



Delft University of Technology

Data for Inquiry and Evidence

Bourgeois, Jacky; Funk, Mathias

Publication date

2024

Document Version

Final published version

Published in

Agenda Key Enabling Methodologies 2024-2027

Citation (APA)

Bourgeois, J., & Funk, M. (2024). Data for Inquiry and Evidence. In *Agenda Key Enabling Methodologies 2024-2027* (2024 ed., pp. 97-107). ClickNL.

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

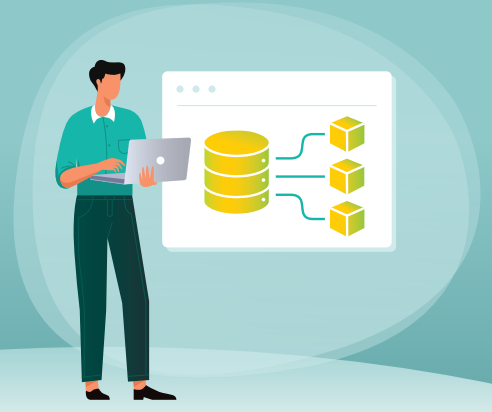
Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

11. DATA FOR INQUIRY AND EVIDENCE



11.1 INTRODUCTION

The KEM category Data for Inquiry and Evidence encompasses a collection of methods and tools for generating insights from data, complementing other qualitative and quantitative design and design research methods. Thereby, it bridges the gap between **Human-Centred Design** and **Data Science**, emphasising the importance of individual context and the stories behind the data. Data for Inquiry and Evidence includes methodologies for utilising data in the design process as well as in the resulting designed products, systems, or services. As a next step these methodologies may be used for generating, analysing or validating data to support mission-driven innovation.

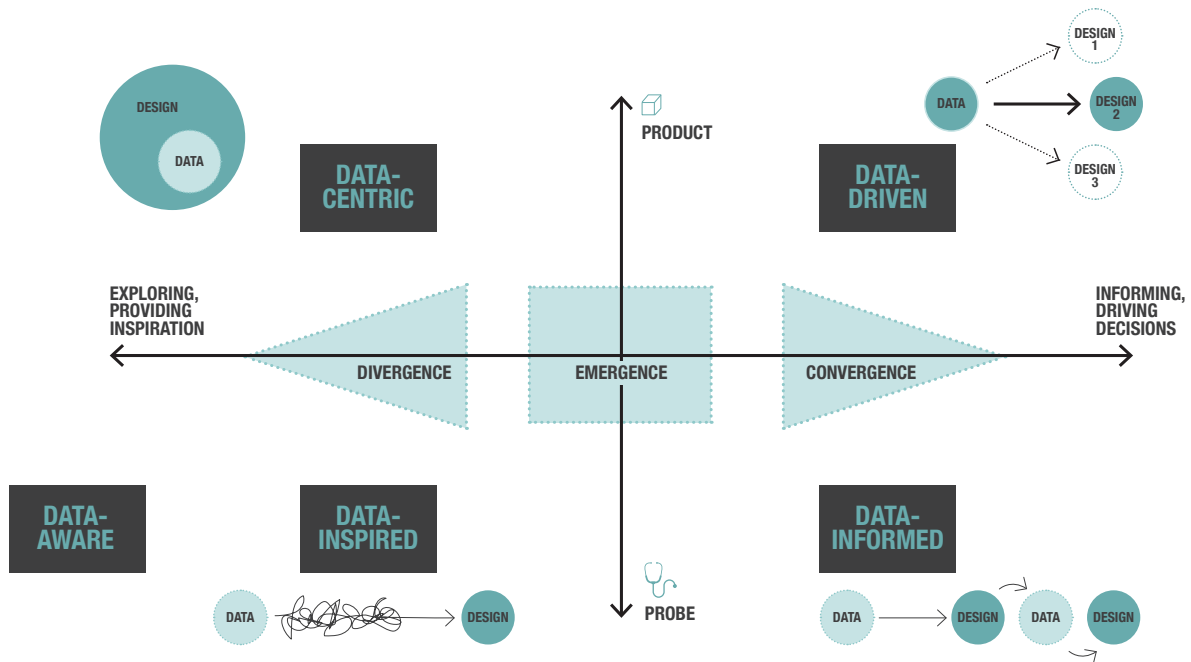


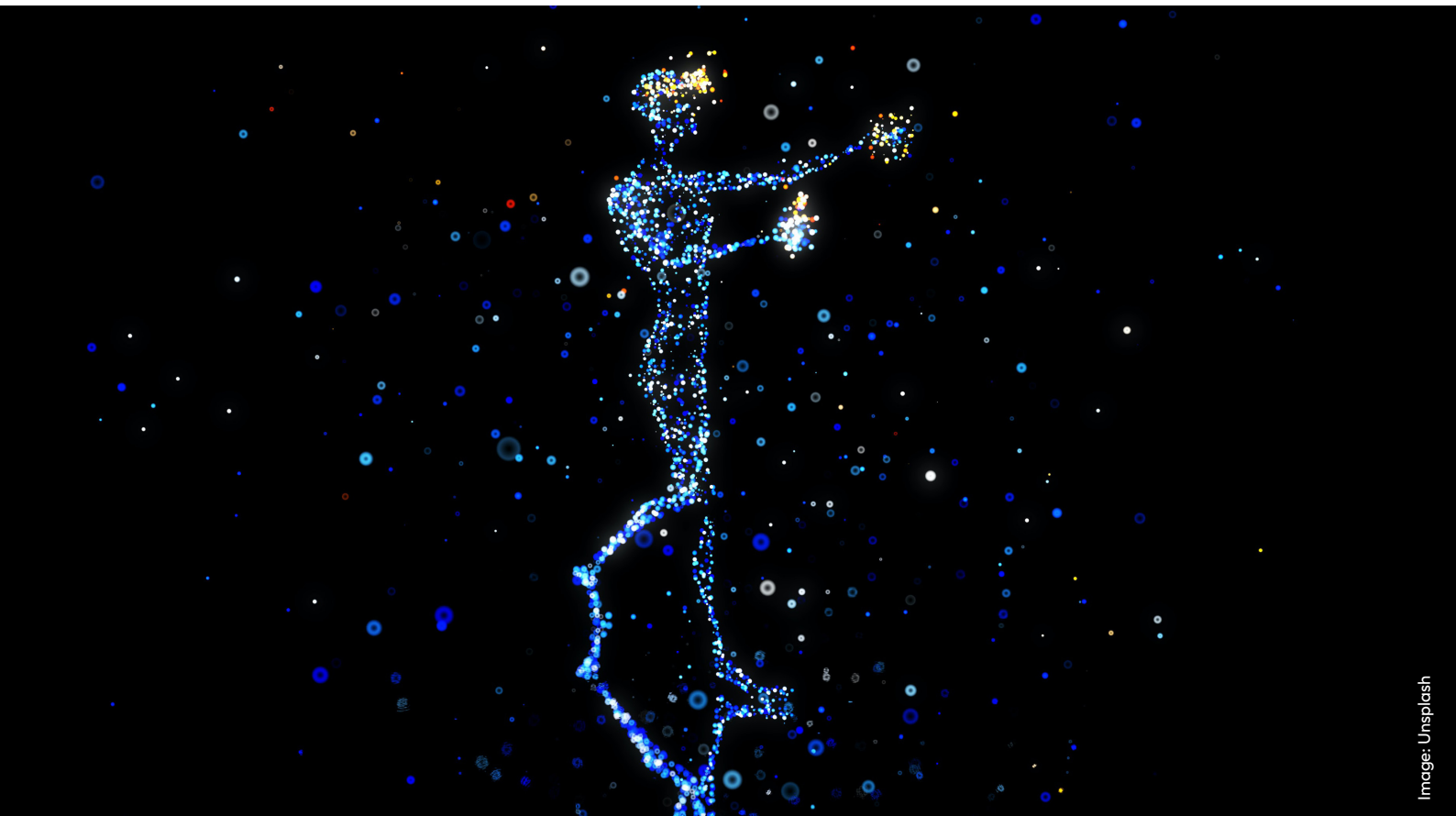
Figure 1. Overview of different data x design approaches (Funk et al., 2024). Data-enabled design is omitted for clarity, see Figure 3.

Within the KEM category Data for Inquiry and Evidence different methods and tools can be charted in a space divided by the product and probe axis, and the axis of exploring versus informing (see Figure 1). The methods on the left side of the figure realise a divergent movement in a design process, where gradually more information and choices are sought. The methods on the right realise a convergent movement that use data directly or indirectly to make choices and reduce uncertainty.

Left and right side correspond to more explorative and informing design phases, respectively. For instance, where data-driven design is more deterministic about determining product design choices, data-aware or data-inspired design is more creative and explorative. That is, design decisions need to be taken not just from data but back to data collection practices, and the right data types are collected to address the right questions.

The upper half of the figure shows methods that focus on data in relation to a product, either by means of a research product in data-centric design (see below) or by iterating on data-driven products. The lower half depicts approaches that focus on involving data in the design process, not necessarily in its outcomes. Here, we see probing and the use of existing data sets to explore possibilities or inform design decisions. The data-enabled design approach is shown in Figure 3.

Next to identifying different approaches to the use of data, Data for Inquiry and Evidence emphasises selecting and connecting appropriate methods. This is similar to how context, data and the design practice are interconnected. By combining well-chosen methods, these methods generate high-quality data and facilitate meaningful interventions. Other key themes for this category are the nature of the data, the processes of data handling, the methods and experiences of data collection and expression, and the risks, tensions and stumbling blocks of working with data (Lee-Smith et al., 2023). These themes provide areas for exploration and critique in understanding the efficacy and challenges associated with working with data in design processes.



11.2 STATE OF THE ART

The current state of the art can be charted by general terminology, human-data interaction, published methods such as data-driven and data-enabled design, and emerging sets of methods on data-informed and data-centric design. The **Ablative Framework**, introduced by Speed and Oberlander (2016), aims to assist designers in understanding and working with data in various ways. It categorises data into three types of value: raw measurements, commercial and social value, and moral and ethical value. The framework distinguishes between designing from, with, and by data:

- Designing from data refers to using data as a source of design inspiration.
- Designing with data involves considering how data flows through systems and its impact on human values.
- Designing by data suggests the possibility of data itself becoming a designer, generating new products and services through data-intensive analysis.

Immediacy is another lens to explore the landscape of methods leveraging data. Gorkovenko et al. (2023) map this spectrum from the operational use of data as a direct function, the data as a quantitative material driving the design process, towards data as material for subjective and contextual inquiry (Figure 2).

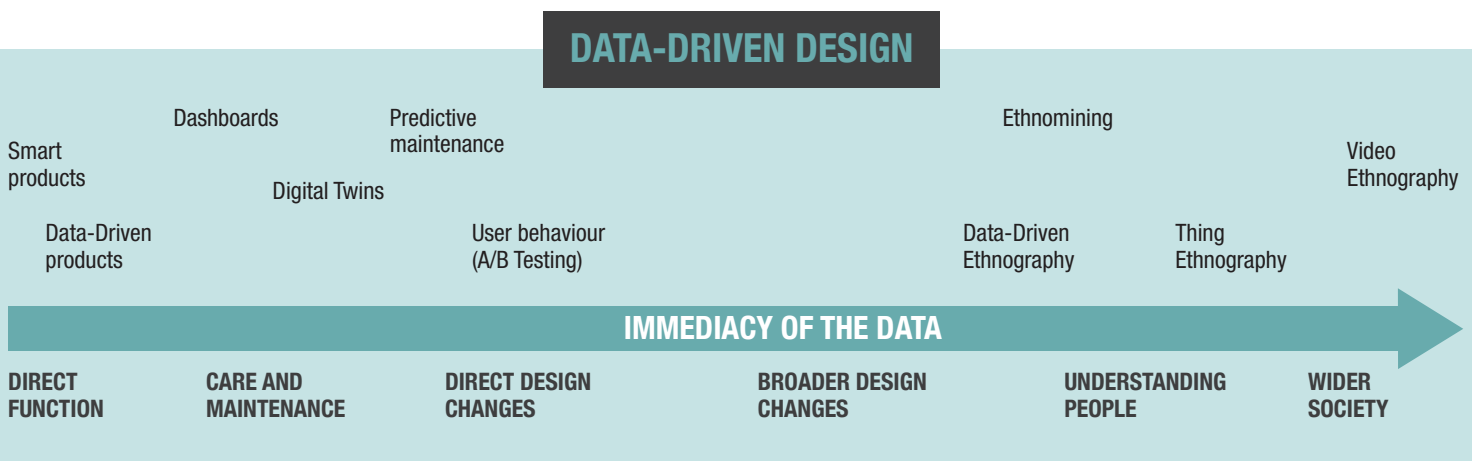


Figure 2. A spectrum of related practices based on how closely the data in question is made use of by the objects of inquiry (Gorkovenko et al., 2023).

While data refers to raw measurements and information, *capta* refers to the contextual understanding and interpretation of data. Data is often seen as objective and detached, while *capta* acknowledges the subjective and interpretive aspects of deriving meaning from data. *Capta* incorporates the idea that data needs to be actively captured and understood within its specific context, taking into account the nuances and complexities of the information being analysed. Any act of data collection is a translation from data to *capta*, and at the same time an act of modelling reality and of what was extracted from contextual reality by means of sensing, reporting, and recording. This modelling step is a necessary step towards agency (compare human-data interaction) in sensemaking and designing with data. In what follows, an overview of methodologies is presented.

HUMAN-DATA INTERACTION

Human-Data Interaction (HDI) encompasses the principles of legibility, negotiability, and agency. Legibility focuses on making data understandable and accessible to users through visualisations and interfaces. Negotiability involves involving users in decision-making processes regarding data collection and usage, allowing them to negotiate terms and conditions. Agency emphasises users' control and autonomy over their personal data, enabling them to determine how the data is accessed and used. Haddadi et al. (2016) further delve into these concepts, discussing the importance of transparency, interactive consent processes, and user empowerment within human-data interactions. Related to HDI, we can further distinguish methods and tools to use data in creative ways.

Data Physicalisation. Leveraging the tangible property of materials, Data Physicalisation combines haptic and visual senses to foster playful and exploratory activities with data. Data Physicalisation can achieve a deeper sense of engagement through unfamiliar and attractive materials (Nissen et al., 2015; Desjardins et al., 2020), enabling the physical construction of visualisation (Huron et al., 2014) or through responsive physicalisation that senses and reacts to the user input.

Data Fiction, for example, in the form of **Epics** (Desjardin & Biggs, 2021), is also an important approach to combine and contrast with data science-focused approaches as a way to actively take perspective and to foreground the conversation. Dourish and Gómez Cruz (2018) disentangle and relate the datafication trend with the data fiction, highlighting the narrative as the common core of both approaches.

The time element is central to all data-capturing behaviours. This is leading to an emerging strand of research on the awareness and the perception of this temporality as a core element of **Data Interaction**. As the soma design approach is increasingly used in human-computer interaction, **Somaesthetic Data** (Alfaras et al., 2020) brings a new way to creatively engage with biosensing technology and the biodata it generates, namely interacting with the digitised response of the body.

DATA-DRIVEN DESIGN

In *Designing with Data: Improving the User Experience with A/B Testing*, King et al. (2017) delve into the concept of **Data-Driven Design**. The core idea behind data-driven design is leveraging user data and insights to inform and guide the design process, ultimately leading to improved user experiences. The authors use **A/B testing** as an example, which is a method that compares two different versions of a design to see which one performs better. This allows designers to make evidence-based decisions rather than relying solely on intuition or assumptions. Data-driven design also involves working closely with other teams, such as data analysts and researchers, to integrate quantitative and qualitative data. King et al. (2017) highlight the value of combining these different data sources to gain a holistic understanding of user experiences. A different form of data-driven design is the use of **Digital Twins** (see Figure 2), both in industrial application ('care and maintenance') and societal awareness and participatory decision making. Digital Twins are data-driven and provide their users with strong immediacy of data.

Another perspective on data-driven design by Van Steenberg et al. (2019) emphasises the integration of data analysis and design processes to understand user behaviour through data collection and analysis. By examining user interactions and preferences, designers can gain valuable insights into how their designs are being used and into the effectiveness of different design elements. This data-driven approach allows designers to make informed decisions about design improvements and optimisations. By continuously evaluating and refining designs based on user data, designers can create more user-centred and tailored experiences. This iterative process allows for constant learning and improvement, ensuring that the design meets the evolving needs of the users. The integration of different types of data, such as quantitative and qualitative data, helps to gain a comprehensive

understanding of the user experience. By combining data from surveys, interviews, and user feedback with quantitative data from analytics tools, designers can better understand the user's motivations, emotions, and needs, which can inform design decisions.

DATA-INFORMED DESIGN

In contrast with data-driven, **Data-Informed Design** is an approach that uses data to support convergence but does not yet drive decision. What is done in this approach informs the way designers and design researchers think about the problem and the problem space (King, 2017). It is rooted in iterative data prototyping and interventions, where data is used to prompt the many roads of the solution space. For example, **Entangled Ethnography** is defined as a general practice of bringing together users, objects, and machine learning to support design processes. **Real Time Contextual Inquiry** uses data streams to trigger moments of discussion and create material for rich analysis (Gorkovenko et al., 2019). **Data-Driven Ethnography** uses trace data from interactions to build rich contexts (Anderson et al., 2009). **Data Probes**, building on cultural and technology probes, are prototypes of concepts which help us prompt and immerse people in some capabilities of data to observe and learn from their reactions (Bourgeois et al., 2014a).

DATA-CENTRIC DESIGN

Data-Centric Design is an emerging mindset that takes opportunity from the many data trails generated by existing products, services, and infrastructure. In contrast to the data-driven approach, data is repurposed from an operational and deterministic process to an exploratory and divergent design process. It revolves around three principles – circularity, participation, and reflexivity – which are bridges to open science and data feminism. **Circularity** aims to minimise extra data collection and instead encourage data reuse and repurpose by accessing and leveraging existing data through mechanisms that adequately inform and ask consent from people represented in the data. **Participation** focuses on actively engaging in partnership with people to collaboratively make sense of and enrich their data. **Reflexivity** aims to foster reflection of people on their data and reflexivity of designers on their design process.

The [Designerly Data Donation](#) (Gomez Ortega et al., 2022) and its tangible representation **DataSlip** (Gomez Ortega, 2024) is a platform that lets designers call for participation in the form of data and active engagement into participatory sense-making. It leverages the data-centric design mindset, seeking alternative ways to participate and demonstrates how data can be a vehicle for contextual inquiry as well as a path towards understanding what responsible data use can mean in practice. With **Telemetry-Informed Design**, Zhang et al. (2016) show how naturalistic 360-degree videos can be leveraged in the design process, by repurposing the camera sensors. Finally, the **Participatory Data Analysis** (Bourgeois et al., 2014b) is an example of active collaboration with people represented in the data to reflect and enrich the meaning of data.

DATA-ENABLED DESIGN

Data-Enabled Design (DED) is a novel approach that aims to innovate by using reliable contextual insights and designing adaptive systems that meet individual user needs (Van Kollenburg & Bogers, 2019; Funk et al., 2024). Data-enabled design views data as an active component in the design process, collected from the context and real end-users through creative methods. The objective is to create complex products and services embedded within intelligent ecosystems, which comprehend users within their context and adapt based on data collection and processing. The data-enabled design process consists of six steps: 1. situating prototypes in everyday life, 2. data collection, 3. analysis to gain insights, 4. design synthesis, 5. using data as a creative design material, and 6. adapting prototypes remotely. These steps ensure that the solutions developed are data-oriented and capable of learning and adapting to user needs within an intelligent ecosystem. The data-enabled design process facilitates two types of explorations: research-oriented contextual exploration and solution-oriented informed exploration. In this way, data-enabled design allows for flexibility and adaptability within the design process. In summary,

data-enabled design leverages data as a creative design material to inform the development of adaptive systems that align with user needs and contextual insights (see Figure 3). Through an **Iterative Data-Enabled Design Loop**, designers can continuously engage with users, collect, and analyse data, and refine their solutions to create personalised and effective design outcomes. This approach bridges the gap between creative, data-inspired or data-centric explorations, and data-driven design processes. This enables designers to create innovative and user-centred products and services within intelligent ecosystems.

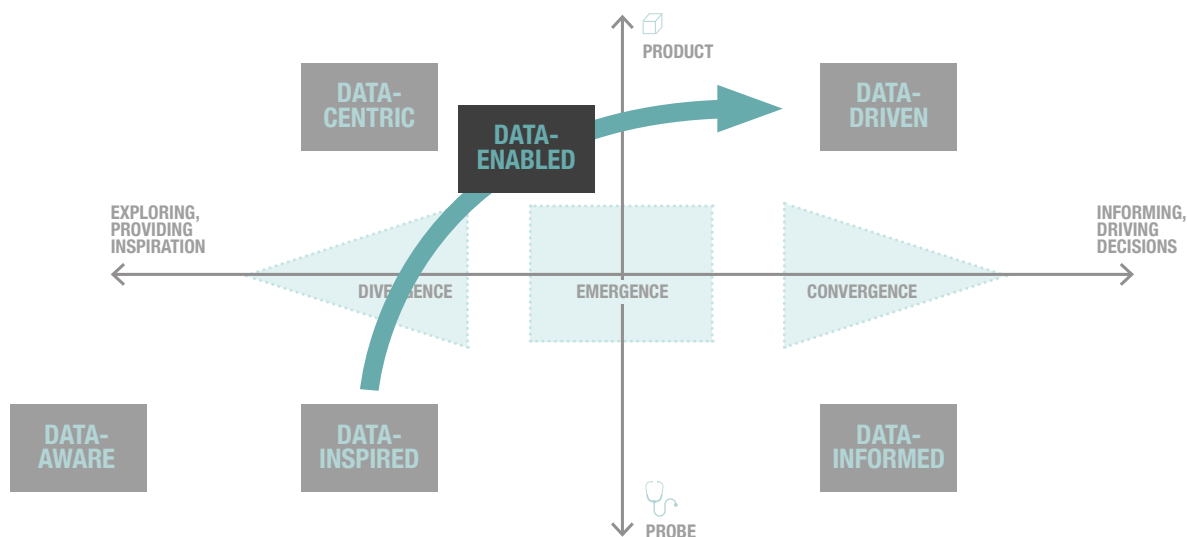


Figure 3. Overview of how data-enabled design fits into the diagram of data x design approaches (also see Figure 1), extending from lower-left to upper-right to the upper-right quadrant. In other words, moving from divergent probe-based explorations to solution focused explorations (Funk et al., 2024).

11.3 CHALLENGES AND RESEARCH QUESTIONS

Data for Inquiry and Evidence is emerging within the disciplines of design research, organisation and transformation science, et cetera. On the one hand, the foundation of human-centred design lies in democratic processes and in a strong focus on user needs (and user agency or participation in data-informed design practices). Digitalisation is a trend in design that enables data to be a central part of the design and design research process; digitalisation is often about making reality machine-readable and opening opportunities for automation and machine learning. Inevitably, this creates concerns, tensions, and friction between the design solution and the use of data. On the other hand, designers must recognise the power of these data opportunities to inform, drive, and evaluate their design. Therefore, a number of core research questions remain.

DATA CREATION AND ACCESS

The way in which data is captured shapes the conversations it supports. How do we collect or generate data? Designers and people, whose behaviour is captured in the data, can often not meaningfully access it. In some problem spaces, design-led data is scarce, while in many cases, data is abundant. But gatekeepers prevent designers and other data stakeholders from using it first-hand. Data is currently explored in isolation because of the (organisational) silos it is captured from, the privacy-preserving processes it must comply with, and the complexity arising from data trails. This keeps the focus on 'thin' data while much human-computer interaction research benefits from 'thick' data. The means of leveraging data as a boundary object to connect and collaborate remain limited. This prevents tapping into the expertise of data participants, leveraging personal data with

appropriately informed consent, and supporting meaningful and reciprocal exchange of values. Research should focus on new data access mechanisms that depart from the data consumption attitude of purely data-driven approaches. These mechanisms should empower stakeholders to leverage available data in collaboration with the relevant parties. Access to data often relies on the design and development of probes and prototypes (Van Kollenburg, 2019).

- How do prototypes shape the data?
- Can we rely on alternative data access methods, such as crowdsourcing or data donation (Gomez Ortega et al., 2022)?
- How do these approaches fit and challenge existing data protection regulations and privacy considerations (for example, the European General Data Protection Regulation)?
- What methods lead to a fair exchange of values and robust insights, as opposed to research driven by data consumption?
- To what extent do these approaches reinforce or mitigate existing inequalities?

DATA MEDIATION AND INTERACTION

Additionally, attention should be devoted to the design and implementation of tools that facilitate the integration of data trails that combine multiple data streams into more comprehensive context mapping, ways of immersion to foster holistic reflections, and pragmatic approaches to complement rather than replace design tools and practices. The way(s) we represent the data to support interpretation and discussion plays a critical role in what insights emerge.

- How do we represent and shape data?

Data is often represented visually through static and dynamic data visualisations (Kurze, 2020) and dashboards (Bogers, 2016).

- How does the way we represent data influence our design (processes) and our interactions with stakeholders?
- What factors influence the way we represent data?
- What tools and techniques do we rely on?
- What are other ways and means we could use to represent and shape the data (for example, physical and tangible (Bae, 2022), and audible (Young, 2019))?
- How do we leverage the various data modalities and materialities to support fair representation and participation with data?

DATA AS A CREATIVE MATERIAL

To say that data, and the technological ‘things’ that interact with them, are quotidian to the lives of many humans is axiomatic. However, this ubiquity of presence, of availability as a resource, has yet to be met with diversity or plurality of use, craft, and experience. Much of how we see the use of data is still rooted and siloed in utilitarian and analytical perspectives of data. To labour the metaphor, if data were wood, we have only been using them to make simple tables and chairs, not buildings, sculptures, boats, and paper. Data is braided into the fabric of our everyday lives. Our interactions, entanglements, and encounters with data run deep, occur with and without technology, and exist in physical and digital contexts. For some, data is seen as a vital component for the utilitarian improvement of said everyday lives. To garner, aggregate, analyse, and communicate metrics, insights, and knowledge underpins how we see data and the technology that interacts with it. However, the data-interaction design space is expanding. Recent and ongoing research is challenging current conventions and proposing alternative narratives. These alternative narratives explore a variety of concepts and values such as ephemerality, decay (Gulotta et al., 2013), negotiation (Cheng et al., 2019), diffraction and (re)interpretation (Desjardins & Biggs, 2021; Sanches et al., 2022), subjectivity (D’ignazio, 2020), locality (Loukissas, 2019), invisibility (Desjardins et al., 2020) and the interaction with analog data. When these narratives are embodied in design ‘outcomes’ they allow us to experience other possible worlds where data is not only a straightforward means to an end but a malleable material that can be shaped to create a diverse range of experiences. These worlds do not only question what we can do with data, but what we can expect of the technology that collects, handles, and expresses these data.

- What alternative possible worlds of human-data-technology already exist?
- What design strategies and tactics can enable diverse uses and expressions of data in our everyday lives?
- What are the potential design outcomes when data we create and express need not be immediately practically ‘useful’?

COLLABORATION AROUND DATA AND INTERDISCIPLINARY DATA COLLABORATIONS

While the lens is focused on data, the research processes are fundamentally human-centred and participatory (Van Kollenburg, 2019; Kurze, 2020; Clarke, 2018). The design field needs data participatory tools and methods that engage, protect, and credit all parties. But who is involved and how? When reporting our experiences with behavioural data, we often fail to shed light on the many hands involved in generating, collecting, storing, processing, analysing, and visualising the data. Bringing visibility to those involved throughout a data-centric design process can better inform and support future designers and researchers engaging in similar activities.

- What is beyond data privacy and open data?
- How do we empower and foster value exchange through data?
- What are mechanisms and tools to facilitate data conversation at scale?

DATA AS EVIDENCE SUPPORTING MISSION-DRIVEN INNOVATION

As a next step for use of data in combination with design and design thinking, the methods and tools presented may also be used to support the inquiry into design options and creation of evidence for mission-driven innovation. This is still a rather new field, with not many established methodologies yet. Still, some explorations of experimental methodologies have been undertaken. For example, in relation to the use of **Data-Driven Predictive Analyses** to get real-time insight on the effects of interventions (Geurts et al., 2022), thereby supporting monitoring. Others have experimented with the use of data-inspired methodologies for policy making (Giest, 2017). For example, they can be used to explore the use of new data sources, or experimenting with data for policy options (Veenstra & Kotterink, 2017). Questions that arise from this use of data for supporting mission-driven innovation are:

- How to use data to guide decisions regarding transitions, which are often complex and have many interlinked aspects?
- Which data sources are suitable for which types of decisions and which data processing tools and algorithms may be used for different types of decisions?
- Which stakeholders and datasets to involve in decision making?
- Which ethical challenges emerge, such as privacy, bias in data, risks to fundamental rights?

11.4 REFERENCES

- Alfaras, M., Tsaknaki, V., Sanches, P., Windlin, C., Umair, M., Sas, C., & Höök, K. (2020). From biodata to somadata. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-14). <https://doi.org/10.1145/3313831.3376684>.
- Anderson, K., Nafus, D., Rattenbury, T., & Aipperspach, R. (2009). Numbers have qualities too: Experiences with ethno-mining. *Ethnographic Praxis in Industry Conference Proceedings*, (1), 1231140. <https://doi.org/10.1111/j.1559-8918.2009.tb00133.x>.
- Bae, S. S., Zheng, C., West, M. E., Do, E. Y. L., Huron, S., & Szafir, D. A. (2022). Making data tangible: A cross-disciplinary design space for data physicalization. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1-18). <http://arxiv.org/abs/2202.10520>.
- Bogers, S., Frens, J., Van Kollenburg, J., Deckers, E., & 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* (pp. 301-311). <https://doi.org/10.1145/2901790.2901855>.
- Bourgeois J., Van der Linden J., & Kortuem, G. (2014a) Conversations with my washing machine. In *Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing* (pp 459-470). New York: ACM. <https://doi.org/10.1145/2632048.2632106>.
- Bourgeois, J., Van der Linden, J., Kortuem, G., Price, B. A., & Rimmer, C. (2014b). *Using participatory data analysis to understand social constraints and opportunities of electricity demand-shifting*. <https://doi.org/10.2991/ict4s-14.2014.49>.
- Cheng, Y. T., Funk, M., Tsai, W. C., & Chen, L. L. (2019). Peekaboo cam: Designing an observational camera for home ecologies concerning privacy. In *Proceedings of the 2019 conference on designing interactive systems* (pp. 823-836). <https://doi.org/10.1145/3322276.3323699>.
- Churchill, E. F. (2017). Data, design, and ethnography. *Interactions*, 25(1), 22-23. <https://doi.org/10.1145/3172893>.
- Clarke, C. L., Wilkinson, H., Watson, J., Wilcockson, J., Kinnaird, L., & Williamson, T. (2018). A seat around the table: participatory data analysis with people living with dementia. *Qualitative Health Research*, 28(9), 1421-1433. <https://doi.org/10.1177/1049732318774768>.

- Desjardins, A., Biggs, H. R., Key, C., & Viny, J. E. (2020). IoT data in the home: Observing entanglements and drawing new encounters. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-13). <https://doi.org/10.1145/3313831.3376342>.
- Desjardins, A., & Biggs, H. R. (2021). Data epics: Embarking on literary journeys of home internet of things data. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1-17). <https://doi.org/10.1145/3411764.3445241>.
- Dourish, P., & Gómez Cruz, E. (2018). Datafication and data fiction: Narrating data and narrating with data. *Big Data & Society*, 5(2). <https://doi.org/10.1177/2053951718784083>.
- Funk, M., Lovei, P., & Noortman, R. (2024, in press). Data-enabled design: Designing with data in contextual and informed explorations. In J. Vanderdonck, P. Palanque, & M. Winckler (Eds.) *Handbook of human computer interaction*. Springer.
- Geurts, A., Gutknecht, R., Warnke, P., Goetheer, A., Schirrmeister, E., Bakker, B., & Meissner, S. (2022). New perspectives on data-supported foresight: A hybrid AI-expert based approach. *Futures and Foresight Science*, 4(1).
- Giest, S. (2017) Big data for policymaking: fad or fasttrack? *Policy Sci.* 50(3), 367-382.
- Gulotta, R., Odom, W., Forlizzi, J., & Faste, H. (2013). Digital artifacts as legacy: exploring the lifespan and value of digital data. In *Proceedings of the SIGCHI conference on human factors in computing systems* (pp. 1813-1822). <https://doi.org/10.1145/2470654.2466240>.
- Gomez Ortega, A., Van Kollenburg, J., Shen, Y., Murray-Rust, D., Nedic, D., Jimenez, J. C., Meijer, W., Chaudhary, P., & Bourgeois, J. (2022). SIG on data as human-centered design material. In *Extended abstracts of the 2022 CHI conference on human factors in computing systems (CHI EA '22)*. New York: ACM. <https://doi.org/10.1145/3491101.3516403>.
- Gomez Ortega, A., Noortman, R., Bourgeois, J., & Kortuem, G. (2024). Dataslip: Into the present and future(s) of personal data. In *Proceedings of the 18th international conference on tangible embedded and embodied interaction (TEI '24)*.
- Gorkovenko, K., Burnett, D., Thorp, J., Richards, D., & Murray-Rust, D. (2019). *Supporting real-time contextual inquiry through sensor data*. Ethnographic praxis in industry (EPIC2019). <https://doi.org/10.1111/1559-8918.2019.01307>.
- Haddadi, H. (2016). *Human-data interaction*. *Encyclopedia of Human Computer Interaction*.
- Huron, S., Carpendale, S., Thudt, A., Tang, A., & Mauwerer, M. (2014). Constructive visualization. In *Proceedings of the 2014 conference on designing interactive systems* (pp. 433-442). <https://doi.org/10.1145/2598510.2598566>.
- King, R., Churchill, E. F., & Tan, C. (2017). *Designing with data: Improving the user experience with A/B testing*. O'Reilly Media.
- Kun, P., Mulder, I., de Götzen, A., & Kortuem, G. (2019). Creative Data Work in the Design Process. In *Proceedings of the 2019 on creativity and cognition* (pp. 346-358). <https://doi.org/10.1145/3325480.3325500>.
- Kurze, A., Bischof, A., Totzauer, S., Storz, M., Eibl, M., Brereton, M., & Berger, A. (2020). Guess the data: Data work to understand how people make sense of and use simple sensor data from homes. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1-12).
- Lee-Smith, M. L., Benjamin, J. J., Desjardins, A., Funk, M., Odom, W., Oogjes, D., & Tsaknaki, V. (2023). Data as a material for design: alternative narratives, divergent pathways, and future directions. In *Extended abstracts of the 2023 CHI conference on human factors in computing systems* (pp. 1-5). <https://doi.org/10.1145/3544549.3573817>.
- Loukissas, Y. (2019). *All data are local: Thinking critically in a data-driven society*. The MIT Press. <https://doi.org/10.7551/mitpress/11543.001.0001>.
- Nissen, B., & Bowers, J. (2015, April). Data-things: digital fabrication situated within participatory data translation activities. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems* (pp. 2467-2476). <https://doi.org/10.1145/2702123.2702245>.

- Sanches, P., Howell, N., Tsaknaki, V., Jenkins, T., & Helms, K. (2022). Diffraction-in-action: designerly explorations of agential realism through lived data. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1-18). <https://doi.org/10.1145/3491102.3502029>.
- Sapienza, A., & Lehmann, S. (2021). A view from data science. *Big Data & Society*, 8(2), 20539517211040198. <https://doi.org/10.1177/20539517211040198>.
- Speed, C., & Oberlander, J. (2016). *Designing from, with and by data: Introducing the ablative framework*. Design Research Society Conference 2016. <https://doi.org/10.21606/drs.2016.433>.
- Van Kollenburg, J., & 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.
- Van Steenbergen, M., Van Grondelle, J., & Rieser, L. (2019). A situational approach to data-driven service innovation. In I. Reinhartz-Berger, J. Zdravkovic, J. Gulden, & R. Schmidt (Eds.) *Enterprise, business-process and information systems modeling*. BPMDS EMMSAD 2019. Lecture Notes in Business Information Processing, vol 352. Springer. https://doi.org/10.1007/978-3-030-20618-5_11.
- Veenstra, A.F., & Kotterink, B. (2017) Data-driven policymaking: the policy lab approach. In P. Parycek (Ed.) *ePart 2017*. LNCS, vol. 10429 (pp. 100–111). Springer. https://doi.org/10.1007/978-3-319-64322-9_9.
- Young, E., Marsden, A., & Coulton, P. (2019). Making the invisible audible: Sonifying qualitative data. In *Proceedings of the 14th international audio mostly conference: A journey in sound* (pp. 124–130). <https://doi.org/10.1145/3356590.3356610>.
- Zhang, X., Brown, H.-F., & 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* (pp. 5350–5359). <https://doi.org/10.1145/2858036.285852>.