scale. While industry analysts posit the need to build machine learning and artificial intelligence into IoT-based services ‘if we’re to have any chance of making sense of the data’ [5], the suggestion here is that such efforts need to be complemented by the design of articulation

mechanisms engaging users in system dialogues that enable data work and reflexively contextualise the data. In addition to the findings of Tolmie et al. and Fischer et al., the ordering work of interviews makes it perspicuous that system dialogues will need to focus user attention on specific assemblages of ‘case materials’, i.e., data that is relevant to delivering a particular personalised service, and support the recipient-designed pre- and post-formulation work that enables the simple topic initiation and follow-up method of contextualisation to produce the ‘insight’ needed to drive the delivery of personalised services. What we are proposing is not as radical as it at might at first sound. The emergence of consumer-oriented connected devices that exploit machine learning (e.g., the latest generation of smart cameras) rely on *user input* to train the underlying algorithms. The same principle might apply more generally; however, it requires a fundamental shift in how context is understood in the design of autonomous consumer-oriented IoT services, not only in a general sense (in which case see Dourish [15]) but also with specific regard to the mundane methodologies that actually enable sensor data to be contextualised *in* interaction. These methods might be embedded in dedicated apps that accompany and enable autonomous consumer-oriented IoT services.<sup>1</sup>

## 6 Conclusion

This paper presents findings from the deployment of a technology probe—the connected shower—and implications for the development of ‘living services’ or autonomous consumer-oriented IoT services that exploit sensing to gain consumer ‘insight’ and drive personalised service innovation. It makes two contributions, one to the design literature on sustainability and understanding the potential of consumer-oriented IoT services to impact water use and the other to the design literature on context and understanding how this might be enabled in sensing-based services. With respect to sustainability, users of the connected shower were sceptical about service propositions trading on their shower data. A proposed shower scheduling service was deemed irrelevant to domestic life. Service propositions that proposed to leverage connected shower data to enable differential charging to promote water conservation and to provide personalised product offers received a mixed reception. While the participants in

<sup>1</sup> It is important to note that there is more to data contextualisation than our account of the ordering work of the interview makes perspicuous; there is as Ryle [47] reminds us ‘no top step on the stairway of accomplishment levels’, which means that any description of action and interaction may be indefinitely extended [48]. Of particular note, we could also take account of the workings of the ‘turn-taking machinery’ [49] and how it orders the interviews’ talk. This would be a substantial study in its own right and so is out of scope here, but understanding the workings of the turn-taking machinery is an area of particular relevance to the design of autonomous services that exploit conversational agents (see Porcheron et al. [41], for example).

our study could see the potential economic benefits of the connected shower in terms of saving money on water and personal cleaning products, these were tempered by the potential impact of their showering activities being ‘readable all the time’ rendering what goes on in the bathroom constantly accountable to fellow household members and by broad concern with the transaction of personal data. Our participants were concerned about what water companies might do with their data and that it would be open to reinterpretation and reuse in ways that were incongruent with their wishes. They suspected that water companies and/or product manufacturers might use their data to steer their patterns of shower use and product consumption or that they might use it to charge them higher tariffs. Broad concern with the lack of transparency and control over data use was also accompanied by concern with data security, all of which raise significant barriers to the widespread adoption of autonomous consumer-oriented IoT services [36].

One potential way to increase the benefits for householders is to design smart shower systems that fit in with their everyday practices. Previous sustainability research has placed emphasis on resource management [e.g., 16, 20]. However, as Strengers [50] points out, this framing can be problematic as it views householders as ‘rational’ actors that actively weigh up the costs of water use on each and every occasion. Household members are of course rational actors, but not in the narrow terms construed by resource management. Rather, resource management is embedded in and made accountable to everyday life and the situated and occasioned needs of individuals (e.g. the need to feel clean, relax, and wash my hair today because I’m going out). It is important, then, to understand the everyday actions and interactions in which water use is embedded and, as Strengers (*ibid.*) puts it, to ‘design devices to support them.’ Thus, if a smart shower is to incentivise the conservation of water, design needs to take seriously the mundane events that shape showering to enable IoT-based services that fit in with and support local practice. Perhaps a starting point could be for a smart shower to learn the types of showers that household members prefer (e.g., a quick shower in the morning, a longer relaxing shower in the evening). This information could be used in demand-side management systems that seek to balance load across the water network and to reward behaviour in accordance with the user’s learned routines or other personal preferences relating to temperature or water flow in order to achieve more sustainable water management.

However, as our study makes perspicuous, the problem here is that the ‘insight’ needed to personalise the smart shower is *not* furnished by sensor data. Rather, it sits *outside* the data. The general assumption that consumer-oriented services built on the back of the IoT are ‘contextually aware’ and that sensing-based systems can discriminate or elaborate the meaning of user activity does not hold. On the contrary, as we have

seen, sensor data requires contextualisation. As Reeves et al. [46] note, the ‘ubiquitous’ vision that underpins the IoT has been mapped to practical engineering challenges to design and build context-aware systems that record, model, and represent environmental information with ever-increasing sophistication. Yet, despite of decades of work, this container view, which treats context as something that effectively surrounds human activity, has largely failed to bear fruit ‘due to the mismatch between a sensor-derived technical representation of a context, and the social perception of a context (*ibid.*).’ More acutely, our study makes it visible that what sensor-derived representations lack is any sense of the social and material circumstances of their production. Absent is any sense of the local household routines, individual showering routines, seasonal variations, moral and economic considerations, and impact of domestic infrastructure on the temporal patterns of showering and water consumption detected by the sensors. Yet it is this that enables user activity to be discriminated and elaborated.

If autonomous consumer-oriented IoT services are to furnish the ‘insight’ needed to deliver personalised services, there is need for a fundamental shift in how context is understood by IoT developers and to complement machine learning and AI sense-making techniques with articulation mechanisms enabling users to contextualise sensor data. In this respect, our study directs attention to the ordering work of the exit interview and the methodological ways in which sensor data is contextualised in the situated doing of data work. This in turn makes it perspicuous that system dialogues are needed to enable contextualisation at scale. These dialogues will need to focus user attention on specific assemblages of ‘case materials’, i.e., data that is relevant to delivering a particular personalised service, and support the recipient-designed pre- and post-formulation work that enables the simple topic initiation and follow-up method of contextualisation to discriminate and elaborate the meaning of user activity. It might be argued that our concern with context is all old news; Dourish [15] told us all about it a long time ago. However, we are not simply dusting down an old topic. Rather we have sought to move beyond general arguments to elaborate something of what the interactional accomplishment of context turns upon and how it might be relevant to the design of a new wave of autonomous consumer-oriented IoT services that seek to garner ‘insight’ into consumer behaviour and leverage it to deliver highly personalised offerings.

The approach outlined here ... takes the mundane details of lived experience as the basis for understanding context ... . . . . Looking at everyday action ... pays off in two ways. Firstly, it brings to our attention a set of problems about the ways in which context is conceived of in current design practice. Secondly, it provides us with a potential solution by furnishing us with the means

to understand where our attention might instead be directed. Paul Dourish (ibid.)

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**Data availability** Data supporting this publication is not openly available as our ethics approval does not allow for the release of transcripts to third parties.

## Compliance with ethical standards

The research reported in this paper was conducted in accordance with the University of Nottingham's ethics procedures: <https://www.nottingham.ac.uk/research/ethics-and-integrity/>

**Conflict of interest** The authors declare that they have no conflict of interest.

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