Data-Enhanced Design: Engaging designers in exploratory sensemaking with multimodal data

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Relevance to Design: Working with data is increasingly important for designers. We articulate a design process that works between ethnography, data analysis and sensemaking and design insight that points to a fluid, exploratory practice for designers engaging with complex data.

Abstract

Research in the wild can reveal human behaviours, contexts, and needs around products that are difficult to observe in the lab. Telemetry data from the use of physical products can help facilitate in the wild research, in particular by suggesting hypotheses that can be explored through machine learning models. This paper explores ways for designers without strong data skills to engage with multimodal data to develop a contextual understanding of product use. This study is framed around a lightweight version of a data enhanced design research process where multimodal telemetry data was captured by a GoPro camera attached to a bicycle. This was combined with the video data and conversation with the rider to carry out an exploratory sensemaking process and generate design research questions that could potentially be addressed through data capture, annotation and machine learning. We identify a range of ways that designers could make use of the data for ideation and developing context through annotating and exploring the data. Participants used data and annotation practices to connect the micro and macro, spot interesting moments, and frame questions around an unfamiliar problem. The work follows the designers' questions, methods, and explorations, both immediate concerns and speculations about working at larger scales with machine learning models. This points to the possibility of tools that help designers to engage with machine learning, not just for optimisation and refinement, but for creative ideation in the early stage of design processes.

1. Introduction

One of the challenges of carrying out design research is getting right into the moment where interesting things happen. There is a constant tension between disrupting what is happening and getting good insight. One way through this is to instrument objects so that they create telemetry data (Gorkovenko et al., 2019) to support contextual enquiry – this creates a picture of what has happened that can guide researchers to interesting insights. These kinds of in the wild research methods are particularly valuable for design because they capture behaviours that may not be observed

in lab studies. Research suggests that sensor data from physical products use can be used in a similar way to analytics in *data driven product design* (Gorkovenko et al., 2020) or *data-enabled design* (van Kollenburg and Bogers, 2019), where data from product use in the wild can inform design cycles.

The connection between data, activity and the design of artefacts is particularly interesting given the possibilities around machine learning to create models that can scale up the amount of time and activity that can be engaged with. In fields such as learning analytics, the potential of machine learning to process data and expand the gaze of learning practitioners has been developed over the last decade (e.g. Gasevic et al., 2014); mining that activity patterns around collaboration

can help to design better ways to work together (Martinez-Maldonado et al., 2019) and so on. Beyond optimisation, however, there is the possibility to bring data into the 'fuzzy front end' of design (Sanders and Stappers, 2008) – the part of the design process where the nature and scope of what is being designed is still being determined. The adoption of data enabled practices – especially around Research through Design (RtD) methodologies – can change the nature of the relations between designer and end user, with more opportunities for co-creation throughout the design and deployment processes (Giaccardi, 2019). Having a closed loop between activity and function gives more agency to the things under design, and allows for continual feedback around user needs.

Early stage product design – the fuzzy front end – poses a different set of questions to optimising well understood situations. Here, the objects and behaviours of interest are less well defined, emerging in concert with the development of product identity and capabilities (Frauenberger, 2020). Modern design practices around co-design see roles shift between designers, researchers and users (Sanders and Stappers, 2008), as we move towards spaces where end users are collectively dreaming their designs (Sanders and Stappers, 2014) and objects redesign themselves by the data the relate to (Speed and Oberlander, 2016). Practically, digitally oriented design team may contain a range of roles – HCI researchers, user researchers, service designers, industrial designers, UX designers, service designers, machine learning experts – all of whom might have a unique understanding of the data coming in, and of the context in which usage is happening. Key questions remain in how data may be used to understand human behaviour and generate design insight, with an appropriate level of trust, confidence and criticality.

There is a rich world of data use within and beyond the design process, across from the direct functioning of products and the creation of data-driven product ecosystems out to broad contextual understanding of human behaviour. In this study, we are concerned with design researchers who want to engage with data with minimal support, in a fast and lightweight manner. As such, we are interested in the strategies and relationships that designers develop when provided with the data traces that can be quickly and economically extracted from an arbitrary physical object. We are interested in findings that can support the creation of tools for designerly investigation based on multimodal data, and in particular the possibilities it gives them for thinking both about product function and the wider relations between users, products and society.

This paper primarily covers the ways designers think about the possibilities of data, and how they approach a first engagement with the possibilities of a data enabled design process. However, it is oriented towards thinking about the opportunities for engagement with machine learning and related techniques. Designing with AI and machine learning systems can be complex, demanding multiple literacies and practices, with uncertainty around capabilities and outputs (Yang et al., 2020). Indeed, uncertainty itself is a key feature to engage with when designing with machine learning (Benjamin et al., 2021) In the study, we use purposefully simple and easily obtainable data collection and analysis methods, in order to reduce 'wow effects', and encourage a pragmatic yet exploratory approach to working with the possibilities of machine learning. This goes in two directions: firstly, the camera used has a simple model of scene classification, which gives probabilistic outputs, giving a basis for discussing the use of uncertain outputs. Secondly, the discussion of making use of data was oriented towards questions of where creating a machine learning model of particular phenomena might play a part in a design process.

The study consists of one-on-one online data exploration and co-design sessions with 20 researchers, designers, developers and engineers. Participants were individually presented with a small set of telemetry data including acceleration, speed, GPS, and scene recognition collected from a GoPro camera. This was collected from a bicycle in use, and the analysis used a combination of the telemetry data, the captured video data, and the opportunity to ask questions of the rider. Through exploring the data, participants were asked to generate research questions, hypotheses and interpretations would build on machine learning analysis of data, and that could lead to improvement of existing products or ideas for new products or services.

1.1. Key Contributions

Through analysis of the collected material, this paper makes the following contributions:

- We provide an overview of the strategies and techniques that designers without particular expertise in data use when engaging with multimodal data, and show that **data can be used for ideation as well as optimisation**.
- We develop the idea of **trajectories of fluid investigation**, where designers move from one domain to another driven by observable features and hypotheses, relating quantitative data to human experience; we show multiple starting points and directions to these investigations, pointing to the need for flexible and lightweight tools.
- We show that **annotation is a key designerly practice for engaging with data** and the world, in order to bring in familiar practices, and to keep the **data for design exploration contextualised**.
- When engaging with the possibility of machine learning, we show that **simple analysis** can go a long way, as many questions raised can be answered with simple models, that **clustering and novelty** are ideas that designers can easily reach for, and that there is the possibility for a natural **engagement with uncertainty**.

It contributes a picture of the opportunities for telemetry data for early stage design research identified by researchers and designers and an indication of how this can connect with the use of machine learning for new forms of design practice.

2. Background

This paper is concerned with ways of supporting design research practice with data. The starting point is design ethnography (Salvador et al., 1999) – that is, the use of ethnographic practices that seek to understand human behaviour as an adjunct to the design process, producing knowledge that aids the refinement and re-conceptualisation of designs. To give context, we first outline the broad connections between digital data and design processes (Section 2.1), before unpacking the current state of the art in data driven design (DDD, Section 2.2). We then contextualise our work by mapping out related fields and concepts within design. There

are multiple ways in which data is entangled in the development of products and understanding the many relations between products and humans. While DDD is central to this work, we map out some related fields of practice to help differentiate and situate this work (Figure 1). These have been roughly placed on a spectrum according to how intimately they are part of a products functioning - for smart or data driven products, their operation is based on the streams of data coming in and out (Section 2.3); for more ethnographic practices, data of various kinds is used to understand either the relations between humans and products or wider social relations, whether or not the products actually make use of data (Figure 2.4). Finally, we touch on broader sensemaking and data annotation practices for working with multimodal data (Section 2.5).

2.1. Overview of Digital Data and Design

While design processes are typically entangled with data, whether checking assumptions, assessing function and quality or showing limitations and opportunities, the rise of digital data and data science practices talk about data in manner distinct from the qualitative, experiential, empirical work traditionally carried out by designers. Sensor data and telemetry captured during the operation of systems support 'in the wild' approaches (Chamberlain et al., 2012) to understand interactions outside the lab. Smart products, and more broadly human-data interaction paradigms (Mortier et al., 2014), alter the way that products and objects function, requiring designers to develop new ways as they create data-enabled artefacts – see the transition in Speed et. al's 'ablative framework' as the traditional approach of designing prodcuts *from* research data moves to designing *with* data as a design material (Speed and Oberlander, 2016). Designers have the potential to draw from the the torrents of 'big' data from sensor systems as well as the 'thick' data produced by ethnographic practices (Smets and Lievens, 2018; Storey, 2016).

Digital data has been deeply intertwined with the development of digital products and services: it is relatively easy to instrument software systems to collect a range of usage data, and the creators of those systems are generally fluent in digital technology. However, data can also be collected around physical products and systems, as we are

concerned with here. This requires both the addition of sensing hardware to the physical device, and often a change in culture for the system creators. There are many different ways to make use of digital data around physical products, ranging from being an active part of the product's function – a smart thermostat that responds to user presence, or a Segway balancing based on gyroscopic data streams – through practices that use data to directly change the design of systems, such as A/B testing or stress modelling, to ways of understanding the human and social contexts around the use of products. While this paper focuses on the more creative and exploratory end of data use, we briefly present some of the important practices around digital data use.

2.2. *Data Driven Design*

This project is situated within the area for Data Driven Design, or Data Enabled Design, where data is used as a resource various stages of a design process. This is a relatively new field, with the bulk of papers published from 2017 onwards (Bertoni, 2020), as technology makes the practices of data collection and analysis easier and more accessible. Despite a special issue dedicated to the topic (Kim et al., 2017), there remains a lack of precise specification of the term (Zheng et al., 2020). Briard et al. (2021) synthesise key issues here to frame challenges in DDD: there is a need for guidelines for how to carry out DDD; how to integrate data analysis into design practices; and in understanding what the particular strengths and weaknesses of DDD are. Bertoni (2020) highlights the uses of DDD in many stages of the design process, but in particular points out its use for concept development, where it can help to generate produce concepts, explore design spaces, and most identify customer needs. The emphasis on this last application implies a missed opportunity: where most applications have a single analyst look at social media and other existing data traces to identify latent customer needs, there is the possibility of using data as a more creative medium, to collaborative generate possibilities and explore the long tails of the design space (Gorkovenko et al., 2020).

In this vein, Kun et al. (2018a) build on techniques designed to improve data literacy to support Generative Data Explorations in order to stimulate the generation of new design ideas, often ideating through the process of exploring public datasets (Kun et al., 2019) or drawing on techniques from data science (Kun et al., 2018b). Seidelin et al. (2020a) explores the possibilities of co-design, where the agency of data helps shape collaborations.

Data Enabled Design (DED) extends to the use of data in co-design contexts, and to understanding the data collection process as a design activity in its own right (van Kollenburg and Bogers, 2019; Feinberg, 2017; Seidelin et al., 2020b). Bogers and Kollenburg work proposes a comprehensive data-enabled design methodology that follows a joined pair of loops: a design research loop turning insights into contexts, syntheses and explorations with data, and an everyday life loop that collects data, generates prototypes and adapts them remotely (Bogers et al., 2016; van Kollenburg and Bogers, 2019). Similarly Gorkovenko et al. (2020, 2019) look at carrying out design processes around data collected from objects in the wild, where the data is used both as a source for ideation and in support of further product development. Data is used as a support for contextual enquiry, following an *entangled ethnography* approach (Murray-Rust et al., 2019) to build up an understanding of rich contexts from both the human and thing perspectives (Giaccardi et al., 2016). This study extends these foundations, looking at what practices could emerge and what competencies would be at play within these kinds of entangled, data enabled design explorations.

2.3. *Data in product operation and design*

Here we look at the ways that data data relates to the functioning and immediate design of products, with varying level of connectedness.

Data Driven Products: At the most deeply connected end of the scale, designers have to work with increasingly data-driven products.As an example, the Hovding helmet (Abrahams, 2019) uses 2000 hours of collected data with 3000 staged accidents to determine whether a rider is in an accident or not; self-driving cars are built on analysis and use of large corpora of real world data (Tomei et al., 2019) to decide how to function (Edu et al., 2020). Strategies for designing these kinds of products are emerging (Wolff et al., 2018), through ways to prototype smart devices (Houben et al., 2016), relate
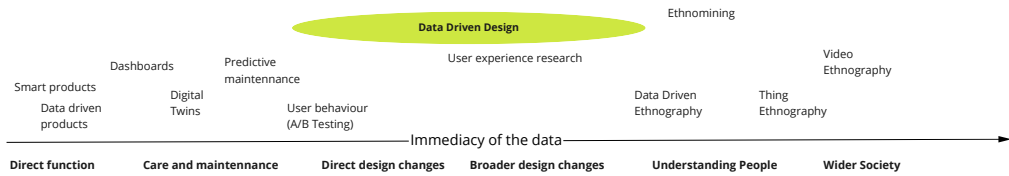
Figure 1. *A spectrum of related practices based on how closely the data in question is made use of by the objects of inquiry. At one end, smart products require data flows for their existence; in the middle, data is used to support the optimisation and creation of products, and towards the right, data is used as a window into user or societal relations.*

data to end users (Yarosh and Zave, 2017) develop context (Bogers et al., 2016) manage the transactional complexity of data interactions (Pschetz et al., 2017) and using data to effect behavioural change (Bourgeois et al., 2014).

Data Supported Operation: Data can also contribute indirectly to the operation of a product or service through predictive maintenance, as data collection is used to build a model of likely component failures. This has typically been applied to high-end systems such as aircraft engines (Austin et al., 2004), with increasing recognition of both the role of human data interaction (Daily and Peterson, 2017) and expansion to other fields such as medical devices (Sipos et al., 2014).

Digital twins: (Grieves, 2014; Grieves and Vickers, 2017) take the predictive models of failure and go further to include complete simulations of the physical object. These parallel simulations can help to understand and ameliorate complex behavioural events, but have also been gaining traction as a resource for design (Tao et al., 2019), and part of design frameworks that support production and manufacture (Tao et al., 2019). Alongside data driven products, digital twins can increase the level of provenance kept about the physical aspects of the objects as well as providing a resource for thinking about and redesigning them (Burnett et al., 2019).

A/B Testing: The use of quantitative data gathered from user engagement with products in the wild is seen in software design, where A/B testing (Kohavi et al., 2013) emerged through the development of web based platforms as a way to carry out experiments in support of design decisions. In 2015, LinkedIn ran 400 simultaneous experiments to determine which interface changes led to better engagement (Xu et al., 2015). The malleability of software products allows a rapid exploration of

design spaces (Kohavi et al., 2014), and builds the idea that small incremental changes can be better optimised through empirical data than designer insight (Kohavi et al., 2009). While effective, there are calls ensure that there are practices in place to avoid over-reliance on data, and ensure that it is not seen as the only source of knowledge (Liikkanen, 2017).

Telemetry Driven Design Processes: A/B testing approaches are often enabled by the collection of extensive user telemetry – for example, users' clicks on a website. This viewpoint opens up many possibilities for working with data, such as using clickstreams to create user personas (Zhang et al., 2016), optimising the design of interfaces (Lomas et al., 2016), or breaking down complex personalization based on the choices of many other users (Bahirat et al., 2018). More generally, it opens the possibility of *interaction mining* – looking for common patterns of interaction and flows in the traces of activity (Deka et al., 2016). In the gaming industry, it is possible to capture the trajectories of users' characters through a game-world, visualising common behaviours and moments of difficulty (Wallner et al., 2014) and developing analytics and clustering approaches to interrogating these datasets (Drachen and Schubert, 2013). Moving towards human experience, galvanic skin response (GSR) sensors and other biometrics can be used to give insight into people's gaming experience (Robinson et al., 2016), cognitive load (Nourbakhsh et al., 2017) or mobile app use (Yao et al., 2014).

2.4. Ethnographic practices with data

On the right hand side of Figure 1, methods shift from directly supporting the design and operation of products into supporting understanding of humans, their practices and relationships. While this may indirectly support product design and function, the immediate knowledge is about human experiences.

Data Driven Ethnography uses data for ethnographic practices to create understanding as well as the optimization oriented approaches above. Ethnomining looks at data as "co(a)gents to assist the researcher in deconstructing the phenomenon being studied" in "collaborative interpretation" interviews with participants (Anderson et al., 2009), using log traces as a viewpoint to understand human behaviour (Churchill, 2017). Particularly as humans move through connected systems, a multi-dimensional synthesis of various streams of data can "emphasize the assemblages that constitute our lives, interweaving digital, embodied, and internal experiences" (Haines, 2017). Working with computational techniques helps not just to scale up qualitative research, but also to build context for a range of inquiries (Evans, 2016).

Trace Data – the records left, consciously or unconsciously, as humans navigate digital worlds – are of particular interest in the ethnographic process (Dubois and Ford, 2015). Alongside traditional experience sample or diary studies, data that records traces of activity can provide a rich post-hoc viewpoint for uncovering participant experiences. Viewing visualisations of activity can help to trigger memory (Bhavnani et al., 2017), and *trace interviews* are a way to focus on individual actors as they navigate complex digital environments — for instance, using editing records to ask Wikipedia editors about their process in responding to unfolding events (Dubois and Ford, 2015). Sensory postcards (Droumeva, 2015) create snapshots of experiences, using mobile phone capture, but avoiding the narrative viewpoint of video.

Video Ethnography uses video capture as the main ethnographic material, rather than data traces. This is a powerful technique, as it can capture a wealth of contextual information which can then be very closely read. It helps to develop rich and detailed pictures of social situations, and has been used with cyclists (Pink et al., 2017; Spinney, 2011) and other forms of mobility (Tuncer et al.,

2020). While this is not data driven in the sense of telemetry or sensor data, it is still a digitally driven practice for gaining insight into human relations.

Thing Ethnography enlists *things* of various sorts into the ethnographic process. This can mean attaching sensors to the objects to experience their viewpoint (Giaccardi et al., 2016, 2020), even in extensive urban contexts (Chang et al., 2017). The same agential object, from an ethnographic viewpoint, can reveal human behaviours around data (Pschetz et al., 2017), but also human social practices (Tallyn et al., 2018). Bringing together data and a consideration for non-human things leads to an understanding of the constellations surrounding the creation and use of products (Coulton and Lindley, 2019), and an understanding of the entanglements throughout design and use (Murray-Rust et al., 2019).

2.5. Sensemaking and Annotation of data

As well as ethnographic practice, there is the more general question of how humans collaborate and make sense of data. Here, two general areas are of interest - sensemaking and annotation.

2.5.1. Sensemaking

The practices of inspecting data, engaging with its content and placing that data in relation to broader contexts (Koesten et al., 2021) is part of a vision that developing meaningful representations from data facilitates insights and intelligent action (Russell et al., 1993) whether individual or collective (Pirolli and Russell, 2011).

Within extended design practice, sensemaking goes beyond traditional engagement. Gaver et al.'s DataCatcher 2016 includes experiential capture and translation of data; Fischer et al. (2017) look at collaboratively carrying out the *data work* to make shared data accountable; and Romat et al. (2019) bring in annotation to articulate and explore hypotheses in a natural manner. These point to an array of approaches and viewpoints for designers to engage with data in their design process, from immediate use to contextual understanding, from monitoring the physical world to shaping the digital.

2.5.2. Multimodal Data Annotation

Moving from how humans make sense of data to including computational techniques, there has

been a constant hunger for *labelled* data, that supports the training of supervised models. The act of labelling datasets with human meaningful codes is a specific form of the more general process of *annotation*, where data is attached to other data through various linkages. This can be at the level of an entire design process – for example, Chandrasegaran (2016) looks at creating tools for creative ideation, using annotations on sketches as a window into the unfolding process. At a lower level, fields such as learning analytics make increasing use of video annotation (Evi-Colombo et al., 2020). Di Mitri (Di Mitri et al., 2019) introduces the Visual Inspection Tool (VIT) for learning analytics, working through the data collection process to processing and exploitation of the insights; they also reference several related tools that help users to annotate datastreams based on synchronised video streams for social signals (Wagner et al., 2013), time series (Kothe et al., 2018) or geographic data (Kothe et al., 2018). In linguistics, special purpose tools are becoming more common to make use of combined audio and video data (Cassidy and Schmidt, 2017). More recently, Rodrigues et. al's MotionNotes is designed to help users add annotations to video footage in order to augment educational and cultural content – for example adding performance notes to video capture dance performance (Rodrigues et al., 2022); Badam's FacetNotes gives ways to use annotation to explore connections in multimodal data such as complex information about flight status or geospatial crime statistics (Badam et al., 2022). All of these techniques help to add human understanding to the data that has been collected, but in general put less emphasis on techniques that support creative ideation around multimodal data streams.

Within the space set out in Figure 1, the study looks starts with data collection, both video and telemetry about the use of a non-smart product. It explores how, in the early stage of a design process, annotation and sensemaking around this data can be used for ideation and suggestions for improvement. We draw particularly from ideas in thing ethnography, looking at trace data collected around everyday practice, to investigate relations between the user and the product in support of open-ended re-design.

3. Method

To investigate how designers and researchers would approach utilising telemetry data within a design research process we collected video and telemetry data from a camera attache to a bicycle, visualized it, and placed the visualisations and videos on an online whiteboard. The data was used as a prompt with 20 designers and researchers who explored it in a series of one-on-one sessions. We were particularly interested in the types of research questions they generate, how they made sense of it, what value they saw in the data, and what further investigations they were able to come up with. The aim was not for the researchers and designers to analyse in depth the data they were presented, but instead to use it as a starting point in considering *what* and *how* they might be able to investigate with off the shelf data collection and visualisation tools, and speculate on the possibility of answering questions through machine learning.

The study was conducted during the height of the COVID 19 lockdown in the United Kingdom, and throughout we took great care to eliminate the need for in person work or exchange of physical materials. Ethics approval was sought and granted through our internal research panel before any data collection was conducted with participants.

3.1. Bicycle Data Collection

We chose a bicycle as the use case study for the research primarily due to the fit between the data that could be captured using off-the-shelf hardware, and a sense it would inspire questions around product usage. A GoPro Hero 8 camera was used to capture accelerometer, gyroscope, GPS, speed, ISO, orientation and audio levels, encoded in MP4 files alongside video footage. It also includes a probabilistic 'scene classification' tag that uses a model to classify the video feed with a probability of belonging to six classes: SNOW, URBAn, INDOor, WATR, VEGEtation, BEACh (see https://gopro.github.io/gpmf-parser/ for a full discussion of features available.) The dataset was generated by the lead researcher using a bicycle with the camera attached to the handlebars. This was felt to provide the participants with a rich source of contextual insight, with data that directly relates the performance of the product, such as its vibration and steering, while

including nascent machine learning labelling capabilities. The data collected was extracted and visualised using a GoPro Telemetry extractor available online (https://goprotelemetryextractor.com/free/) and displayed as line graphs and a map.

The lead researcher conducted two, nearly identical, 5-minute cycles through a park at noon and again at 7pm. During both cycles the researcher cycled on a paved road, a bike path, a mud track, and through grass. The setup was intended to provide participants with a range of data about activities and variations while also keeping the time frame short enough so that details are still visible within the data visualisations.

3.2. Recruitment

The focus of the research was in understanding the value of telemetry and video data for design research. We therefore aimed to include a diverse range of disciplines related to design, including product designers, HCI researchers, service designers, design researchers, ethnographers, and even those with software engineering backgrounds. All of these roles may use such data to generate knowledge and insight that might feed onto the design process within their day jobs.

A total of 20 participants were recruited through Twitter and relevant design-related LinkedIn groups, with snowball sampling and participant referrals (Table 1). All participants were reimbursed with a £20 Amazon gift voucher.

3.3. Procedure

The study was composed of a series of one-on-one remote online data exploration sessions with each session lasting 1hr 51 min on average with the longest session lasting 2hr 11 min. The study was conducted using a video conferencing tool and the online whiteboard Miro (https://miro.com/). The calls were recorded and transcribed.

All interviews were conducted by the lead researcher. Since the lead researcher was also the subject of the video and data collection, they were able to answer questions about their subjective experience relating to the data. For clarity, in the text, they will be referred to as 'subject' when in this role. The participants could ask the subject about the terrain and context that may not have been apparent from the video.

The overarching task of the participants was to speculate about design research questions (DRQs[1]) We were interested in understanding how participants went about formulating DRQs and speculating as to ways to answer them, as well as how they developed a critical perspective on the limits and possibilities of the dataset and the self-reported experiences of the researcher.

The data exploration tasks were held on a Miro board composed of 6 different frames arranged vertically:

1. introduction to the research aim of the study. They were asked to explore if they can develop design research investigations, which could be supported through telemetry data gathering. The data was used as an example of what could be collected in their own research.
2. training, introducing the participants to the functions of Miro.
3. details of the bike itself, including 6 images of the bike and its components, such as the front tyre, back tyre, GoPro mounting, chain, and a view of each side of the bike. Beside the images of the bike were 9 sticky notes on which to generate design research questions. These questions were intended as an initial brainstorming exercise.
4. the two videos from the day and evening cycles. After watching the videos and having a look at the types of data that is visualised each participant was asked to write two DRQs to investigate further. They were then told that we did not expect them to be able to answer their questions, instead they should aim to develop hypotheses around their process for answering them.
5. all of the telemetry data visualizations which were extracted from the MP4 files. The day and evening cycle runs were placed beside each other. Visualisations included: GPS map with speed and elevation; Acceleration data line graph; Gyroscope data line graph; Speed in m/s line graph; Scene classification line graph, including classifications of vegetation, indoor, urban, snow, water and beach; Image uniformity line graph; Audio levels line graph;

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[1]We use DRQs to refer to the participant generated questions recorded in the sessions, as distinct from the research questions that this paper as a whole engages with.

ID	Role/ Job Title	Age	Gender	Years of Experience	Based in
P1	Research Associate (HCI)	29	M	6	Germany
P2	PhD Student (HCI)	39	M	20	UK
P3	Research Associate (Design)	24	M	2	UK
P4	PhD Student (HCI)	30	M	6	Netherlands
P5	UX & Service Design	36	F	10	Switzerland
P6	Research Associate & Lecturer (Design)	29	M	4	UK
P7	PhD Student (HCI)	25	M	3-4	UK
P8	Interaction Designer	22	M	4	UK
P9	Creative Technologist	27	F	3.5	UK
P10	Design Researcher	22	M	4	UK
P11	Lecturer in Design	39	M	15	UK
P12	Lecturer in Design	41	F	-	UK
P13	Creative Technologist & Designer	31	M	13	UK
P14	Product Designer	32	M	5+	Ukraine
P15	Research Fellow (HCI)	36	M	-	UK
P16	Design Innovator	52	F	20	UK
P17	Postdoctoral Researcher (HCI)	27	F	9	UK
P18	Engineering based Researcher	36	F	9	USA
P19	Principle Ergonomics Specialist	43	M	14	UK
P20	Research Developer	24	M	2-6	UK

Table 1. *Participant Demographics, showing current role, age and gender, years of experience within the field of design and current country of residence .*

Camera orientation line graph; and ISO level line graph.

6. a space for the participants to reflect on the potential for telemetry data to be used within design research.

The lead researcher took an active part in the data exploration process. They encouraged participants to annotate the data visualisations with notes and keywords to identify moments they find interesting and ask questions about the experience and context of riding the bike.

3.4. Analysis

The lead researcher used thematic analysis (Braun and Clarke, 2006) to inductively code the transcripts in Nvivo (https://www.qsrinternational.com). This initial set of codes was then exported into a Miro board together with quotes from the transcripts. Two researchers conducted an affinity mapping session to cluster related codes, and identify themes. As clusters began to settle, two more researchers joined the analysis process and engaged in discussion until a consensus was reached.

4. Results

4.1. Features of Interest

The participants' brainstorming activities covered a diverse set of areas, including context of use, bike characteristics, the user experience of riding the bike, and the cyclist's behaviour. Questions regarding **context** investigated aspects of the weather, terrain, traffic, and infrastructure. **Bike characteristics** often focused on the potential of data to identify faults and suggest maintenance, for example P17 asked *"When does the chain guard become damaged?"*. **User experience** focused on confidence levels and safety, for example P13 asked: *"Can confidence be evaluated by looking at behaviours before an event?"*. **Cyclist behaviour** questions aimed to capture specific features of their skills, riding style, and actions. Questions also investigated potential relationships between themes, for example P11 asked: *"Does cycling on the pavement impact your confidence?"*, combining **context** and **behaviour**.

Participants' final research questions and scope were guided by their interaction with the data streams and apparent patterns, which implied underlying relationships worthy of further investigation. These relationships were articulated as correlations or 'cause and effect' scenarios, such as the impact of cycling speed on rider confidence. Combining the data streams allowed the participants to begin to make inferences about less easily quantified features, such as road safety and user experience. For example once P14 observed the researcher's cycling technique caused the bike to swing left and right, they wondered if the data could allow them to *"spot the drunk bikers"*. Participants also questioned the researcher about

their experience at different points in the rides, which helped ground investigations around user experience:

> *"So what I am interested in here is being able to tell if the amount of stability in the camera can [identify] what terrain you are on."* [P8]

4.2. Sense Making

To make sense of the data participants often cross referenced between the telemetry data visualisations and the video. Participants, including P10, P16 and P17 identified moments of interest within the videos first and then tried to find them within the visualised data. They found this practice helpful in delineating the data based on terrain – Figure 2 shows a participants investigation. They identified when the bell was rung, and then looked into whether the proximity of pedestrians had an effect on the rider's speed. Meanwhile, P3, P4, P5, P7, P8, and P20, utilised the opposite approach, identifying quantitative data of interest—such as spikes in gyroscope or accelerometer (Figure 3)—and watching the video to understand what was happening at that moment.

> *"Potentially there's one way of looking at it which is like looking at the video first then looking for events and trying to match them up but there's also looking at the graphs and sort of like things that are happening and lining those up."* [P3]

The participants also asked the researcher to self-report their experience at certain points of the ride, to draw connections to the quantitative data, e.g. P17 wanted to correlate the bumpiness of the terrain as seen in the gyroscope data with the confidence of the rider, shown in Figure 4.

The participants reported that through exploring the data they aimed to challenge their assumptions about the meaning of the data. For example P11 speculated that less wind resistance contributed to a faster evening cycle, but when exploring the graphs concluded that it *"is not necessarily the wind, but the surface of the road"* [p11], challenging their initial hypothesis. This process of making sense of the data often involved a discussion with the researcher about ways of reading the graphs, or contextualising what was happening at each point from the researcher's perspective on the bike ride:
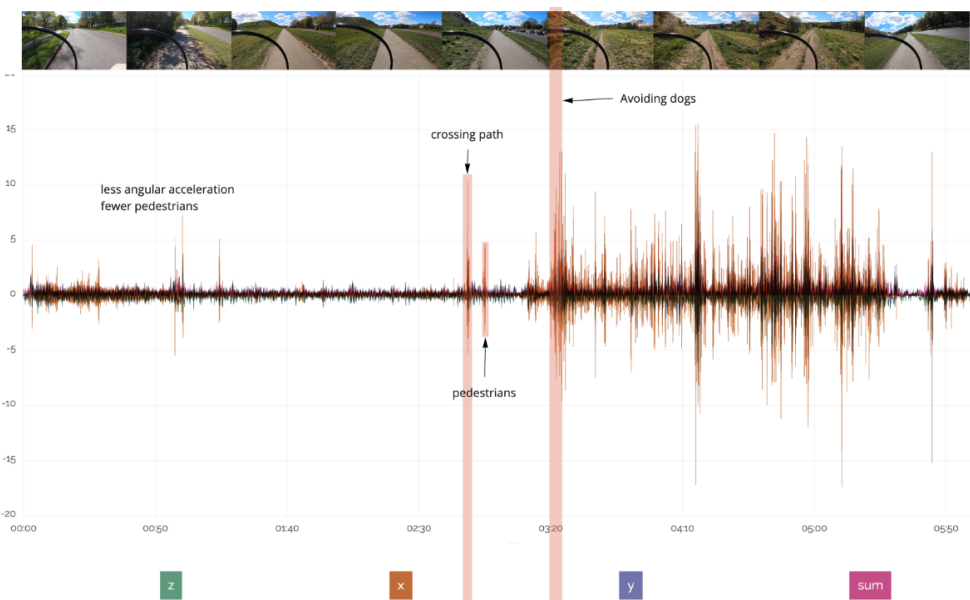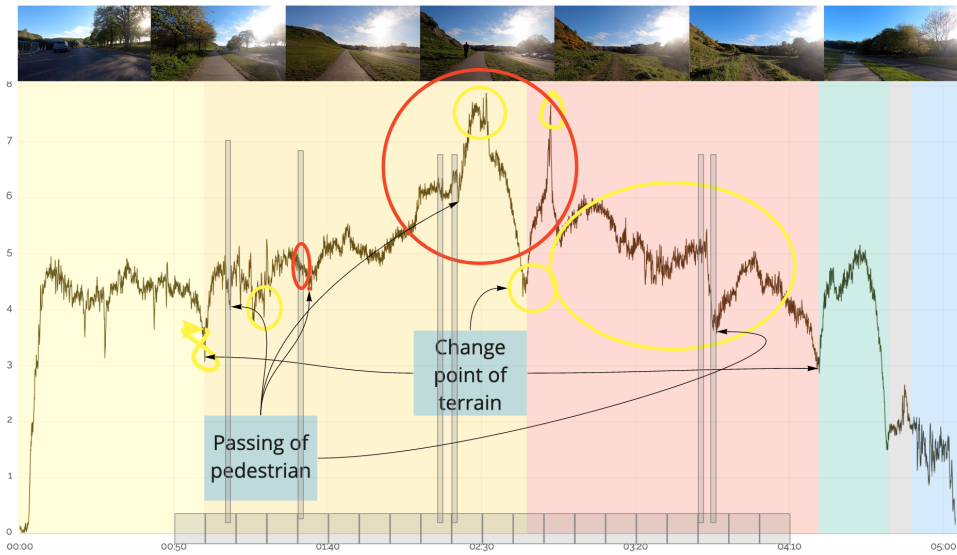
> *"I think it would always be valuable to have this conversation with another person, so that you can have new point of views you can question yourself. Our conversation I think brought me to a different end point from where I started."* [P5]

Participants annotated visualisations with notes and highlighted areas using shapes to indicate terrain, hypothesis, user experience, points of interest, maximum and minimum data points. To develop the relationship between datasets, participants marked moments of interest using shapes and aligned them vertically across the different datasets. Whenever events were identified, they were annotated with sticky notes. A single annotation could at times be connected to multiple points of interest in the data. At times the participants required assistance from the researcher in matching up moments from the video onto the data visualisations, such as when the researcher passed by pedestrians or there was a transition in the road surface. Most participants found the initial experience of looking at the diverse data streams overwhelming and difficult. However they often concluded that through triangulation and further data gathering they would be able to challenge their assumptions and explore their hypothesis.

4.3. Research at Scale

The data was seen as a useful component of the design of further qualitative and quantitative studies. Participants speculated on additional data streams they would require to gain a wider picture of the context. They also felt a need for a more accurate representation of the lived experiences of a cyclist.

Participants designed potential studies with: multiple bikes but a single rider to understand how different bikes perform compared to each other [P13]; multiple riders with a single bike to investigate different riding styles or personas [P12, P13, P14, P15, P17, P18, P19]; rides with variations in bike components and settings to identify how to optimise a bike's performance [P6, P13, P18]. Participants identified that they require large amounts of telemetry data collection over extended periods of time—P3 was interested in large-scale performance analysis: *"if you have 10000 people at some point patterns start to emerge right, because*

Figure 2. *Graph of cyclist speed annotated by P10, showing events of particular interest identified within the video: indication of change of terrain and interaction with other path users, segmentation added to support analysis and the a hypothesis to investigate what was causing other changes..*

Figure 3. *Gyroscope data annotated by P3, showing sections annotated based on observed events in the video (marked in red)..*

you decrease the individual variance in different [cyclist] levels but you start to identify patterns".

Investigations around the cyclist's behaviour were imagined to be researched through research methods familiar to the participants. They imagined using familiar methods to understand user behaviour, with the telemetry data as an additional source of insight. Diary studies, contextual inquiry, and experience sampling could utilise telemetry
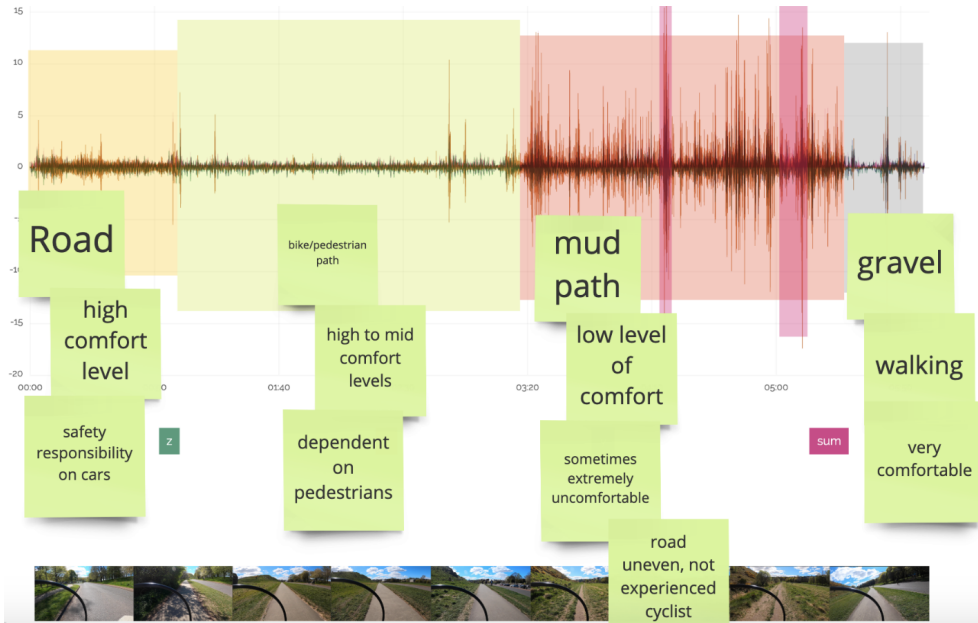
Figure 4. *Graph of accelerometer data annotated by P17, showing segmentation of the ride based on visual inspection of the data traces, highlighting of particular events of interest. Qualitative annotations have been added to each segment based on elicitation from the video subject, to talk about physical features of the environment (surfaces), the immediate comfort level of the rider, and the social factors around the ride..*

data, while not being completely reliant on it. P4 felt there is potential to allow participants to annotate the data they generate themselves *"for more qualitative insights on what happened then and then, perhaps even have some kind of communication channel between researchers and users, maybe even during activities"*.

Ultimately the participants felt that a data-driven research process would be an interdisciplinary task, requiring *"designers and engineers and computer scientists to have a look and make sense out of it"* [P1]. Participant 18, an engineering researcher, provided an in-depth description of their research process to investigate how confidence relates to the motion of the bike:

"I would ask people to ride this path initially whether or not it was their usual path if they fit into the [user] group. So it would be some sort of like research uh activity where they do the data collection and then we come in and we have a conversation about cycling in general and then getting down to the topic of confidence and then maybe looking over the video stream and like indexing moments where they they

believed that confidence was an issue. [...] I would need to decide how many riders and how many rides are going to be enough information. [...] How much data would we need to know that the detection of these moments is not by chance. [...] It would really be in conversation with uh the person that's going to manage this algorithm who probably won't be me." [P18]

4.4. Computer Supported Sense Making

The process of analysis, although educational, proved difficult for many of the participants, leading many to imagine how visualisation tools for design research should support them in making sense of the data. Some participants, like P2, P3, and P13, felt the line graphs were too abstract and disconnected from the activity of riding a bike. It forced them to think about the context of the product and user in a manner unfamiliar to themselves, with a participant stating:

"... honestly I was thinking of this as like maybe I'm missing something that's really interesting and it's just a lack of a certain sort of technical

literacy that is [causing] me to miss data that's in plain sight... expertise on certain signals in the data [is needed] and relying on those with true expertise to kind of check my work." [P18]

The participants felt that the data visualisations need to be made more accessible. They saw opportunities to overlay graphs onto the video, *"on top of each other"* [P3], use more familiar speedometers, and allow for interactive features, such as being able to place a marker within the video which then appears in other visualisations. For spatially bound data, such as the camera orientation, P19 imagined *"a visualisation of the bike in 3D"*.

Data-driven design tools could be made more accessible through computer aided analysis. Participants expressed an interest in seeing further statistical information overlaid onto the graphs, such as value ranges and the mean of a range of data, which could help them understand the quantitative data. P17 explained she wanted to see *"some sort of calculation to show you average speed on that terrain, [...] it should help you with figuring out the math of it and pointing out [data] errors"*.

The graphs from the scene classification model, generated discussions around how ML can be incorporated into a research process. Participants, such as P1, found that ML can help automate the detection of people, cars, dogs, and other cyclists nearby, which could be helpful in aiding the researcher in identifying moments of interest. Meanwhile P13 speculated that after building a training dataset, it can be continuously expanded and tested in order to identify data events of interest. Automating the highlighting of the data could help the design researcher save time and focus their investigation, *"It could condense the footage to the moments I really want to see"* [P3]. Filtering the data would require the researcher to set up queries based on predefined parameters: *"Show me this and this set of data every time I decelerate"* [P1].

"I think automating some of the highlighting moments for then a person to go in and look because the first thing that I would want to do is scrub through the video and place a little marker about all the interesting things I'm interested in [...] That's just a visual reference for me to then go and look at see what's happening with the line." [P3]

4.5. Barriers and Concerns

When discussing privacy and ethics, participants were concerned about the implications of utilising such a research approach at scale. If data capture became part of the design of products to support research that may in turn limit people's privacy. The participants questioned the acceptability of data gathering from a user perspective and some felt that it is *"dystopian in nature"* (P3). P19 raised concerns that given the context, there could be a need to remove certain events from the data gathered, such as when serious accidents occur. P4 felt that a way to mitigate unnecessary data gathering is to use targeted data collection in order to *"design artefacts that are less invasive"*.

"I can imagine a price banding between products that are collecting data in order to improve the product itself and you can opt out and pay for the more expensive one, that sound like a very Amazon way of designing a product, but then should it be a luxury to not have data regarding the use of a thing?" [P3]

Participants felt that there are further barriers and concerns to adopting telemetry data as part of design research. Quantitative data driven design insights taken from telemetry data streams were seen to be potentially biased and misleading. When exploring the data the participants were mindful of the fact they made assumptions, which required cross-checking and discussions with the researcher about what they think happened at certain points. They felt that data could be misinterpreted or that a label might be a missclassification of an event.

"The activity and the data representing the activity there is a difference between the lived experience and these graphs that get outputted in the end." [P3]

The participants were able to observe discrepancies in the data. There were some indications that the GPS data is not accurate. For example the elevation of the day cycle had a maximum elevation of 40 meters, while the evening cycle had a maximum elevation of 45 meters, despite the fact the cycles were done on the same route. This raised questions about how the GoPro was actually measuring elevation and if there are similar discrepancies in other parts of the dataset. P5 reflected *"this variations of 5 meters are ringing a*

bell that something is not quite right". Similarly the scene classification produced by the simple model in the GoPro looked very different for the day and evening cycles. During the day cycle the scene model classed the majority of the cycle as vegetation with about 40% to 65% certainty, in contrast the evening cycle, which had different lighting conditions with the sun visible within the shot, did not classify vegetation with a high probability. *"I can say I might trust it more on a sunny day during the day time, rather than in the evening or in the morning"* [P1]. This led to participants raising questions about the trustworthiness of the data and how to identify when data is inaccurate.

> *"The only difference is the lighting condition, so the question is given then the contrast in the colours, whether this causes the difference, although it seems the same. How do you prevent these types of misinterpretations?"* [P1]

4.6. Potential of Utilising Telemetry Data

A key discussion was the role that design as a discipline and practice has in making use of telemetry data. Opinions varied in how empirical and structured a process that utilises data has to be, varying from playful exploration to controlled quantitative studies. P2 felt that from his experience *"working with designers, this wouldn't be useful to spark creative ideas[...]"*, although he did allow that *"counter-intuitive open, probably quite simplistic play, gives the designers a way into a conversation."*

In contrast, P11 felt that the visualisations *"actually helped me to think about the bike creatively in a very short period of time"* and other participants were keen to use the data in a very structured research approach in order to identify and solve problems around the product in a way that would allow for optimisation and better user experience design. For example, P3 felt that there is potential to match users with a bike that matches their needs and riding style, tuning the *"suspension, the size of the wheels, the weight of it"* for a better user experience.

The participants identified that by examining user behaviours and user needs, they would be able to generate personas, or understand user needs across populations, which can lead to design insights that might speciate the product. *"You might be able to see how to differentiate the bikes further based on how people are using them."* [P3]

It was difficult for the participants to envision how the data feeds directly into the redesign of the bike but they were easily able to envision how the data can become a key design feature in itself. For example P1 and P9 saw potential for data to help identify dangerous situations and aid cyclists through various alerts; P7 saw that the data can be used to create bikes that autonomously react to their environment by intelligently changing their speed; P2 felt that data can help cyclists identify when the bike needs maintenance; and P4 saw potential to use the data to empower users to achieve training and performance goals.

> *"It would be more interesting if you could just empower users to be what they want to be, which might be to just have more fun."* [P4]

Finally telemetry data could have broader beneficial implications. These could be in helping quantify the benefits of greener city infrastructure [P12]. Or encourage empathy between cyclists, pedestrians, and drivers from a *"real emotional perspective"* [P16].

5. Discussion

This study paints a picture of what can be carried out by design teams, with little investment into data tooling and analysis. The participants developed and deployed quick, ad-hoc strategies, where data mediated between different spheres of knowledge. This is in line with the Hinrichs' ideas of *sandcastles* (Hinrichs et al., 2019), where visualisations provoke insight, interpretation, speculation and mediate between ideas and theories across disciplines. Of particular interest here were the trajectories that participants took through the investigation, as they fluidly shifted between observation, reflection, analysis, critique and theory building. Here, after noting limitations of the study, we start by discussing and contextualising what happened as participants started their exploration, looking at the trajectories they took, and the practices of annotation and zooming in and zooming out that emerged. We then go on to unpack what this might mean for designers including video and telemetry data as a creative material within their design processes, and point to the avenues to connect this to computational intelligence.

5.1. Limitations

This study was conducted during a lockdown in response to the SARS-Cov2 virus, which limited the possibilites for face-to-face interaction – hence all interviews were conducted over a video link. There was only video data of a single subject (the lead researcher) to explore. While it would have been interesting to have more data sources, this is not a significant problem as there was variety in the participants who worked with the footage and their responses. The task was not strongly contextualised: it is likely that working around a clear process of redesign would have produced different results. Finally, there was a skew within the participants towards people with academic positions rather than industry practitioners.

5.2. Designers building relations with data

5.2.1. Uses of data

There was a wide range of ideas about how to use data within bicycle design and redesign. This included traditional starting points such as ways to carry out predictive maintenance and design changes, but extended out to rethinking bicycles and their relations to society or recasting bikes as sensors to quantify the case for greener city infrastructure. Participants identified several research configurations that can utilise telemetry data: sensorising multiple bikes and asking a rider to ride them on the same terrain to understand how they perform; sensorising multiple bikes that belong to different riders to investigate behaviors and patterns of use; recruiting multiple riders with a single bike design to investigate different riding styles or personas; and investigating how to optimise a bike by changing how it is configured. The participants in general were not able to identify in detail what aspects of the telemetry data they would focus on to draw conclusions, but they did know they require large amounts of data over prolonged periods of time and help from data scientists. This indicates that presenting an articulated set of possibilities for working with data, and a sense of what would be needed for each, would be helpful for designers and design researchers to develop relations with data driven practices. This reflects previous research that designers find data overwhelming and collaboration across disciplines is required to make use of it (Lu et al., 2021).

5.2.2. Mediation and synthesis between datasets

Having multiple sources of data available allowed the participants to develop their own trajectories of investigation, carrying out synthesis across the datasets. Participants found the quantitative visualisations alone difficult to engage with. However, combining the video footage, sensor telemetry data and conversation with the rider, provided multiple entry points into sense-making and exploring their research questions. Participants made use of multiple entry points for inquiry, starting with moments of interest in the video, points of change in the graph, curiosity about interpretations of the values displayed and so on. They could the contextualise their question by moving to other data sources, including asking the subject as their investigation or conceptualisation unfolded, creating a trajectory through the qualitative and quantitative space. Some of the richest moments of interaction in the study came from the participants creating bridges between these, whether P10 identifying when the bell was rung and pedestrians were passed using the video to explore how the speed of the rider was affected, or P3 using the spikes in the accelerometer data to investigate what happened contextually through the video. Figure 5 visualises an illustrative subset of these trajectories. This is somewhat characteristic of design processes, that draw on tacit knowledge, situational understanding and empirical practices in order to make changes in complex situations (Cross, 2001).

5.2.3. Making sense of the data

It was encouraging to see participants not only using the data to understand the ride and generate follow-on ideas, but also use their knowledge of the world and insight into the situation to start to understand the data itself. Raw quantitative data is at heart just a collection of numbers – there may be a spike or a trough on a graph but those variations have very little intrinsic meaning. Presented without context behind them, they can easily lead to wild misunderstandings of what is really going on - for example, the moment when Google interpreted a flood of searchers for Michael Jackson as an automated attack, rather than a reaction to reports of his death (Pittman, 2009). The participants used a variety of approaches to knit the events together to better understand the context and from that gain a better understanding of what
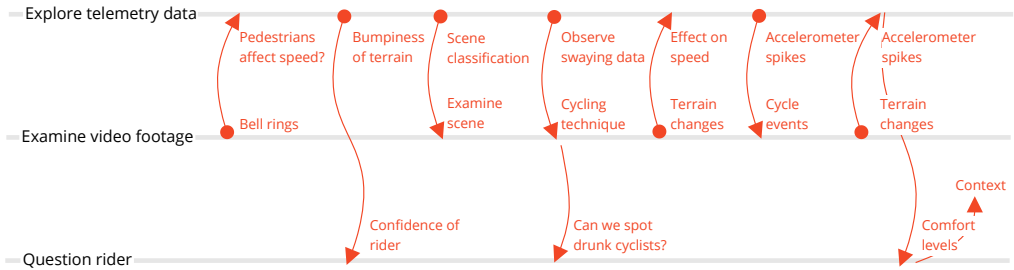
Figure 5. *Selected trajectories of investigation. Each circle indicates the nucleation point of an investigation, with arrows pointing to sources of information to engage with.*

the shape of a line might actually mean in gyroscope data. While obvious, this observation has some important implications. While in this case researchers were able to question the rider in detail, that would not necessarily be the case if testing was being done at scale. The process of understanding here unfolded between quantitative data, participant, video footage and subject, and being able to access social and physical intuitions about the situation was a key way for the participants to get a better feel for what the data was describing.

5.2.4. Contextual grounding:
Following from this, the participants tended to want the data to be contextually grounded and were not ready to just believe everything – even though they were happy to imagine building and training complex models on the telemetry data. Combining a variety of qualitative and quantitative data sources helped validate and challenge assumptions. This is reflected in the research of van Kollenburg and Bogers (2019), where combining data and participant knowledge from the use of a connected baby bottle helped reveal contexts, behaviours, and experiences.

This demonstrates a sense that the quantitative data is seen as only part of the process, and while it is a useful seed or trigger, it does not need to be privileged over other kinds of knowledge work and research. There was a reluctance to see data as the only answer, as *"even with the most rich of data different stories can be told"* [P16], following the view that an understanding of the the situation through empathetic imagining is emergent from the research encounter, rather than predetermined (Pink et al., 2017).

5.3. Annotation as a source of entanglements

Annotation was one of the key practices within this study, through the design of the materials but also through its usefulness in crossing boundaries and developing shared senses of meaning. Annotation tends to fit a designerly way of working – it allows for competing or conflicting labels, working through connection and the layering of multiple fields of knowledge. Early design work around the use of annotations (Li et al., 2009) looked at this last point, in particular the collaborative and communicative use of annotation, and the way that annotation can allow interaction between different specialist viewpoints.

Inconsistencies in labelling can be the start of a process of questioning, leading to valuable insight – for example, understanding the causes behind discrepancies in elevation data that P5 observed. Several participants developed a practice of 'checking in' about the meanings of various labels and data signatures, which prompted a rethinking and development of their understanding – not just looking at the graphs. This relates to practices emerging in the learning community, where the practice of annotation transforms static artefacts such as books into 'a context for discussion, analysis, and shared inquiry' (Kalir, 2022).

Within this curiosity, there were different styles of investigation, where some designers started to think in terms of structured studies, others were

more interested in the experiential aspects, balancing looking at the person who was the subject of the data and looking at the data itself. There is a power in the unstructured nature of the annotation process, and here participants could develop their own pathways of attention - as "Annotations appear and interrelate without a preconceived order", (Fernández Contreras, 2021) their creation can be motivated by detailed investigation or broad speculation as appropriate. Within this particular context, the annotations were not constrained by ontology (Kantorovitch et al., 2016) or placement on a timeline (see all the example softwares).

As well as a contrast here to the practice of video ethnography, which has also been used with cyclists as a means to "generate and share empathetic encounters with participants" (Pink et al., 2017), of "'feeling there' when you can't be there" (Spinney, 2011). The style of investigation carried out here is in some ways more surface-level, as the participants could not drill down to the same level of e.g. gaze and attention (Tuncer et al., 2020). The tradeoff is that participants could cast a wider net in thinking about what the data might imply, and more directly how to appropriate it into a design process. There is a a link here to *entanglement* theories (Frauenberger, 2020), that look at how understanding arises about fluid situations, where complex networks arise, and the objects under discussion are ontologically precarious, being to some extent constructed through the investigation (Barad, 2007).

Pragmatically, annotation has multiple possibilities that can be appropriated for use in early stage design and RtD research:

- Annotation provides a way to navigate multimodal complex datasets, and integrates viewpoints across different domains of knowledge (Cassidy and Schmidt, 2017; Badam et al., 2022; Chandrasegaran, 2016).
- Annotation can form the basis of collaboration patterns. This is already present in CAD models (Li et al., 2009) as a generic coordination tool, but can give rise to specific practices. This includes critique, discussion and feedback on what is happening, e.g. critical feedback in nursing contexts (Cattaneo et al., 2020), as well as collaborative annotations on shared material as a distance learning technique (Zhu et al., 2020).

- Annotation supports sensemaking in new fields - in particular, providing a way in for less data-literate designers working with telemetry data, as shown by the progression of annotations here from speeds to accelerations to thinking into terrain and vibration.
- Annotation connects humans and computational systems. This can include machine annotations for warnings and errors on code or digital models but also extends to machine learning systems through the creation of the labels on which models are built, for example in education with multimodal machine learning analytics (Di Mitri et al., 2019).

Where annotations can connect between human and machine agencies, they create new possibilities within the messier, interconnected world of post-industrial design (Giaccardi and Redström, 2020). Curious annotation from designers can propagate to inform models built by data scientists, that change product functions or provide design insights.

5.4. Zooming in and Zooming Out

The scope of the design researchers vision moved between small scale physical phenomena and broader 'macro' views, for example going seeing a spike on the graph to asking the subject what happened there, or using the graph of speed as a prompt to question the practice of rapid cycling and its effect on bystanders. This went in both direction, questioning how personal experiences of issues with bike maintainance or social regulations around speed might come through in the data traces. The initial focus on the physicality of the bicycle allowed a move towards thinking about the state of the rider, their experience and emotional connection, and from there to wider questions. This led to the generation of a wide range of research questions, from ways to carry out predictive maintenance and design changes out to rethinking bicycles and their relations to society. From the micro level data, participants develop possibilities around the implications of a bike that could sense a drunk rider to recasting bikes as sensors to quantify the case for greener city infrastructure. Telemetry data appears to offer a useful space for imagination here, as it bridges

between direct physical concerns and the potential for working at scale and over time.

There is a relation here to the development of 'zooming in and zooming out' (Nicolini, 2009b) as a technique within practice theory – a set of theories that look at socio-material practices as the central object of enquiry (Nicolini, 2012). Again, connecting to the way annotations work to create links across different datasets, in this work there was a fluid sense of "moving between data and theory" (Nicolini, 2009b), as participants move from phenomenon to model to implications and back. As P4 put it: *"There's always this back and forth between the questions that emerged from data that you observed and your original kind of purpose of why did you start to research in the first place"*. The data drew people into particular activities, for example using changes in speed to look into whether the cyclist was looking out at the view (P17), and then pivoting to ask about the others around in that moment, and whether directing attention away from the road was a safety concern. Some approaches differentiate and bound sections of practices to develop distinctions – segmenting graphs to find points of change and looking at the differences, finding particular moments in the video and detailing happenings around them (P16); others move from these segmentations out to how a rider relates to others on the road (P16) and the other actors in the space (P14) and the windows that could be found into their activities. Participants were particularly sensitive to the limits of zooming in, the idea that "when pushed to an extreme, the ecological validity and interpretive capacity of the description diminish" (Nicolini, 2009a).

Part of the impact of working with data here is the decentering of the rider. This gives space to understand the situations in terms of others in the space, the terrain, the bike and society more generally – the *stuff* of Shove and Pantzar's 'stuff, skills and images' (Shove and Pantzar (2005), as interpreted by Kuijer (2014, p.26)). Working with the abstract traces follows the Wittgensteinian pathway that it is the actions carried out, rather than the beliefs and goals around them, that are central to developing meaningful understandings of action (Nicolini, 2009a), but also gives space for the material things to become more present in an account of the situation. Participants journeys touched on all of these, e.g. P14 working between movement of the stuff in space (wobbling bicycle), out to images

of drunken cycling as a practice, and back towards problems with the production of safe cycling. Multimodal data can function here as a means to enlist material things into the co-understanding of the space (Giaccardi et al., 2016), and as a way to bring together the strands of practice theory in a manageable way.

5.5. *Connections between design and machine learning through data exploration*

One of the main observations from participants was the importance of context and how different data streams lined up. While is not clear from a visual inspection whether a peak on the gyroscope was likely to be the bike tipping over, machine learning approaches allow the possibility of transforming annotated labels into classifiers. These observations are reflective of other work in the intersection of UX designers and ML (Yang et al., 2018), highlighting the need to find just what levels of data literacy are required to work in conjunction with ML or data science colleagues. However, there was support for the idea of tools that could point to moments of interest through segmenting or pattern matching on the data, or systems that could allow users to explore hypotheses and relations through the data – machine learning that supports human agency in the process. Overall, they indicated that there is a strong potential for approaches that augment and assist human labelling, and can support research journeys and investigations, rather than providing black-box output.

There is, of course, a challenge in relating a common sense understanding of the world to the statistical view presented by ML algorithms (Dove et al., 2017), although as ML becomes more ubiquitous and less mystical, there is the opportunity for design research to mediate with the "intimate human experience of lifeworlds; and to productively engage with emerging personal, societal and ethical issues" (Benjamin et al., 2021). Presenting the automatic classification of scenes as vegetation, indoor, snow, water as provided by the GoPro, provoked confusion with the participants, who did not immediately have a way in to understand the *thingly uncertainty* of the camera's operation (Benjamin et al., 2021). These observations are reflective of other work in the intersection of UX designers and ML (Yang et al., 2018), highlighting the need to find just what levels of data literacy are required to

work in conjunction with ML or their data science colleagues within an industrial section. However, the use of annotation, of contextual grounding, and the investigative strategies available 5 point to ways to bring both the development and interpretation of ML models into the design process, in ways familiar to design researchers.

5.6. Key Implications and Takeaways

To bring this together, we offer a set of key takeaways and extrapolations for understanding the relations between designers and multimodal telemetry data in the fuzzy front end of the design process synthesised from the previous findings and discussion.

- **Data can be used for ideation as well as optimisation**. Following on from related work (e.g. Kun et al., 2019; Gorkovenko et al., 2020), in this study data offered a jumping off point for creative thought about a new system. The practice of forming hypotheses and thinking into studies was helpful as a way into design ideation – working from a position of uncertainty about what was 'really' in the data encouraged a hypothesis oriented view of the situation, and allowed the participants to work from a position of curiosity, bringing their existing practices into engagement with data.
- **Annotation is a key practice for designers engaging with data**. We saw that annotation here allowed designers to question, model and connect across various datasets. This practice of labelling appears to be a key means to engage with data, as it i) allows designers to use familiar practices; ii) supports multiple perspectives on the data; iii) combines human interpretation with the foundation of machine learning models and iv) allows a combination of interpretation and critique that supports interdisciplinary practices.
- **Data for design ideation can remain contextualised**. In contrast to many practices where data is extracted from situations and analysed into crisp, decontextualised results, the practices that designers reached for here pointed to a mode of working where a connection was maintained between the data and the situation it was captured in. Rather than acting as an abstract description, data became a

way to ask questions about maintenance, social interaction and user experience.
- **Tools for engaging with data need to support fluid investigation**. The key affordance of the simple static visualisations and videos used here was that they allowed multiple pathways through the exploration, with trajectories from data to video to questions and back again. Rather than linear analyses, tools need to support this kind of gradual weaving together of annotation, analysis, grounding and contextualisation. Participants took different pathways here, some starting from phenomena of interest and moving towards the data, some investigating features of the data to discover the phenomena behind them (Section 4.2). Allowing individual investigative routes would help engage a range of designers and processes.
- **Data can be overwhelming at first; connecting to the world helps**. Several participants noted that the initial sense of looking at data graphs took them outside their comfort zone, and felt challenging. A key strategy for dealing with this was working on the connection between the data and the world, using it as a prompt for investigation rather than a decontextualised material. The potential to explore hypotheses that arose in relation to the data was seen as comforting, to ground speculation in something familiar.
- **There is space for simple analysis**. Many designerly requests would be well satisfied not with complex models, but with tools that allowed simple statistical analysis to be run over the traces: trends, variation, thresholds, mean values and so on would be useful responses to many enquiries. Providing a fluid and natural way to ask these simple questions of data would greatly lower barriers to entry here.
- **Uncertainty is not always a limiting factor**. When data is used for creativity support, questions over model uncertainty or data robustness have a different weight; the data directs attention rather than providing answers. When it meets with the natural skepticism of design practitioners about models that provide perfect answers, and a sense of *thingly uncertainty* (Benjamin et al., 2021) about how things experience the world, the idea that model outputs and data summaries are not perfect maintains a sense of open investigation.

- **Clustering and novelty are compelling**. The more common requests from designers were for models that can help to cluster or stratify different populations, and those that can help to spot novel moments worthy of further analysis. This may be because they are familiar practices: market analysis relies heavily on customer segmentation; most practices of video or participant analysis rely on somehow picking out moments of interest for detailed interrogation.

6. Conclusion

Through a data-exploration exercise with 20 designers, researchers, developers, and engineers, this paper contributes an exploration of the potential for low-cost telemetry data for design research around physical products, in this case a bicycle. The participants combined an exploration of visualised data traces with time-aligned video footage and direct interaction with the rider. Despite not being data scientists, the participants were able to make use of the telemetry data to initiate questions around physical characteristics and performance of the bike, user experience and larger behavioural questions. The raw telemetry visualisation supported several designerly strategies – mediating between different datasets and approaches, supporting creation and exploration of ad-hoc models, and connecting small scale behaviours to wider contexts. This suggested a rich set of ways designers can engage with this kind of data, from contextual grounding for concepts and hypotheses to a way to interact with machine learning systems. Of particular interest were the trajectories that designers took between looking at telemetry, video capture and engaging with the research subject. They also used strategies of zooming in and out to mediate between micro-data, potential for analysis and wider social questions. Overall, even this raw presentation of telemetry data, in combination with video footage and interview possibilities, was enough to stimulate creative thought, open design possibilities, and motivate a wide range of design research questions. This demonstrates both the possibility and the need for tools that help convert creative data analysis into functioning machine learning models or data driven systems that can support new kinds of design processes.

References

Abrahams, L. (2019). The 'world's safest' bike helmet has its own airbag. Metro.

Anderson, K., Nafus, D., Rattenbury, T., and Aipperspach, R. (2009). Numbers Have Qualities Too: Experiences with Ethno-Mining. *Ethnographic Praxis in Industry Conference Proceedings*, 2009(1):123–140.

Austin, J., Jackson, T., Fletcher, M., Jessop, M., Cowley, P., and Lobner, P. (2004). Predictive Maintenance: Distributed Aircraft engine diagnostics. In Foster, I. and Kesselman, C., editors, *The Grid 2 (Second Edition)*, The Morgan Kaufmann Series in Computer Architecture and Design, pages 69–79. Morgan Kaufmann, Burlington.

Badam, S. K., Chandrasegaran, S., and Elmqvist, N. (2022). Integrating annotations into multidimensional visual dashboards. *Information Visualization*, 21(3):270–284.

Bahirat, P., He, Y., Menon, A., and Knijnenburg, B. (2018). A Data-Driven Approach to Developing IoT Privacy-Setting Interfaces. In *23rd International Conference on Intelligent User Interfaces*, IUI '18, pages 165–176, New York, NY, USA. Association for Computing Machinery.

Barad, K. M. (2007). *Meeting the Universe Halfway Quantum Physics and the Entanglement of Matter and Meaning*. Duke University Press, Durham.

Benjamin, J. J., Berger, A., Merrill, N., and Pierce, J. (2021). Machine Learning Uncertainty as a Design Material: A Post-Phenomenological Inquiry. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–14, Yokohama Japan. ACM.

Bertoni, A. (2020). Data-Driven Design in Concept Development: Systematic Review and Missed Opportunities. *Proceedings of the Design Society: DESIGN Conference*, 1:101–110.

Bhavnani, Y., Rodden, K., Guarnotta, L. C., Lynn, M. T., Chizari, S., and Granka, L. (2017). Understanding mobile phone activities via retrospective review of visualizations of usage data. In *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services*, pages 1–10. Association for Computing Machinery, New York, NY, USA.

Bogers, S., Frens, J., van Kollenburg, J., Deckers, E., and Hummels, C. (2016). Connected Baby Bottle: A Design Case Study Towards a Framework for Data-Enabled Design. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*, DIS '16, pages 301–311, New York, NY, USA. Association for Computing Machinery.

Bourgeois, J., van der Linden, J., Kortuem, G., Price, B. A., and Rimmer, C. (2014). Conversations with my washing machine: An in-the-wild study of demand shifting with self-generated energy. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, UbiComp '14, pages 459–470, New York, NY, USA. Association for Computing Machinery.

Braun, V. and Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2):77–101.

Briard, T., Jean, C., Aoussat, A., Véron, P., Le Cardinal, J., and Wartzack, S. (2021). Data-driven Design Challenges in the Early Stages of the Product Development Process. *Proceedings of the Design Society*, 1:851–860.

Burnett, D., Thorp, J., Richards, D., Gorkovenko, K., and Murray-Rust, D. (2019). Digital twins as a resource for design research. In *Proceedings of the 8th ACM International Symposium on Pervasive Displays*, PerDis '19, pages 1–2, New York, NY, USA. Association for Computing Machinery.

Cassidy, S. and Schmidt, T. (2017). Tools for Multimodal Annotation. In Ide, N. and Pustejovsky, J., editors, *Handbook of Linguistic Annotation*, pages 209–227. Springer Netherlands, Dordrecht.

Cattaneo, A. A., Boldrini, E., and Lubinu, F. (2020). "Take a look at this!". Video annotation as a means to foster evidence-based and reflective external and self-given feedback: A preliminary study in operati on room technician training. *Nurse Education in Practice*, 44:102770.

Chamberlain, A., Crabtree, A., Rodden, T., Jones, M., and Rogers, Y. (2012). Research in the wild: Understanding 'in the wild' approaches to design and development. In *Proceedings of the Designing Interactive Systems Conference*, DIS '12, pages 795–796, New York, NY, USA. Association for Computing Machinery.

Chandrasegaran, R. S. K. (2016). Tools and Methods to Analyze Multimodal Data in Collaborative Design Ideation. *Open Access Dissertations*.

Chang, W.-W., Giaccardi, E., Chen, L.-L., and Liang, R.-H. (2017). "Interview with Things": A First-thing Perspective to Understand the Scooter's Everyday Socio-material Network in Taiwan. In *Proceedings of the 2017 Conference on Designing Interactive Systems*, DIS '17, pages 1001–1012, New York, NY, USA. Association for Computing Machinery.

Churchill, E. F. (2017). Data, design, and ethnography. *Interactions*, 25(1):22–23.

Coulton, P. and Lindley, J. G. (2019). More-Than Human Centred Design: Considering Other Things. *The Design Journal*, 22(4):463–481.

Cross, N. (2001). Designerly ways of knowing: Design discipline versus design science. *Design issues*, 17(3):49–55.

Daily, J. and Peterson, J. (2017). Predictive Maintenance: How Big Data Analysis Can Improve Maintenance. In Richter, K. and Walther, J., editors, *Supply Chain Integration Challenges in Commercial Aerospace: A Comprehensive Perspective on the Aviation Value Chain*, pages 267–278. Springer International Publishing, Cham.

Deka, B., Huang, Z., and Kumar, R. (2016). ERICA: Interaction Mining Mobile Apps. In *Proceedings of the 29th Annual Symposium on User Interface Software and Technology*, UIST '16, pages 767–776, New York, NY, USA. Association for Computing Machinery.

Di Mitri, D., Schneider, J., Klemke, R., Specht, M., and Drachsler, H. (2019). Read Between the Lines: An Annotation Tool for Multimodal Data for Learning. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge*, LAK19, pages 51–60, New York, NY, USA. Association for Computing Machinery.

Dove, G., Halskov, K., Forlizzi, J., and Zimmerman, J. (2017). UX Design Innovation: Challenges for Working with Machine Learning as a Design Material. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, CHI '17, pages 278–288, New York, NY, USA. Association for Computing Machinery.

Drachen, A. and Schubert, M. (2013). Spatial game analytics and visualization. In *2013 IEEE Conference on Computational Inteligence in Games (CIG)*, pages 1–8.

Droumeva, M. (2015). Sensory postcards: Using mobile media for digital ethnographies. http://ethnographymatters.net/blog/2015/06/29/sensory-postcards-using-mobile-media-for-digital-ethnographies/.

Dubois, E. and Ford, H. (2015). Trace interviews: An actor-centered approach. *International Journal of Communication*, 9:2067–2091.

Edu, J. S., Such, J. M., and Suarez-Tangil, G. (2020). Smart home personal assistants: a security and privacy review. *ACM Computing Surveys (CSUR)*, 53(6):1–36.

Evans, B. (2016). Paco—Applying Computational Methods to Scale Qualitative Methods. *Ethnographic Praxis in Industry Conference Proceedings*, 2016(1):348–368.

Evi-Colombo, A., Cattaneo, A., and Bétrancourt, M. (2020). Technical and Pedagogical Affordances of Video Annotation: A Literature Review. *Journal of Educational Multimedia and Hypermedia*, 29(3):193–226.

Feinberg, M. (2017). A Design Perspective on Data. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 2952–2963, Denver Colorado USA. ACM.

Fernández Contreras, J. (2021). Annotation as Review: Graphic Thinking in Enric Miralles' Ph. D. Thesis. *Architecture and Culture*, pages 1–12.

Fischer, J. E., Crabtree, A., Colley, J. A., Rodden, T., and Costanza, E. (2017). Data Work: How Energy Advisors and Clients Make IoT Data Accountable. *Computer Supported Cooperative Work (CSCW)*, 26(4):597–626.

Frauenberger, C. (2020). Entanglement HCI The Next Wave? *ACM Transactions on Computer-Human Interaction*, 27(1):1–27.

Gasevic, D., Rose, C., Siemens, G., Wolff, A., and Zdrahal, Z. (2014). Learning analytics and machine learning. In *Proceedings of the Fourth International Conference on Learning Analytics And Knowledge*, LAK '14, pages 287–288, New York, NY, USA. Association for Computing Machinery.

Gaver, W., Boucher, A., Jarvis, N., Cameron, D., Hauenstein, M., Pennington, S., Bowers, J., Pike, J., Beitra, R., and Ovalle, L. (2016). The Datacatcher: Batch Deployment and Documentation of 130 Location-Aware, Mobile Devices That Put Sociopolitically-Relevant Big Data in People's Hands: Polyphonic Interpretation at Scale. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 1597–1607. Association for Computing Machinery, New York, NY, USA.

Giaccardi, E. (2019). Histories and futures of research through design: From prototypes to connected things. *International Journal of Design*, 13(3):139–155.

Giaccardi, E., Cila, N., Speed, C., and Caldwell, M. (2016). Thing Ethnography: Doing Design Research with Non-Humans. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems*, DIS '16, pages 377–387, New York, NY, USA. Association for Computing Machinery.

Giaccardi, E. and Redström, J. (2020). Technology and More-Than-Human Design. *Design Issues*, 36(4):33–44.

Giaccardi, E., Speed, C., Cila, N., and Caldwell, M. L. (2020). Things as Co-Ethnographers : Implications of a Thing Perspective for Design and Anthropology. In Smith, R. C., Vangkilde, K. T., Kjaersgaard, M. G., Otto, T., Halse, Y., and Binder, T., editors, *Design Anthropological Futures*, page 14. Bloomsbury.

Gorkovenko, K., Burnett, D., Thorp, J., Richards, D., and Murray-Rust, D. (2019). Supporting Real-Time Contextual Inquiry Through Sensor Data. In *Ethnographic Praxis in Industry (EPIC2019)*.

Gorkovenko, K., Burnett, D. J., Thorp, J. K., Richards, D., and Murray-Rust, D. (2020). Exploring The Future of Data-Driven Product Design. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, CHI '20, pages 1–14, New York, NY, USA. Association for Computing Machinery.

Grieves, M. (2014). Digital twin: Manufacturing excellence through virtual factory replication. *White paper*, 1:1–7.

Grieves, M. and Vickers, J. (2017). Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems. In Kahlen, F.-J., Flumerfelt, S., and Alves, A., editors, *Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches*, pages 85–113. Springer International Publishing, Cham.

Haines, J. K. (2017). Towards Multi-Dimensional Ethnography. *Ethnographic Praxis in Industry Conference Proceedings*, 2017(1):127–141.

Hinrichs, U., Forlini, S., and Moynihan, B. (2019). In defense of sandcastles: Research thinking through visualization in digital humanities. *Digital Scholarship in the Humanities*, 34(Supplement_1):i80–i99.

Houben, S., Golsteijn, C., Gallacher, S., Johnson, R., Bakker, S., Marquardt, N., Capra, L., and Rogers, Y. (2016). Physikit: Data Engagement Through Physical Ambient Visualizations in the Home. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 1608–1619. Association for Computing Machinery, New York, NY, USA.

Kalir, J. H. (2022). Designing a Social Learning Analytics Tool for Open Annotation and Collaborative Learning. In Prinsloo, P., Slade, S., and Khalil, M., editors, *Learning Analytics in Open and Distributed Learning: Potential and Challenges*, SpringerBriefs in Education, pages 77–89. Springer Nature, Singapore.

Kantorovitch, J., Niskanen, I., Zafeiropoulos, A., Liapis, A., Gonzalez, J. M. G., Didaskalou, A., and Motta, E. (2016). Knowledge Extraction and Annotation Tools to Support Creativity at the Initial Stage of Product Design: Requirements and Assessment. In Kunifuji, S., Papadopoulos, G. A., Skulimowski, A. M., and Kacprzyk, J., editors, *Knowledge, Information and Creativity Support Systems*, Advances in Intelligent Systems and Computing, pages 145–159, Cham. Springer International Publishing.

Kim, H. H. M., Liu, Y., Wang, C. C., and Wang, Y. (2017). Special Issue: Data-Driven Design (D3). *Journal of Mechanical Design*, 139(11).

Koesten, L., Gregory, K., Groth, P., and Simperl, E. (2021). Talking datasets – understanding data sensemaking behaviours. *International Journal of Human-Computer Studies*, 146:102562.

Kohavi, R., Deng, A., Frasca, B., Walker, T., Xu, Y., and Pohlmann, N. (2013). Online controlled experiments at large scale. In *Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '13, pages 1168–1176, New York, NY, USA. Association for Computing Machinery.

Kohavi, R., Deng, A., Longbotham, R., and Xu, Y. (2014). Seven rules of thumb for web site experimenters. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '14, pages 1857–1866, New York, NY, USA. Association for Computing Machinery.

Kohavi, R., Longbotham, R., Sommerfield, D., and Henne, R. M. (2009). Controlled experiments on the web: Survey and practical guide. *Data Mining and Knowledge Discovery*, 18(1):140–181.

Kothe, C., Grivich, M., Brunner, C., and Medine, D. (2018). Lab Streaming Layer. Swartz Center for Computational Neuroscience.

Kuijer, L. (2014). *Implications of Social Practice Theory for Sustainable Design*. PhD thesis, TU Delft.

Kun, P., Mulder, I., de Götzen, A., and Kortuem, G. (2019). Creative Data Work in the Design Process. In *Proceedings of the 2019 on Creativity and Cognition*, C&C '19, pages 346–358, New York, NY, USA. Association for Computing Machinery.

Kun, P., Mulder, I., and Kortuem, G. (2018a). Data Exploration for Generative Design Research. In *DRS 2018: Design as a Catalyst for Change*, pages 1342–1356. Design Research Society.

Kun, P., Mulder, I., and Kortuem, G. (2018b). Design enquiry through data: Appropriating a data science workflow for the design process. In *Proceedings of the 32nd International BCS Human Computer Interaction Conference 32*, pages 1–12.

Li, C., McMahon, C., and Newnes, L. (2009). Annotation in design processes: Classification of approaches. In *DS 58-8: Proceedings of ICED 09, the 17th International Conference on Engineering Design, Vol. 8, Design Information and Knowledge, Palo Alto, CA, USA, 24.-27.08. 2009*.

Liikkanen, L. A. (2017). The data-driven design era in professional web design. *Interactions*, 24(5):52–57.

Lomas, J. D., Forlizzi, J., Poonwala, N., Patel, N., Shodhan, S., Patel, K., Koedinger, K., and Brunskill, E. (2016). Interface Design Optimization as a Multi-Armed Bandit Problem. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 4142–4153. Association for Computing Machinery, New York, NY, USA.

Lu, J., Gomez Ortega, A., Gonçalves, M., and Bourgeois, J. (2021). The impact of data on the role of designers and their process. *Proceedings of the Design Society*, 1:3021–3030.

Martinez-Maldonado, R., Kay, J., Buckingham Shum, S., and Yacef, K. (2019). Collocated Collaboration Analytics: Principles and Dilemmas for Mining Multimodal Interaction Data. *Human–Computer Interaction*, 34(1):1–50.

Mortier, R., Haddadi, H., Henderson, T., McAuley, D., and Crowcroft, J. (2014). Human-Data Interaction: The Human Face of the Data-Driven Society. SSRN Scholarly Paper ID 2508051, Social Science Research Network, Rochester, NY.

Murray-Rust, D., Gorkovenko, K., Burnett, D., and Richards, D. (2019). Entangled Ethnography: Towards a collective future understanding. In *Proceedings of the Halfway to the Future Symposium 2019*, HTTF 2019, pages 1–10, New York, NY, USA. Association for Computing Machinery.

Nicolini, D. (2009a). Zooming In and Out: Studying Practices by Switching Theoretical Lenses and Trailing Connections. *Organization Studies*, 30(12):1391–1418.

Nicolini, D. (2009b). Zooming in and zooming out: A package of method and theory to study work practices. In Worline, M., editor, *Organizational Ethnography: Studying the Complexities of Everyday Life*, pages 120–138. SAGE Publications Ltd.

Nicolini, D. (2012). *Practice Theory, Work, and Organization: An Introduction*. OUP Oxford.

Nourbakhsh, N., Chen, F., Wang, Y., and Calvo, R. A. (2017). Detecting Users' Cognitive Load by Galvanic Skin Response with Affective Interference. *ACM Transactions on Interactive Intelligent Systems*, 7(3):12:1–12:20.

Pink, S., Sumartojo, S., Lupton, D., and LaBond, C. H. (2017). Empathetic technologies: Digital materiality and video ethnography. *Visual Studies*, 32(4):371–381.

Pirolli, P. and Russell, D. M. (2011). Introduction to this special issue on sensemaking. *Human–Computer Interaction*, 26(1-2):1–8.

Pittman, R. J. (2009). Outpouring of searches for the late Michael Jackson.

Pschetz, L., Tallyn, E., Gianni, R., and Speed, C. (2017). Bitbarista: Exploring Perceptions of Data Transactions in the Internet of Things. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 2964–2975. Association for Computing Machinery, New York, NY, USA.

Robinson, R., Isbister, K., and Rubin, Z. (2016). All the Feels: Introducing Biometric Data to Online Gameplay Streams. In *Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play Companion Extended Abstracts*, CHI PLAY Companion '16, pages 261–267, New York, NY, USA. Association for Computing Machinery.

Rodrigues, R., Madeira, R. N., and Correia, N. (2022). Exploring the User Interaction with a Multimodal Web-Based Video Annotator. In Lv, Z. and Song, H., editors, *Intelligent Technologies for Interactive Entertainment*, Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, pages 13–22, Cham. Springer International Publishing.

Romat, H., Henry Riche, N., Hinckley, K., Lee, B., Appert, C., Pietriga, E., and Collins, C. (2019). ActiveInk: (Th)Inking with Data. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pages 1–13, New York, NY, USA. Association for Computing Machinery.

Russell, D. M., Stefik, M. J., Pirolli, P., and Card, S. K. (1993). The cost structure of sensemaking. In *Proceedings of the INTERACT '93 and CHI '93 Conference on Human Factors in Computing Systems*, CHI '93, page 269–276, New York, NY, USA. Association for Computing Machinery.

Salvador, T., Bell, G., and Anderson, K. (1999). Design Ethnography. *Design Management Journal (Former Series)*, 10(4):35–41.

Sanders, E. B.-N. and Stappers, P. J. (2008). Co-creation and the new landscapes of design. *Co-design*, 4(1):5–18.

Sanders, L. and Stappers, P. J. (2014). From designing to co-designing to collective dreaming: Three slices in time. *Interactions*, 21(6):24–33.

Seidelin, C., Dittrich, Y., and Grönvall, E. (2020a). Co-designing Data Experiments: Domain Experts' Exploration and Experimentation with self-selected Data Sources. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*, pages 1–11, New York, NY, USA. Association for Computing Machinery.

Seidelin, C., Dittrich, Y., and Grönvall, E. (2020b). Foregrounding data in co-design – An exploration of how data may become an object of design. *International Journal of Human-Computer Studies*, 143:102505.

Shove, E. and Pantzar, M. (2005). Consumers, producers and practices: Understanding the invention and reinvention of Nordic walking. *Journal of consumer culture*, 5(1):43–64.

Sipos, R., Fradkin, D., Moerchen, F., and Wang, Z. (2014). Log-based predictive maintenance. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '14, pages 1867–1876, New York, NY, USA. Association for Computing Machinery.

Smets, A. and Lievens, B. (2018). Human Sensemaking in the Smart City: A Research Approach Merging Big and Thick Data. *Ethnographic Praxis in Industry Conference Proceedings*, 2018(1):179–194.

Speed, C. and Oberlander, J. (2016). Designing from, with and by Data: Introducing the ablative framework. In *Design Research Society Conference 2016*.

Spinney, J. (2011). A Chance to Catch a Breath: Using Mobile Video Ethnography in Cycling Research. *Mobilities*, 6(2):161–182.

Storey, M. A. (2016). Lies, damned lies, and analytics: Why big data needs thick data. In Menzies, T., Williams, L., and Zimmermann, T., editors, *Perspectives on Data Science for Software Engineering*, pages 369–374. Morgan Kaufmann, Boston.

Tallyn, E., Pschetz, L., Gianni, R., Speed, C., and Elsden, C. (2018). Exploring machine autonomy and provenance data in coffee consumption. *Proceedings of the ACM on Human-Computer Interaction*, 2(CSCW):170.

Tao, F., Sui, F., Liu, A., Qi, Q., Zhang, M., Song, B., Guo, Z., Lu, S. C.-Y., and Nee, A. Y. C. (2019). Digital twin-driven product design framework. *International Journal of Production Research*, 57(12):3935–3953.

Tomei, M., Schwing, A., Narayanasamy, S., and Kumar, R. (2019). Sensor training data reduction for autonomous vehicles. In *Proceedings of the 2019 Workshop on Hot Topics in Video Analytics and Intelligent Edges*, HotEdgeVideo'19, page 45–50, New York, NY, USA. Association for Computing Machinery.

Tuncer, S., Laurier, E., Brown, B., and Licoppe, C. (2020). Notes on the practices and appearances of e-scooter users in public space. *Journal of Transport Geography*, 85:102702.

van Kollenburg, J. and Bogers, S. (2019). *Data-Enabled Design : A Situated Design Approach That Uses Data as Creative Material When Designing for Intelligent Ecosystems*. PhD Thesis 1 (Research TU/e / Graduation TU/e), Eindhoven University of Technology, Eindhoven.

Wagner, J., Lingenfelser, F., Baur, T., Damian, I., Kistler, F., and André, E. (2013). The social signal interpretation (SSI) framework: Multimodal signal processing and recognition in real-time. In *Proceedings of the 21st ACM International Conference on Multimedia*, pages 831–834.

Wallner, G., Kriglstein, S., Gnadlinger, F., Heiml, M., and Kranzer, J. (2014). Game user telemetry in practice: A case study. In *Proceedings of the 11th Conference on Advances in Computer Entertainment Technology*, ACE '14, pages 1–4, New York, NY, USA. Association for Computing Machinery.

Wolff, A., Seffah, A., Kortuem, G., and van der Linden, J. (2018). Designing for Effective Interactions with Data in the Internet of Things. In *Proceedings of the 2018 ACM Conference Companion Publication on Designing Interactive Systems*, DIS '18 Companion, pages 415–418, New York, NY, USA. Association for Computing Machinery.

Xu, Y., Chen, N., Fernandez, A., Sinno, O., and Bhasin, A. (2015). From Infrastructure to Culture: A/B Testing Challenges in Large Scale Social Networks. In *Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '15, pages 2227–2236, New York, NY, USA. Association for Computing Machinery.

Yang, Q., Scuito, A., Zimmerman, J., Forlizzi, J., and Steinfeld, A. (2018). Investigating how experienced ux designers effectively work with machine learning. In *Proceedings of the 2018 Designing Interactive Systems Conference*, DIS '18, page 585–596, New York, NY, USA. Association for Computing Machinery.

Yang, Q., Steinfeld, A., Rosé, C., and Zimmerman, J. (2020). Re-examining whether, why, and how human-AI interaction is uniquely difficult to design. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pages 1–13.

Yao, L., Liu, Y., Li, W., Zhou, L., Ge, Y., Chai, J., and Sun, X. (2014). Using Physiological Measures to Evaluate User Experience of Mobile Applications. In Harris, D., editor, *Engineering Psychology and Cognitive Ergonomics*, Lecture Notes in Computer Science, pages 301–310, Cham. Springer International Publishing.

Yarosh, S. and Zave, P. (2017). Locked or Not? Mental Models of IoT Feature Interaction. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pages 2993–2997. Association for Computing Machinery, New York, NY, USA.

Zhang, X., Brown, H.-F., and Shankar, A. (2016). Data-driven Personas: Constructing Archetypal Users with Clickstreams and User Telemetry. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 5350–5359. Association for Computing Machinery, New York, NY, USA.

Zheng, P., Xu, X., and Chen, C.-H. (2020). A data-driven cyber-physical approach for personalised smart, connected product co-development in a cloud-based environment. *Journal of Intelligent Manufacturing*, 31(1):3–18.

Zhu, X., Chen, B., Avadhanam, R. M., Shui, H., and Zhang, R. Z. (2020). Reading and connecting: Using social annotation in online classes. *Information and Learning Sciences*, 121(5/6):261–271.