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Developing a Design Inquiry Method for Data Exploration

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Abstract. The increasing availability of large-scale datasets such as sensor data or social media data and increasingly accessible data science tools create unique opportunities for design. However, the relationship between data science practices and design methods is still underdeveloped. In this paper, we propose that data exploration activities can be effectively embedded within a broader design inquiry framework and define a new design method, coined Data Exploration for Design, to support methodical designerly data exploration. The design method addresses the novice's learning curve and supporting developing a data exploration inquiry mindset with procedures and curated tools. The empirical evaluation highlights support for producing exploration outcomes that are worth the additional technical effort. We close the paper by positioning the findings in design methodology literature and motivating data exploration principles for design inquiry. The principles urge to acknowledge biases in data collection, spending time with the data, using visualizations as a means-to-an-end, and designers being part of the data collection.

Keywords: data exploration; design methods; digital design; technology

1 Introduction

Large data infrastructures are becoming common in design practice and generate opportunities to use data in new ways in design inquiry. Ever since the 'big data boom' [1], industries have been following a datafication trend to render virtually any phenomenon in data and make digital products where data is a core part of the experience [2]. In the current work, we refer to data in the 'big data era' as complex or heterogeneous datasets, such as quantitative data, sensor data, open data, or data in large data infrastructures [3]. Taking advantage of such a wide variety of data has been based on decades of computer science research on information visualization [4], data mining [5], or information seeking [6]. The plethora of data practices has informed the emergence of both experts and non-experts leveraging large data infrastructures. While experts, such as engineers or analysts, use professional tooling, non-experts creatively utilize data in new ways using end-user tooling [7]. For example, citizen science

activists can install and collect bottom-up environmental data or use open data. In another example, user researchers and anthropologists use digital ethnography techniques to research people through their digital footprint, as digital products are increasingly incorporate data collection (i.e., logging) of user actions [8]. Such examples indicate a changing landscape of data in the design process, especially regarding inquiring worldly phenomena through data; however, data techniques are still scarce in the design process.

Designers have a long tradition in appropriating techniques and tools from other fields. Similarly, the design field can find inspiration in how other fields have incorporated inquiry from the big data era. Numerous fields, such as natural sciences, social sciences, and humanities, have established new epistemological traditions to respond to the big data era [9]. Through the repurposing of existing datasets for new types of big data-enabled inquiries, paradigm shifts have been witnessed in fields such as biology [10] or computational social sciences [11]. Speed and Oberlander [12] presented a theoretical framework to categorize different uses of data in design research, primarily focused on utilizing data-collecting artifacts in the design process. Giaccardi et al. [13] have investigated equipping everyday objects with data collection capabilities to expand ethnographic inquiry. Similarly, Bogers et al. [14] have expanded on design probes [15] with data-collecting sensors. Common in these examples is the reliance of data expert collaborators (i.e., data scientists), indicating the complicated nature of bringing big data techniques into the design process. Practitioners from the industry have confirmed such data expert reliance for designing interactive products [16, 17]. To conclude, while the big data era has been triggering new approaches to inquiry in various fields, including design, designers still primarily approach data through data expert collaborators. Contrary to the previous approaches relying on data experts in the process, our previous work [18, 19] has explored how designers as 'data non-experts' can leverage data. Our investigations confirm that new types of insights can be gained from 'big data approaches' to fuel the design process, and designers themselves are able to conduct data practices using non-expert tooling.

Despite the large variety of earlier [4–8] or adjacent [9–11] examples of how different fields and professions use big data techniques, data-centric design techniques are still scarce in design practice. In the current study, we approach existing data techniques and tools through a methodology lens to motivate a design method for data exploration. By observing the use of the developed design method, we generate systematic knowledge about using data in the design process and generate value for design practice. Specifically, we frame data exploration from a design inquiry perspective and contribute to design practice in the big data era by presenting data exploration as a design method. These terms will be unpacked later from a design methodology perspective.

The following research questions guided our study:

1) How can data exploration be approached as a design inquiry method?
2) What kind of mindset and expectations do designers assume while using data exploration as a design inquiry method?

The research questions have first motivated a design method approach for data exploration based on earlier work from other scientific and professional fields using data techniques. In the following, we present the design method and a corresponding study we conducted to learn about the mindset and expectations of creativity support in

design inquiry through data. The contributions of the current study are two-fold. First, the study provides a design inquiry method for data exploration that can foster methodical inquiry through data in design practice. With the method, we support the initial learning curve for data non-expert designers and consider how methods evolve and integrate into the thinking processes with data. To this end, our second contribution is a set of principles to follow data exploration as a design inquiry, when data exploration is fundamentally intertwined with design inquiry beyond the usage of the method.

2 Towards a Design Inquiry Method for Data Exploration

In this section, we first frame design inquiry as a fundamental element of the design process and then focus on data exploration as an approach for design inquiry. Afterwards, in the second part of the section, we present a contemporary perspective on developing design methods and an overview of non-expert approaches for gaining data competences. We conclude the section with a design rationale for a design inquiry method for data exploration.

It is widely accepted that design has a specific type of inquiry and action. Nelson and Stolterman [20] deliberately distinguish design's approach of inquiry from sciences, while highlighting that design inquiry is a fundamental part of the design process. More recently, Dalsgaard [21] has suggested a view on inquiry as a move from uncertain situations towards stable situations, iterating on framing and reframing the design problem, developing hypotheses addressing the problem, experimenting with and refining hypotheses, and acting to change the situation. Dalsgaard also clarifies his understanding with a definition: [design inquiry is a] "*...explorative and transformative process through which designers draw upon their repertoire of knowledge and competences as well as resources in the situation, including instruments, in order to create something novel and appropriate that changes an incoherent or undesirable situation for the better"* [21]. The different understandings of design inquiry bear resemblance with the transitioning between ill-defined and well-defined understanding of problem spaces, as presented by Maher et al. [22], further expanding to the co-evolution of problem and design spaces by Cross and Dorst [23].

The different design inquiry notions from above share the underlying concept of design inquiry as an **exploratory** and **open-ended** move between unknown and known states of a design situation. In the following section, we will introduce data exploration and position it in relation to design inquiry.

2.1 Data Exploration for Design Inquiry

Data exploration techniques have existed for decades, starting from coining the term of Exploratory Data Analysis (EDA) by Tukey [24, 25]. EDA was defined as using different statistical tools to describe and explore numerical datasets to find inferences from data. Since then, EDA has taken a more expansive meaning and now includes a broad array of approaches and methods for exploring data. Alspaugh et al. [26]

elaborate on a more contemporary view on emerging data exploration strategies. They define data exploration as an *"open-ended information analysis, which does not require a precisely stated goal"*. Alspaugh et al. looked at EDA on a spectrum between exploratory and directed analysis, with the following description what they see as exploration: *"Exploration is opportunistic; actions are driven in reaction to data, in a bottom-up fashion, often guided by high-level concerns and motivated by knowledge of the domain or problem space."* EDA's characteristics of **exploratory** and **open-ended** resemble design inquiry as discussed earlier, highlighting an opportunity to consider matching opportunistic data practices with design practices. In keeping with Alspaugh and colleagues' work, in earlier work, we [19] presented a perspective that combines the different data exploration steps with the diverging-converging steps familiar in design work since Jones [27]. Our rendering of data exploration as diverging-converging steps revealed how data exploration can be combined with creative work, such as design. This perspective was motivated by the similarity of data exploration and design inquiry following an opportunistic inquiry process. In an earlier study [18], we observed how designers appropriate a generic data science understanding of inquiry; an inquiry focused on answering questions about a phenomenon through inferences from a dataset, including data acquisition, if necessary. We highlighted that leveraging data approaches requires precise question-formulation due to the computational, automated characteristic of data techniques. We also observed the tension in how designers use data tools primarily made for deductive and inductive data analysis work are creatively re-appropriated, following *abductive reasoning* dominant in design inquiry [28, 29]. On a theoretical level, these earlier studies on data exploration and design inquiry highlight that it is not only possible to use data exploration for design work, they also provide foundations and a shared vocabulary. However, it remains unclear *how* designers can utilize data techniques in practice. In different words, despite the long history of data exploration and its successful wide-spreading in different disciplines, data techniques have not yet become an integral part of designers' toolbox. We address this by building on the parallel between data exploration and design inquiry by developing a design method in the current work. As we will show in the next section, the proposed design method will 'scaffold' existing data techniques for design practice and support the designers' learning curve of the method.

Next, we elaborate on considerations for developing design methods. As we will argue, by discussing data exploration as a design method, one important aspect is to support the learning of a method. In that regard, in a later section we elaborate on how non-expert communities gain data competences. These aspects will then be combined into a design rationale for a design method.

2.2 Developing Design Methods

Design methods, techniques, and tools are commonly used for different design activities, such as problem finding, problem framing, or defining a problem and design space. Since the seminal Design Methods book [27, 30], many method and tool collections have attempted to support designers of any experience level by codifying best practices and enabling designers to collaborate better with colleagues from different backgrounds. Jones selected design methods from different disciplines, for

example, presenting *interviewing users* as a design method borrowed from social sciences, highlighting the ever-existing approach of designers to appropriate methods, techniques, and tools from adjacent disciplines to design. We explored similar appropriation of methods, techniques, and tools from end-user data communities to designers in earlier work [18]. While our previous study confirmed the general adaptability of such data practices to design work, it has remained unclear how the thinking process changes when appropriating data practices. Such thinking aspect, and generally the mental component of methods, has been becoming central in recent works, as shown in the following examples. Daalhuizen [31] reconceptualized methods as mental tools rather than prescribed recipes towards specific design outcomes. A corresponding notion was highlighted by Gray [32], who found that designers integrate methods in their mindset as tools to answer different questions. This view refines the understanding of methods from 'process prescriptions' towards influences on designers' mindset. Schønheyder and Nordby [33] showed how design methods used in practice evolve and adapt to circumstances. These findings urge developers of design methodologies not only to attend methods as 'process descriptions', but also to consider the corresponding **mindset**; the tacit component of how designers grow together with their methods and how methods become an integral part of designers' thinking patterns. In the development of a method, **step-by-step guides can help to support novices**. However, it appears to be more crucial to consider the higher-level design activity goals a designer wants to achieve by using a method and developing the method to foster the intended mindset. In this way, designers of methods need to consider that the users of methods grow expertise and open-endedly adapt methods during use.

Designers in practice also diverge opportunistically from a structured plan or methodical process [34]. In an opportunistic practice, where the designers follow the design situation with any methods and resources at hand (such as available data), it is then most valuable to suggest strategic and methodical ways of using a method in **'designing the design process'** [35]. The considerations of a tacit mindset, the novices' support through step-by-step guides, and methods in an opportunistic design process guide us to develop a design method. These considerations provide guidelines on how existing data techniques could be "scaffolded" into a design method to make them more accessible in general design processes. Next, we review non-expert data practices suitable for designers without specific data skills, assuming designers' limited data expertise.

2.3 Supporting Non-experts Learning and Using Data

Along with the developments of computation and the growing ubiquity of data, data science has emerged as a field unifying the emerging practices, data techniques, and know-how in the big data era [36]. In keeping with our earlier findings [18], we investigate the end-user spectrum of data science and its suitability for supporting data exploration as a design method. In this focus, gaining data competence is the primary goal. Different approaches illustrate how data literacy is understood and what sort of educational scaffolds are in place. Baumer [37] showed a curriculum of teaching data competencies in undergraduate education, emphasizing to teach a whole spectrum of tools to prepare students working with data in real settings. The core of Baumer's

inquiry process starts with asking a question and ends with an answer gained from data, and then communicate the findings. The tactic of using data for the whole inquiry helped students to learn how to 'think with data'. Outside traditional curriculums, Hill and colleagues [38] explored teaching data science as a way of 'democratizing data science' for community empowerment. Their approach was based on teaching basic programming to remain as closest possible to expert data science practices. They particularly emphasized being able to ask questions for investigation from data, and in this process, being able to acquire data from online sources (such as capturing data Wikipedia), then analyzing it, and developing a visualization to communicate the findings. While Hill and colleagues' [38] approach provided a flexible set of skills and tools, it also came with a steep learning curve cost. D'Ignazio and Bhargava [39] approached this problem from a more learning-centered angle. They created a set of learning tools for data literacy, designed to avoid programming explicitly, and targeted data skill acquisition through tailored, single-purpose data tools – DataBasic. These tools can be used with actual datasets and for actual visualization and analysis work, but they are primarily learning tools, scaffolding more complicated data operations. In another work, D'Ignazio [40] added to the work on DataBasic tools from her experiences with applying and teaching data literacy positioned in creative work, such as design. Both the programmatic way of Hill et al. and D'Ignazio's and Bhargava's learning tools approached data work using a set of tools, rather than focusing on one single tool [18]. Such use of smaller tools performing the elements of a data workflow is a best practice, with roots in software engineering.

In conclusion, lessons from different non-expert practices can make data science practices accessible to designers without advanced programming skills, through toolsets calibrated for users' expertise. Such non-expert practices and toolsets are **holistic**, covering not only data acquisition and analysis as steps but the related cognitive aspects of formulating a question from the data and inferring an answer.

2.4 Design Rationale

The above-reviewed work on design inquiry and non-expert ways of learning and using data has helped to extract guiding design principles for developing a design method for data exploration. First of all, we concluded that data exploration could intertwine fundamentally with design inquiry, as an **open-ended** and **holistic** process. We refer to support data coming in various shapes, formats, or topics with the terms open-ended, catering to the unlimited types of design situations designers face. Under holistic, we mean supporting the complete data workflow, from asking a question to be addressed by data, to data collection and transformation, and inferring from data. Assuming that most designers lack data expertise, a design method should lower the threshold to enable a designer leveraging real data in real design situations. Furthermore, a design method should guide to set realistic expectations about data, but also indicate the potentials of data with growing data expertise.

The aforementioned *open-ended* and *holistic* design principles of approaching data exploration in design work lead to the creative usage of data in the design process. To interpret such creative usage of data in practical terms, we use the four levels of the creativity framework by Sanders and Stappers [41], a practical framework for everyday

manifestations of creativity. In this framework, Sanders and Stappers define *Doing, Adapting, Making, and Creating* in increasing order of expertise/interest as can be seen in people's lives. They argue that people can be simultaneously on different levels of creativity for different areas of life. Considering designers' relatively low level of data expertise, we assume that most designers today would be on the levels of *Doing* and *Adapting* to utilize data. Table 1 presents an adjustment of their framework for our design rationale to serve as guidance for developing our design method. Based on the framework, we mainly address the levels of *Doing* and *Adapting*, as a way to be able to *Do* with data and *Adapt* data techniques for design inquiry.

Table 1. Four levels of creativity based on [41], adjusted for interpreting creative use of data exploration in design inquiry.

Level	Type	Description
4	Creating	The highest level of expertise/interest in this spectrum addresses such cases that fundamentally transform the design practice intertwined with data.
3	Making	This high level refers to *"asserting own ability or skill"* in utilizing data in one's generic design practice.
2	Adapting	The appropriation of techniques starts to happen at this level. This appropriation can be guided and inspired by appropriating data thinking and existing data techniques into one's process.
1	Doing	The level of being able to transform a dataset independent of a tool (thus having a sense of how to manipulate a dataset) is part of general technical literacy, at least through basic knowledge of spreadsheets software (e.g., Excel).

The principles of *open-ended* and *holistic*, together with the four levels of creativity defined in the creativity framework [41], have been made operational for developing a design method for data exploration following the taxonomy of Sanders, Brandt, and Binder [42]. In their terms, *tools* are "material components used in design activities"; a *toolkit* is a collection of tools used in combination for a specific purpose; a *technique* is a description how tools and techniques are put into action; a *method* is a combination of tools, toolkits, techniques put together strategically towards a specific design research plan, and at last, an *approach* refers to an overall mindset for conducting the design research plan.

In keeping with the taxonomy, we construct our design method consisting of 1) a workshop procedure; 2) a curated recommendation of existing software tools; and 3) design tools (card decks and booklets), all of which elaborated in the next section. We approach these different 'elements' of a design method to guide not only to set realistic expectations about data but also to indicate the potentials of data with growing data expertise. We address our assumption about designers lacking data expertise by scaffolding existing data exploration techniques in the format of familiar design tools. Furthermore, we support a dynamic skill acquisition process for an open-ended and holistic data exploration for design inquiry. The following section presents the resulting design method for data exploration, referred to as Data Exploration for Design (DEfD) method.

3 Data Exploration for Design Method

The Data Exploration for Design (DEfD) method aims to guide designers to explore and use datasets for design inquiry creatively. The purpose of such a creative exploration of data is to enable extracting valuable inferences for the design process, which otherwise would have been harder to technically infeasible to find by using other design inquiry methods.

In keeping with Sanders, Brandt, and Binder's taxonomy [42], the presented DEfD method consists of three disjunct components; a method outline, recommended software tools for data operations, and design tools. A method outline forms the primary basis, which combines data exploration and design inquiry into an intertwined approach through a procedure of conceptual stages. We complement the method outline with end-user software tools commonly used by other non-expert data communities. Furthermore, we developed a set of card decks and booklets to support novices' learning curve during the workshop. The next sections present each of these different components of the method, respectively.

3.1 Method Outline

The DEfD method outline has been developed in keeping with the Exploratory Data Inquiry framework (EDI) from our earlier work [19]. Figure 1 shows how the EDI methodology can be framed more directly as iterative stages. The design method follows EDI's three conceptual stages of problem framing, exploring, and inferring. The three stages integrate into an inquiry within a design situation.

In the next part of the paper, we illustrate this outline with a workshop structure for a one-day workshop setting, where the input to the design process is a design brief and an available dataset. The one-day format does not restrict conducting the method, as methods evolve and integrate with individual design practices [31–33].

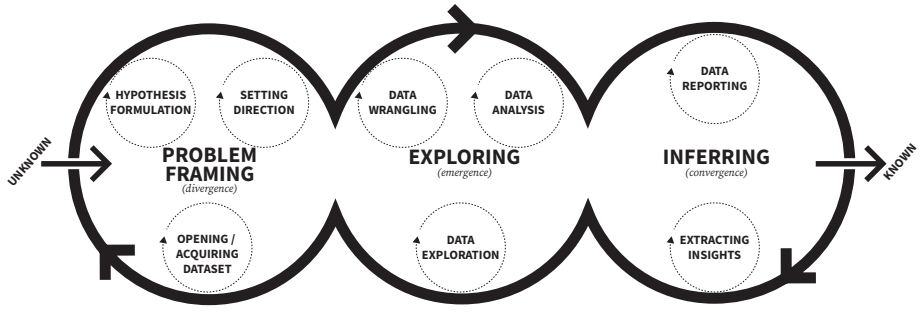

Fig. 1. The outline of the DEfD method, following the three conceptual stages from the EDI methodology. The different conceptual stages proceed in sequential order, but iteratively.

Problem framing: The first conceptual stage of the design method is centered around framing the problem to explore through data. During this stage, the designer sets up a data exploration by formulating a hypothesis, opening or acquiring a dataset, and setting a direction for the data exploration. Hypotheses emerge in various shapes; it can be an explicit hypothesis or research question or an opportunistic 'curiosity' or a 'hunch' when the problem formulation is still in the early stages. Data exploration continuously proceeds from implicit hunches towards explicit research questions used for proving a hypothesis. Following a hypothesis or research question, a direction can be set for exploration. Such direction bridges between how to explore a hypothesis and what data is available for such exploration. If a dataset is already available, it is a much lower effort to set the data exploration strategy that suits the data, such as what type of methods and tools can be used for the given dataset. Similarly, when a specific data exploration method or tool is readily available, data acquisition can be defined accordingly.

The three components mentioned above are continuously evolving in the Problem Framing conceptual stage. In other words, if the design process builds on a design brief, then in this stage, the brief is being explored from a data perspective. Typical questions in this stage are: "What hypothesis do we want to inquire about?"; "What datasets are available?"; "How will we explore the data?" The co-evolution process of designing provides answers to these questions, as the design problem unfolds. Therefore, iterating back to this conceptual stage is expected while using the method.

Exploring: The second conceptual stage of the method centers around the actual exploration of the data and necessary data operations. During this stage, the designer is wrangling (transforming and cleaning) the data, exploring it, and conducting different data analyses. These steps attempt to productively process the dataset to explore and analyze it in ways that can fuel inferences into the design inquiry. Data wrangling is an essential step in working with data, as significant proportions of time are spent on cleaning and processing the data. Cleaning and transforming the data are iterative steps to decrease the extent of corrupted data and to shape the data for different exploration and analysis tools. The most valuable time to inquire into a design problem is spent on data exploration and data analysis, by increasingly understanding the problem space and finding answers to hypotheses and research questions. The available dataset, the research questions, and the design situation result in myriad combinations for data exploration and analysis.

Connected to the direction set in the previous conceptual stage, the designer will explore the data pursuing a particular interest (i.e., research question) in mind, however throughout the process itself, as the understanding of the problem grows, the research question may continuously evolve. Thus, iterating between Exploring and Problem Framing conceptual stages is expected while using the method.

Inferring: The third conceptual stage of the DEfD method is centered around extracting valuable inferences from the explored dataset. During this stage, the designer extracts insights and works on reporting the findings from the inquiry process. The conclusions from the data exploration process trigger a new iteration of inquiry with the same or a different design method or help to proceed further in the design process. The steps in this conceptual stage build on representations and visualizations generated from the Exploring stage. Such outputs can be utilized further in the design process as boundary objects, contributing to the increasing understanding of the design situation

and problem space. Beyond visualizations, alternative inferences are different insights, such as answers to a research question. While explicit answers to research questions often end up in a report or presentation to stakeholders, implicit findings also generate value throughout the data exploration process. Such 'small insights' help to build the common sense thinking about the problem domain. These different insight types can lead to iterating back to the previous conceptual stages, which is an expected proceeding through the method.

Different types of tools support the three conceptual stages. As can be seen from the description of the three conceptual stages, designing is intertwined with thinking and working with data. A combination of design tools and non-expert data tools support these processes (see Table 2). Under design tools, we refer to supporting through learning materials. Under non-expert data tools, we refer to publicly available software tools that are wide-spread and widely supported by non-expert communities.

Table 2. Design tools and curated non-expert data tools used in the DEfD method.

Stages	Problem framing	Exploring	Inferring
Design tools	'Basic data types and techniques' card deck 'Questions for data' booklet	'Data techniques' card deck 'Questions for data' booklet 'Working with data 101' booklet	'Questions for data' booklet
Non-expert data tools		Spreadsheet software (e.g., Excel) Data wrangling tools (e.g., OpenRefine) Data visualization tools (e.g., RAWGraphs) Data analysis tools (e.g., Voyant Tools – text analysis, Gephi – network analysis)	Data visualization tools (e.g., RAWGraphs)

Next, we present the design tools we developed and then a curated set of software tools.

3.2 Design Tools

This section introduces design tools we developed; two card decks and two booklets to scaffold various best practices for data. Although a substantial part of data exploration happens through software tools, the cognitive aspects of data exploration, such as how to *think* with data, need to be learned through practice. The cognitive aspects, such as computational thinking or sense-making of data, are part of the tacit knowledge gained during the initial **learning curve** that will become part of a designer's mindset. To support this learning curve, we developed design tools in formats familiar to designers. Next, we present our design rationale for card decks and booklets and then introduce them in detail.

Card decks are ubiquitous design tools [43] and have also been effectively used for data visualization [44]. Card deck-based tools have also been used to bring theoretical academic work into design practice, using card decks as tools to facilitate workshops (e.g., [45, 46]). Following such examples, we have approached the support of open-

ended data exploration in a domain-general and extendable way by using card decks and booklets. We have aimed with the card decks and booklets to introduce low-key design tools that are easy to reproduce with a home printer, tailored for specific datasets and design situations. For example, additional cards can extend a card deck with cards about different data types or domain-specific exploration possibilities. The booklets are eight-page foldouts, which is a limited format to contain focused information. We have deliberately left un-designed how to use the card decks and the booklets to foster creative exploration and intertwining how these design tools can integrate into designers' practices. However, we have expected some typical uses of the card decks, such as 'forced pairing' of cards to trigger new ideas by combining different cards or using the cards to 'reverse engineer' and model existing data projects.

The following sections present the basic card decks and booklets prepared for the current study. As specified before, we envisage these design tools tailored and extended for different uses of the DEfD method.

Card decks: In this section, we first present two card decks and then discuss the extensibility to alter and create new card decks.

*Basic data types and techniques***:** The 'Basic data types and techniques' cards provide a quick overview of the basic data types and the most common and essential data techniques applied on datasets (see Figure 2). These cards can remind the user to consider alternative options or can be a quick reference for browsing through a dataset. One part of the card deck is cards summarizing the various data types commonly found in datasets describing everyday phenomena, such as numerical data, geo-located data, categorical data, or textual data. The other part of the card deck collects fundamental actions to apply to data, such as comparing or identifying data points. These activities are so prevalent that they go unnoticed in most cases. However, when someone is unfamiliar with using computational thinking, these activities do not naturally come up (such as selecting a datapoint - *identify*).

Data techniques: The 'Data techniques' card deck summarizes typical techniques to apply on a dataset to extract further meaningful information out of the data (see Figure 3). An example data technique is *map visualization*, which can easily be accomplished, for instance, when the dataset contains GPS coordinates. The related data technique card provides a basic overview of what kind of input(s) such a technique requires (e.g., GPS coordinates or addresses). One explicit aim of the data techniques card deck is to trigger the considerations of exploring data through additional techniques (i.e., not to fixate on one exploration), and in this way, to stretch learning and going beyond familiar methods.

Extensibility: At the core of our design rationale is to tailor the card decks to specific datasets and specific design situations. Datasets from different domains, such as metadata of library records or location coordinates of urban space artifacts, require different data exploration approaches, yet designers can face both examples. Thus, we emphasize that the presented card decks are just initial decks that we created for the reported study in the paper, and tailoring of the card decks should be part of the design work. Furthermore, bespoke card decks support different layers of abstractions; a card deck that summarizes different visualization charts can be valuable for a dataset containing many numerical and categorical data columns. Such a bespoke card deck could provide more detailed visualization choices than the cards from Figure 3.

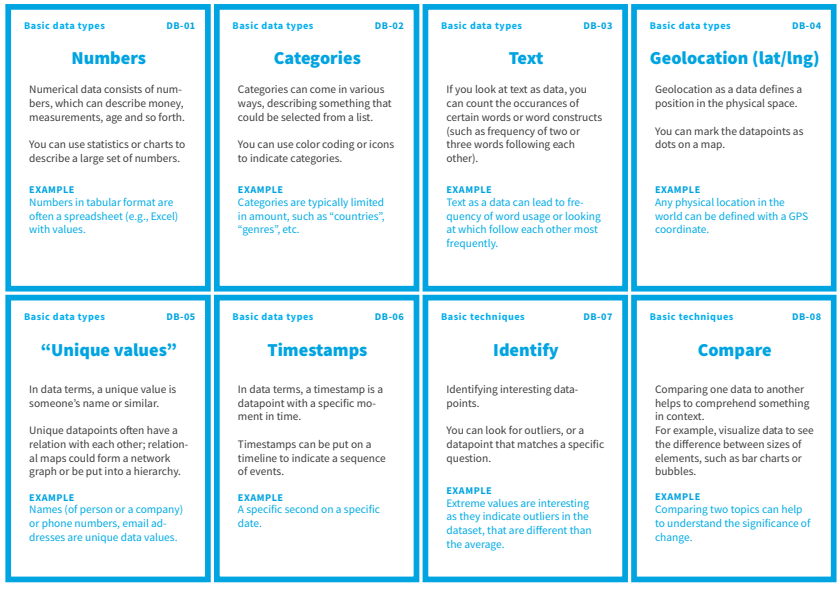

Fig 2. The Basics of data cards contain the most elementary data types and data techniques.

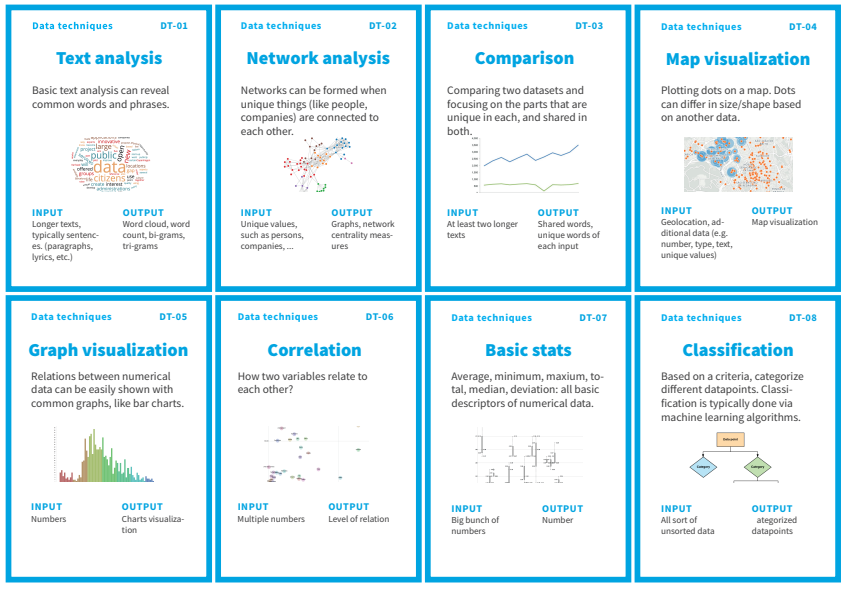

Fig. 3. The Data techniques cards show common techniques to extract information out of data.

Booklets: This section presents two booklets and discusses the extensibility to alter and create new booklets.

Questions for data: This booklet aims to guide designers to get unstuck from a confusing situation (see Figure 4). The booklet builds on the insight that, for the first time, it is daunting to open an unfamiliar dataset without knowing its content. The booklet contains questions hinting towards strategies to process the dataset and overcome the initial challenges. Depending on different situations, these questions aim to: 1) look at raw data and not knowing the next step; 2) look at a visualization and not knowing how to read it; 3) looking at data and not knowing how to extract further insights from it. The booklet's questions may seem trivial, but during a learning process can serve as a spark of inspiration for a sense-making process.
Working with data 101: This booklet aims to provide a practical guide starting from the basics of opening a comma-separated value (CSV) file – the most common format to store and share tabular datasets – towards more advanced data operations on it (see Figure 5). The booklet follows the insight that there are some fundamental data operations for a learner, such as filtering or sorting data, which knowledge will be acquired early in the learning curve. Mastering these basics saves time during the design process. Furthermore, having the fundamental operations collected in one booklet emphasizes the right terminology to search for further information.
Extensibility: Similar to the card decks, the design rationale of the booklets is to customize them for specific datasets and design situations, and therefore they are made in an 8-pages *'fanzine'* format, which enables tailoring easily. We chose this format to keep the content concise and focused, easily printed on home and office printers, and to fold quickly. Potential bespoke booklets involve supporting different design method steps, such as guiding data acquisition or data cleaning.

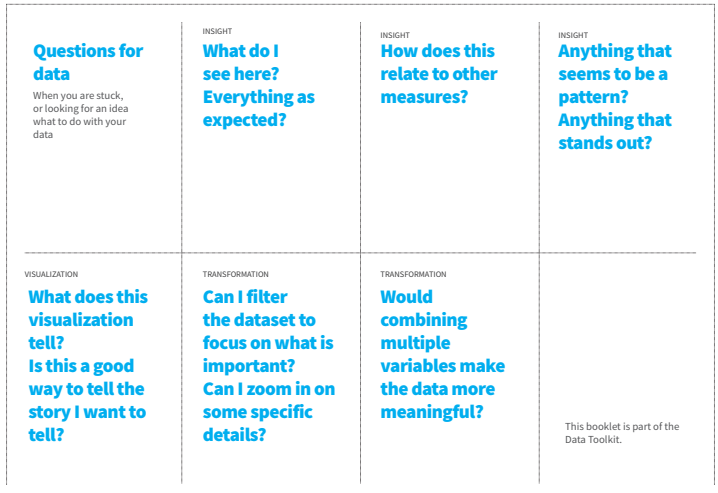

Fig. 4. The 'Questions for data' booklet contains triggering questions to extract insight from a dataset or visualization and to inspire the next steps of the data transformation.

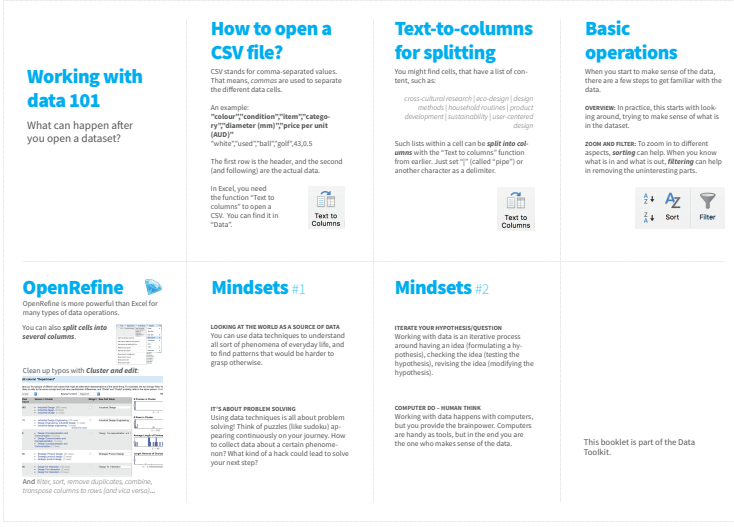

Fig. 5. The 'Working with data 101' booklet contains practical knowledge of how to open and manipulate a CSV format dataset.

3.3 Curation of End-user Data Tools

In practice, software tools are essential to leverage data, and thus curating suitable software is especially important. From the perspectives of data expertise and goals with data, data journalists and librarians share a resemblance with designers. Thus, we based our curation of tools on investigating other end-user data communities and their recommended tools. Reviewing such communities' handbooks and toolkits, we concluded the following set of criteria for software tool recommendations:

- Open source or publicly available for free;
- Available on major operating systems (or working on the web);
- Relatively easy to learn, providing a high-ceiling on functionalities;
- Supporting a non-programmatic workflow with data.

Multiple software tools match these criteria for the different steps identified in the Exploring conceptual stage. In the following, we will present our curation criteria for the core data actions:

Data wrangling (cleaning and transforming datasets): for essential operations on a dataset, we recommend common spreadsheet software, such as Microsoft Excel or Google Sheets. Spreadsheet software is widely available and often part of digital literacy education. Such software enables direct manipulation of the data and easy sorting-filtering transformations. Furthermore, for cleaning and augmenting a dataset, we recommend OpenRefine [47]. This open-source tool provides advanced functionalities to clean and augment a dataset. While spreadsheet software is capable

of these functions, OpenRefine is more robust and approachable for non-experts, especially when working with non-numerical (i.e., textual) data.

Data exploration and data analysis: spreadsheet software allows initial explorations to understand the dataset. Choosing data exploration and analysis tools largely depend on the data types in the dataset. For visualizing numerical or hierarchical data, RAWGraphs [48] provides advanced charting options beyond spreadsheet software. This online and open-source tool provides superior charting options over spreadsheet software and is very easy to use. The generated visualizations can be exported in a generic vector format, enabling further editing and additional graphic design work. For design inquiry, we also envision the usefulness of working with textual data and networked data, which require more specific tools. Although we did not introduce such tools during the study reported in Section 4 due to lack of time, there are well-spread tools that can be used by designers. Voyant Tools [49] provide an online environment to conduct text analysis, made for digital humanities scholarly research. Gephi [50] provides an open-source robust network visualization tool, widely used by researchers, including non-expert data end-users.

The tools mentioned above are recommended based on potential added value for design inquiry, available help online, and active communities around. However, better or more suitable tools may become available in the future. We have chosen easy-to-learn tools developed for non-experts, and thus our workshop procedure does not include formal tutorials on their use. While these tools can do advanced data manipulation or data analysis work, such functions require further proficiency (or longer workshop formats to provide time for learning).

The following section presents an empirical study we conducted to assess the DEfD method's applicability and inquire into the creativity support expectations when using data exploration for design inquiry.

4 Study Setup

A pilot study with novice designers (i.e., design students) has been conducted to assess whether and how the DEfD method helps use data techniques as a mode of design inquiry. Following the method description introduced in the previous section, this section presents the study's methodological setup.

4.1 Participants and Setup

Thirteen students (female, n=7; male, n=6) participated in the current study. The students could enroll in the study as a one-day elective class offering, without incentives (other than participating in a learning workshop). The students' general interest in participating was to improve data skills applicable in their design practice. The students were first-year master-level students from the Faculty of Industrial Design Engineering of Delft University of Technology, studying different orientations of design (strategic design, n=1; interaction design/user research, n=5; industrial/product design, n=6). All thirteen participants had a bachelor-level degree in design. During the study,

participants worked in duos or triads. We assumed that students with a design background would have (prior) tacit data knowledge to inform their approach for design inquiry through data. Under tacit data knowledge, we hypothesized participants to have some familiarity with spreadsheet software (e.g., Excel) from earlier studies, and a general familiarity with general types of visualizations (e.g., charts or graphs). Before the workshop, participants filled a self-assessment survey on their skills, as shown in Table 3 (Section 3.4 Data collection will provide more details on assessment).

Table 3. Overview of the study participants' skill self-assessment.

Programming skills (between 1-7, 7 highest)	**Data analysis skills** (between 1-7, 7 highest)	**Technical literacy** (between 1-7, 7 highest)
2.53 (SD: 1.80)	2.46 (SD: 1.05)	3.46 (SD: 2.18)

4.2 Materials

The workshop followed the method outline and tools, as introduced in section 3. At the beginning of the workshop, participants received a design brief, a dataset, suggested software tools to use, and the design tools (card decks and booklets).

Dataset: The provided dataset was a database of the internal repository for master thesis records of the participants' design faculty. The dataset contained 2040 rows and six columns of metadata, including the theses' Title, Abstract, Mentors, or Keywords. All participants were first-year master students enrolled in educational programs that require to conduct a graduation project (the equivalent of a master thesis) as the final step of their degrees. The provided dataset with earlier graduation projects was personally meaningful for the participants, as they will need to define their own project, find faculty mentors for supervision, and so forth. Our intention with providing this dataset was to reduce the domain knowledge acquisition required to understand the dataset.

Design brief: Based on the dataset, the participants received a design brief to define three initial research questions in the context of student graduations and find answers through a data exploration process by the end of the workshop. At the end of the workshop, they were asked to present their findings in a visual format.

Design tools: The participants were provided with the *'Basic data types and techniques'* and *'Data techniques'* card decks, and the '*Questions for Data'* and *'Working with Data 101'* booklets.

Curated end-user data tools: The participants could freely choose tools to inspect and analyze the provided dataset, but we recommended Microsoft Excel or Google Sheets, OpenRefine, and RAWGraphs for anticipated needs (see more in 2.3).

4.3 Procedure

The first author facilitated the workshop as a learning workshop to teach design students data competencies, as depicted in Figure 6.

Fig. 6. Impressions from the workshop and the study setup.

The workshop procedure followed the earlier described outline of the DEfD method (section 3) as the following:

1. Introducing the task: At the beginning of the workshop, we held a basic introduction about using data in design and elaborating on a generic data workflow. After this, the participants formed groups (n=2-3). The groups received the dataset, the data toolkit, and a design brief.

2. Opening dataset and setting direction: The groups downloaded and opened the dataset to initiate the inquiry process. In connection, the groups read the design brief and defined at least three questions to investigate from the data.

3. Data transformation: The next activity was to familiarize with the dataset, using spreadsheet software or OpenRefine as a suggested software tool, and find answers for the research questions from the previous step. We expected that the questions would evolve as the dataset is continuously further explored. After providing some time for the participants to familiarize themselves with the dataset and realize that the data needs to be cleaned, a facilitator intervention was planned by showing examples of the capabilities of OpenRefine for data cleaning and a quick tutorial of RAWGraphs, the suggested visualization tool.

4. Data exploration: Informed by the previous step, the following activity was to explore the dataset using OpenRefine and RAWGraphs to extract insights.

5. Communicating the insights: For the workshop's closing, the groups were tasked to prepare a short presentation about their exploration process and found insights. They

were explicitly asked to make it visual (i.e., present visualizations). The presentations were audio-video recorded.

After the student groups' presentations, the workshop ended with completing a survey about the workshop's learning goals and a Creativity Support Index questionnaire (see Data collection section 3.4). At the end of the workshop, an audio-recorded group discussion took place to capture additional qualitative insights.

4.4 Data Collection

Before the workshop, we asked the participants to self-assess their relevant skills to understand how they used data exploration as a design inquiry method. After the workshop, a quantitative tool was used to measure the design method's creativity support, as elaborated in the following.

Prior to the workshop: At the beginning of the workshop, the participants were asked to self-assess their related skills, using a Likert scale rating from "1 - strongly disagree" to "7 - strongly agree" (for results, see Table 3), on the following:

- My programming skills are great.
- My data analysis skills are great.
- I'm very technology literate.

During the workshop: Throughout the workshop, we took notes and photos about the participants' process, and audio-video recorded the presentations and the final reflective group discussion. Furthermore, we collected the presentations the groups prepared as tangible process outcomes.

After the workshop: For (research) data collection at the end of the workshop, we used the Creativity Support Index [51], a quantitative, psychometric tool to extract relevant insights into the mindset and expectations of the participants by assessing the design method for its creativity support for design inquiry.

5. Results

Observing the participants' processes clearly showed that exploring an unfamiliar dataset is not a straightforward task. Even though the dataset context was familiar for the participants, they were initially baffled to inquire the dataset for extracting valuable insights for future design steps. After receiving the design brief, the design tools, and the dataset, the groups defined research questions and data hypotheses to set a direction for exploration. They then started with opening the dataset, filtering, and sorting the data. After noticing the struggles with the *Data transformation* activity, a facilitator intervention provided a brief tutorial on tips and tricks with OpenRefine. Our approach for facilitating the participants' learning was to let them figure the type of computational thinking required for the process first and then follow with technical tutorials. In other words, we intended to wait with a formal tutorial until 'unknown

unknowns' can become more 'known unknowns'. We noted that after the initial learning curve of using new tools, the participants managed to 'zoom in' on their interests in the dataset through filtering and eliminating subsets of the data outside of their inquiry. Some groups even went further in deriving new data from the dataset, namely using the raw data they derived new data columns from counting appearances of keywords. The groups commented that they needed to shift their thinking for transforming the data, indicating their general lack of everyday practice with computational thinking.

The data transformation work was complemented with *data exploration,* for which the primary mean was exploratory visualization of the data, using charts from regular spreadsheet software and RAWGraphs, as shown in Figure 7. By introducing an end-user visualization tool such as RAWGraphs, it was necessary to engage in additional data transformation steps to fit the dataset into formats that can be inputted into the tool. While the groups appreciated the atypical charting options of RAWGraphs going beyond the default charts from spreadsheet software, they lacked guidance on selecting appropriate charts for their specific communication needs.

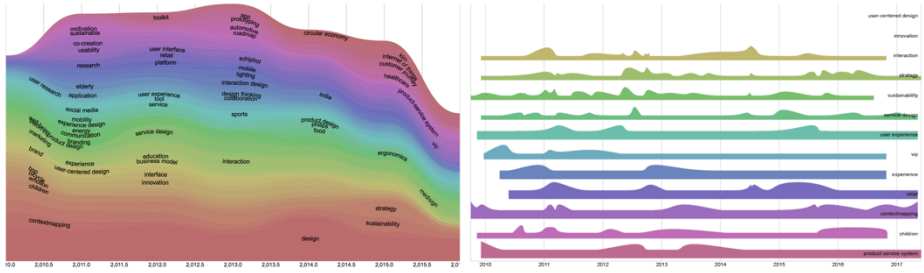

Fig. 7. Example visualizations from the participants' exploration process. The two visualizations show the most popular thesis keywords per year.

In their process, the groups approached visualizations as 'means-to-an-end' and not as the primary output of the inquiry process. Following the workshop learning goals of teaching a holistic understanding of data, the inquiry happened through cleaning, transforming, filtering the data, and visualizing certain aspects. While the design brief specified to communicate their results at the end of the workshop (and for communicating it, visualizations are essential), the groups did not put much effort into fine-tuning the visualizations. In general, the workshop's learning goals of teaching a holistic understanding of data were supported by the card decks and booklets introduced. However, the participants primarily reported the time spent on using the curated tools as the dominant source of learning.

In the following, we present the creativity support evaluation outcomes of the DEfD method, providing a detailed understanding of how participants perceived data exploration for design inquiry and their expectations regarding tools or methods supporting the task.

5.1 Creativity Support Evaluation

The CSI assessment results indicate an average of 73.85 (SD = 9.44) CSI score for the DEfD method in this study (n = 13). Such an overall score does not tell much about the given method's creativity support performance; nevertheless, it can compare the given method with other comparable approaches [51]. Following the example by Cherry and Latulipe [51], in Table 4, we report the results with respect to average factor counts, factor score, and weighted factor score for each of the six factors. Average factor counts indicate the number of times participants chose a given factor important (between 0 and 5). In other words, this measure indicates whether the participants find such an aspect important of a creativity support tool for the specific context. Average factor scores indicate how well the Data Exploration method scored (between 0 and 20) for the different factors. The high rankings of Exploration and Results Worth Effort indicate that participants found these two factors especially important of a creativity support tool for design inquiry. The average weighted factor scores are most sensitive to the factors that are marked more important (as average factor scores), and for both Exploration and Results Worth Effort factors, the weighted scores were rated higher than the other factors.

Table 4. The study's detailed CSI results show that participants rated *Results Worth Effort* and *Exploration* factors as most important. The average weighted score for these two categories has also been found highest.

Scale	**Avg. factor counts (SD)** (between 0-5, highest 5)	**Avg. factor score (SD)** (between 0-20, highest 20)	**Avg. weighted factor score (SD)** (between 0-100, highest 100)
Results Worth Effort	**3.00** (1.78)	16.15 (1.47)	**48.85** (30.92)
Exploration	**3.85** (1.07)	14.62 (1.29)	**55.85** (16.63)
Collaboration	2.08 (1.44)	14.15 (1.92)	28.46 (23.42)
Immersion	1.77 (1.42)	14.00 (2.38)	28.92 (28.15)
Expressiveness	2.31 (1.25)	13.54 (1.66)	30.46 (15.51)
Enjoyment	1.92 (1.44)	15.00 (1.27)	29.00 (21.94)

Overall, the CSI analysis outcomes confirm our design decisions that exploration and generating meaningful outcomes that are worth their effort are important, and the design direction is generally validated. In the next section, the results are interpreted and positioned in design literature. We particularly discuss principles of using data exploration tools for inquiry and the methodical use of data exploration in the design process.

6. Discussion

With the DEfD method, we proposed expanding designers' repertoire to methodologically use existing data and existing data tools for design inquiry. We developed the DEfD method by elaborating on established practices and tools from other end-user data communities.

We evaluated the design method for its ways of creativity support, and the outcomes revealed that *Exploration* and *Results Worth Effort* are key characteristics of using data exploration in the context of design inquiry. While a high score of Exploration is not surprising in investigating data exploration as a way of design inquiry, Results Worth Effort needs further interpretation. The *effort* involved consists of the potential value of insights gained through data exploration and the learning curve to extract such insights. Data science techniques promise access to insights and perspectives of phenomena that otherwise would be hard to extract with more traditional design inquiry approaches. Since designers are rarely trained in data science techniques, the learning curve involves thinking and working with data. In the current work, we supported the learning of both thinking and working with data through a set of design tools – card decks and booklets – to guide the participants in an unfacilitated manner in incorporating the method's underlying skills. Interpreting these for the current study, generating results worth their effort partially acknowledged the different techniques' learning curve and the unfamiliar approach. With the learning curve in mind, the participants found that the insights that can be gained even with unfamiliar tools that are hard to use, or not fully designed with a designer workflow in mind, are valuable. In other words, the generated results were worth their effort.

6.1 Data Exploration as Design Inquiry Principles

The results' interpretation highlights the importance of selecting what tools and techniques to use in conducting data exploration as a design method. Previously elaborated in Section 3.3, we selected software tools inspired by other end-user data communities, such as data journalists, librarians, and digital humanities scholars. Those tools are designed for non-programmers working with data, and therefore are suitable for lowering the learning curve threshold effectively while providing functional capabilities to gain new perspectives about a given dataset. In Section 2.2, we highlighted that a method's mindset is an influential component that describes the tacit thinking behind actions that otherwise would just seem opportunistic use of different tools. Our design approach for the DEfD method to scaffold existing techniques and tools guides *what* actions to take and *how*, but does not address *why* such actions are useful in an inquiry process. To address this question for using data tools for inquiry, we use Dalsgaard's [21] framework of 'instruments of inquiry' to reflect on the study. This framework considers five main qualities of instruments of inquiry: perception (revealing and hiding facets of a design situation), conception (develop and hypotheses about a design situation), externalization (make imagined design solutions), knowing-through-action (generating knowledge by acting with an instrument), and mediation (mediate between actors and artifacts in a design situation). These five qualities and the findings of the study indicate that designers can have repeatable value in using data exploration as a design inquiry method in different design situations following the mindset that we encapsulate as principles in the following:

1. Acknowledge biases in data collection: Designers using data exploration as a design inquiry method need to be aware and perceptive what aspects the data collection shows and hides about a problem area. Data acquisition can carry built-in biases and limitations, which skew the inferences obtained from the data.

2. Spend time with the data: There is immense value in time spent on exploring the data to build contextual knowledge about the design situation. While entering a new domain, having access to a dataset may speed the initial process of building up the domain knowledge somewhat quicker, in longer time-frames, knowing the dataset and the domain intertwines.
3. Visualizations are a means-to-an-end: In working with the data, representations such as visualizations have a two-folded function. First, they help human cognition understand and contextualize the data, and second, they become shareable units of design work that can be used with other actors. As such, the goal of design inquiry is not to craft a visualization, as opposed to information design and communicating findings.
4. Be part of data collection: Spending time with the data in the design process means a continuous co-evolution of learning the problem space [23]. New research questions and hypotheses emerge throughout the unfolding process that might not be possible to answer from the initial dataset. Consequently, designers should be involved in the data collection, either hands-on or defining in-detail what data to collect.

These principles are domain-general and inform designers' agency both for using data exploration by themselves or improve their collaboration with data experts.

6.2 Data Exploration in the Design Process

Data exploration as a mode of design inquiry seems feasible and valuable to be used in the design process to 'access' the data footprints of human experiences, but when is it a reasonable choice to use data exploration? More informed choices can be made to suit a specific design situation by comparing data exploration as a design inquiry to other design techniques. Sanders and Stappers [52] provide an overview of different generative, i.e., exploratory design research techniques. In their work, they primarily compare two modes of *designing with* or *designing for* the users while elaborating upon the traditions of probes, prototyping, and toolkits for the early phase of design. Within this perspective, we position data exploration as a design method primarily in the generative phase of design, following a 'designing for' mindset (see Figure 8).

Other data-centered design approaches have also emerged in this space. Bogers et al.'s [14] data-collecting technology probes have shown novel ways to gain rich and contextual data using sensors. Similarly, Giaccardi et al.'s [13] Thing Ethnography was an exploration of ethnographic inquiry through equipping everyday objects with a camera. A camera in this context becomes a data-collecting sensor that is capable of rich data collection. The approaches of these examples share similar technological complexity, often beyond the scope and resources available for a design team. There are two main differences between the current work and the state-of-the-art from above. First, the DEfD method scaffolds existing non-expert techniques and tools to enable the designers themselves to conduct data exploration. Second, our current approach has focused on using existing data (such as inquiring data from a data infrastructure) and supporting designers to learn the necessary skills to process the data and guide how to extract value. For using existing data, the main concern is not how to acquire the data, but how to look at the data. Practically, 'looking at data' is informed by the findings of design theory and methodology. First, as Cardoso et al. [53] highlight, questions are at

the core of inquiry, and questions make designers explicitly formulate interests from a dataset. Second, designers are opportunistic and use different methods for different inquiries [35]. In conclusion, designers can use other types of inquiry, such as qualitative research, to complement data exploration insights.

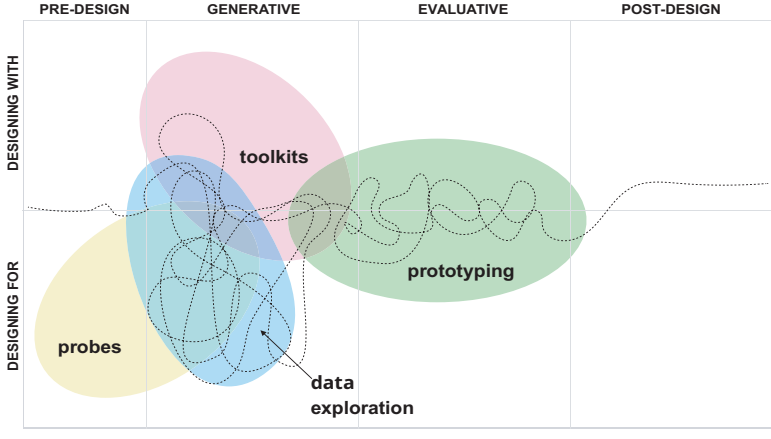

Fig. 8. The DEfD method can complement generative codesign processes (based on [52])

6.3 Limitations

The current study aimed to investigate the development of a design inquiry method for data exploration. We derived a design method, referred to as the DEfD method, based on literature and informed by our earlier work, and then tested the resulting design method as a one-day learning workshop. A primary limitation of the current study is that the DEfD method was tested with a group of design students (n=13) and the first author's facilitation. While we see the value for data exploration as a design method for designers of all levels of expertise, the study participants were master design students. Master-level design students are quite tech-savvy and data literate, but they might not represent the whole design profession or designers working in less technical domains. It is also important to note that the study's design brief and provided dataset (metadata of graduation thesis records) set up a limited problem space with specific properties, which does not model all sorts of potential design contexts. With these caveats, it is difficult to assess the effectiveness and added value of data exploration as a design method outside of academic learning environments at the current stage. Overall, the study's contributions are a design method for data exploration and principles for using data exploration for design inquiry.

7. Conclusions and Future Work

It can be concluded that the Data Exploration for Design method enables designers to use data exploration for design inquiry. We outlined a method based on three conceptual stages of *Problem framing*, *Exploring,* and *Inferring*, which stages guide data exploration in different design situations. We also developed two sets of card decks and booklets to support the method's learning curve and develop holistic data competence. These card decks and booklets are tailorable and extensible for different design situations and datasets. In the current work, the method was tested during a workshop and was proven useful in exploring data and in generating valuable outcomes for the design process. Furthermore, using the method contributed to the participants' holistic data literacy, informing how to use data exploration for design inquiry creatively. Based on the study results, we extracted a set of principles that describe the core mindset of the DEfD method.

Future work points in various directions. In further studies, we intend to integrate the DEfD method in real-world design situations and conduct studies on the method's usage with design research practitioners to ensure the current approach's validity. Furthermore, exposing the method to be used in different design situations would help in expanding the card decks and booklets. Finally, based on the study's findings, new software tools can be developed that support more creative and designerly work with data.

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