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Data in design: How big data and thick data inform design thinking projects

Marzia Mortati [a,*], Stefano Magistretti [b], Cabirio Cautela [a], Claudio Dell'Era [b]

[a] Politecnico di Milano, Design Department, Italy
[b] Politecnico di Milano, Department of Management Engineering, Italy

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ABSTRACT

Scholars and practitioners have recognized that making innovation happen today requires renewed approaches focused on agility, dynamicity, and other organizational capabilities that enable firms to cope with uncertainty and complexity. In turn, the literature has shown that design thinking is a useful methodology to cope with ill-defined and wicked problems. In this study, we address the question of the little-known role of different types of data in innovation projects characterized by ill-defined problems requiring creativity to be solved. Rooted in qualitative observation (thick data) and quantitative analyses (big data), we investigate the role of data in eight design thinking projects dealing with ill-defined and wicked problems. Our findings highlight the practical and theoretical implications of eight practices that differently make use of big and thick data, informing academics and practitioners on how different types of data are utilized in design thinking projects and the related principles and practices.

1. Introduction

The world we live in is undoubtedly volatile, uncertain, complex, and ambiguous (VUCA) (Bennett and Lemoine, 2014). The exogenous shock of the COVID-19 pandemic has shown that traditional strategic planning and the stage-gate approach to innovation are no longer effective (Voegtlin et al., 2019; Nakata, 2020). Making innovation happen today requires renewed approaches focused on agility (Troise et al., 2022), dynamicity (Hanelt et al., 2021), and other organizational capabilities that enable firms to cope with complexity (Menz et al., 2021). These contextual elements have led current research to emphasize the wickedness of innovation problems (Magistretti et al., 2021a; Verganti et al., 2021), particularly when involving digital environments and new technologies (Nambisan et al., 2019; Menz et al., 2021). In these cases, wickedness derives from uncertainty around the potential of new technologies and the ensuing difficulties for exploitation (Jafari-Sadeghi et al., 2021). Shedding light on how firms can effectively adopt diverse technologies to cope with wicked problems and uncertainty (Sun et al., 2020; Sanasi and Ghezzi, 2022) could thus help enhance our theoretical and practical understanding.

Scholars have identified a series of new technologies relevant for innovation, each with different strengths and weaknesses, including artificial intelligence, big data, additive manufacturing, virtual and augmented reality (Urbinati et al., 2020; Verganti et al., 2020). In this study, we focus on a single technology, big data, referring to datasets that are large in volume, diverse in sources and types, and quickly created (Johansen and Euchner, 2013). Despite having received much attention from researchers across various disciplines, such as innovation, marketing, and digital transformation (Lindstrom, 2006; George et al., 2016; Nambisan et al., 2017; Urbinati et al., 2019), little is known about the use of big data in innovation, namely the practices implemented when big data enable innovation, rather than their objective. This lack of knowledge becomes more relevant when projects face ill-defined problems (Buchanan, 1992). Indeed, in these cases, the boundaries and determinants of a problem are more uncertain, and the role that data might or might not play in supporting the definition and solution of the problem remains unclear.

Problems can be broadly distinguished according to their *a priori* structure, from well-defined to ill-defined (Mumford et al., 1994; Unsworth, 2001; Baer et al., 2013). In well-defined problems, all the information, variables, and stakeholders are fixed and known from the start. Conversely, in ill-defined problems, information is confusing and not well formulated, and the values among clients and decision-makers conflict (Buchanan, 1992). The literature has shown that a useful methodology to cope with ill-defined and wicked problems is design thinking (Brown, 2008; Martin, 2009; Micheli et al., 2019) and the underlying principles, including human-centeredness, creating empathy with users, learning-by-doing, and iteration (Carlgren et al., 2016).

* Corresponding author. Politecnico di Milano, Design Department, Via Durando, 10, 20158, Milan, Italy.
E-mail address: marzia.mortati@polimi.it (M. Mortati).

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Nevertheless, knowledge of how big data can inform design thinking is limited. In particular, design thinking is rooted in the use of non-numerical and qualitative data (i.e., contextual user observation, participant interviews, focus groups) (Micheli et al., 2019), providing a situated understanding of people's behavior. In anthropology and the social sciences, such qualitative evidence is also known as thick data (Geertz, 1973) or enriched data, derived from contextual observation and the analysis of people's real experiences and emotions (Latzko-Toth et al., 2017). Yet, how big data analyses can complement this contextual understanding remains an open question, as evidenced by recent scholarly calls (e.g., Simsek et al., 2019). As such, our research aims to unveil how different types of data (i.e., big and thick) are utilized in design thinking projects.

A recognized advantage of the new digital paradigm is the integration of big data that firms have at their disposal from various sources, both internal (collected through their information systems) and external (obtained from people's digital interactions) (McAfee and Brynjolfsson, 2012; Chae, 2015; Abbasi et al., 2016; Chandy et al., 2017; Del Vecchio et al., 2018). A significant amount of big data is generated by users interacting with digital products and services, enabling a deeper understanding of customer behaviors and preferences (Kaplan and Haenlein, 2010). This has made it increasingly clear that big data can be critical to designing and innovating products, processes, and services. Indeed, digital technologies allow retrieving a massive amount and variety of data, providing insights to foster innovation (Hopkins and Brynjolfsson, 2010; Trabucchi et al., 2018; Sestino et al., 2020). Furthermore, scholars have shown that the advantages of big data include greater operational efficiency, higher service quality (real-time data), and access to a broader scientific community (Urbinati et al., 2020). However, new issues have also come to light, since vast amounts of data require new interpretation techniques (Erevelles et al., 2016). The speed at which data are generated is difficult to master, and exploiting insights in a digital environment is becoming harder (Chen and Zhang, 2014). Due to the volume, variety, and variability of these data sources, firms are also facing challenges in harvesting, managing, processing, and creating value from big data, hence seeking tailored methodologies, processes, and tools to exploit them (Schroeck et al., 2012; Labrie et al., 2018).

Conversely, when firms have to deal with ill-defined problems, where creativity and design thinking methods play a key role in envisioning valuable solutions (Gruber et al., 2015; Pham et al., 2021; Artusi and Bellini, 2022), big data would seem less valuable. One reason is that it is difficult to predict how to use big data *ex ante* in creative environments (Garbuio and Lin, 2021), since innovation challenges entail multiple and conflicting interests and needs. Moreover, the literature shows that when creativity and human-centered design principles are central (Martin, 2009; Carlgren et al., 2016), ethnographic techniques are better placed to help collect meaningful data that provide contextualized behavioral insights (Micheli et al., 2019), namely thick data. However, in creative environments, thick data are no longer enough, as the speed at which markets evolve and the increasing volatility, uncertainty, complexity, and ambiguity of the environment call for new ways to extract insights from large volumes of dispersed and ambiguous information (Mumford et al., 1994; Bennett and Lemoine, 2014; Dong et al., 2016). Thus, creative innovation projects, such as design thinking, necessitate the integrated use of numerous types of data. In particular, beyond traditional qualitative thick data, recent studies (e.g., Bartoloni et al., 2021; Granato et al., 2021; Pham et al., 2021) highlight the contribution of big data to design thinking projects. However, how different types of data inform design thinking projects remains unclear.

Design thinking projects dealing with wicked problems and rooted in a blend of qualitative (e.g., observation and interpretation of user needs – thick data) and quantitative analyses (e.g., user profiling or social behavior – big data) provide the ideal empirical setting to study the practices that firms adopt in these cases. We therefore investigate how different types of data are utilized and blended in design thinking projects, informing academics and practitioners on how design thinking principles and practices are transformed when employing different types of data. In view of the exploratory nature of our study, we adopt a case study methodology (Yin, 2011) to compare eight design thinking projects characterized by the use of different data (i.e., big and thick) sources. Relying on semi-structured interviews and secondary data, we built a unique dataset that we analyzed using an inductive approach (Gioia et al., 2013). The coding helped us identify heuristic patterns and a set of practices that firms adopt to foster innovation by relying on big and thick data. In addition to some practical and theoretical implications, the empirical results highlight eight practices that underpin the four overarching design thinking activities that Gruber et al. (2015) identify as: (i) *observe and learn*, (ii) *synthesize and frame*, (iii) *vision and opportunity*, (iv) *solve and realize*.

Our study contributes to several literature streams. First, in terms of technology innovation, we enrich current understanding of the big data dynamics and practices to manage different data sources (Urbinati et al., 2019). Second, we contribute to the design thinking field by showing how data can support firms in dealing with wicked problems, thereby expanding the themes in the current literature (Micheli et al., 2019; Magistretti et al., 2021a). Finally, we provide a temporal view of the use of big data. In particular, instead of adopting an ontological perspective, we propose a phenomenological view of different practices that dynamically coexist and evolve (Teece, 2007; Felin et al., 2012; Cloutier and Langley, 2020).

2. Theoretical background

2.1. Data in innovation

Several studies underline the fundamental role of data analytics as an enabler of innovation (Nambisan et al., 2017; Trabucchi et al., 2017, 2018). The advantages of data analytics can be classified according to the entity that derives benefits from the innovation processes and outcomes (George and Lin, 2017), or the people and objects from which data are collected (Maglio and Lim, 2016). More recent empirical studies investigate different strategies adopted to fully exploit the potentialities embedded in data analytics. For example, Trabucchi et al. (2017, 2018) describe two alternative data-driven strategies: 1) generating new sources of knowledge to support organizational processes; 2) exploiting datasets to develop products and services. Data-driven innovation is an emerging phenomenon based on integrating digital data and analytics. According to Rizk et al. (2020), data can contribute to several innovation phases: from discovery to development, and from diffusion to post-diffusion (Garud et al., 2013; Fichman et al., 2014; George and Lin, 2017; Nambisan et al., 2017). According to Wu et al. (2019), a common role of data analytics is in the discovery phase, supporting or even inspiring innovators with new or emerging knowledge combinations they could otherwise not feasibly obtain. These combinations can be achieved by identifying patterns in existing datasets able to enlighten unmet user needs or revealing innovation opportunities (Kuehl et al., 2016). In this phase, data analytics can also be particularly effective in detecting the problems to tackle (Herterich et al., 2015), and assessing embryonic ideas (Kusiak, 2009). According to Chien et al. (2016), data analytics is fundamental in the development phase to inform and support design decisions, capturing preliminary user feedback, and improving their experience. Especially in digital solutions, data analytics is a crucial tool to monitor and test performance along their entire lifecycle (Martinez and Walton, 2014; Wrasse et al., 2015). Data analytics can also play different roles over the product lifecycle, for example, supporting the predictive maintenance of products (Lee et al., 2014; Neely, 2008), and customized services (Lehrer et al., 2018). Moreover, data also afford the possibility of continuously monitoring user engagement during the diffusion phase (Okazaki et al., 2015), and according to Huang et al. (2017), a fundamental tool to scale up minimum viable products. Finally, data analytics can also be beneficial in the post-diffusion phase by generating virtuous innovation loops, not only to improve existing products and services, but also to stimulate the generation of new ones (Buganza et al., 2015; Trabucchi et al., 2018; Trabucchi and Buganza, 2019).

The role that data play in innovation has significantly expanded with the emergence of big data, as intensely debated by academics and practitioners (Chen et al., 2012; Sivarajah et al., 2017), due to the direct link with other digital technologies, such as the Internet of Things (IoT) and Artificial Intelligence (AI). While scholars have variously defined big data, the 3Vs model encompasses some common features (Anshari et al., 2016; McAfee and Brynjolfsson, 2012): *volume* (huge amount of data), *velocity* (continuous stream of data), and *variety* (different types of data collected from various sources) (Trabucchi and Buganza, 2019). More recently, the 3Vs model has been enriched with the inclusion of *veracity* (the use of reliable data and confident interpretations), *variability* (managing and interpreting the continuous stream of data and changes thereto), and *value* (exploitation opportunities of the value embedded in data) (Del Vecchio et al., 2018; Fan and Bifet, 2013).

The value that resides in big data can be its ownership, a key asset that potentially allows differentiating (Gonfalonieri, 2019) or fostering innovation, making use of different internal and external data sources (Sorescu, 2017). Urbinati et al. (2020) argue that the main benefits of big data include increased operational efficiency, higher quality of service (real-time data), supporting research through electronic communication, and access to a larger scientific community. According to Waller and Fawcett (2013), data is generally regarded as a driver of improved decision-making and profitability. Knowledge derived from data analysis leads to increased innovation and business performance. Numerous studies emphasize the potential value of big data and how to interpret them to devise more valuable and innovative solutions for end users. However, vast amounts of data require new interpretation techniques (Erevelles et al., 2016). Not only is the speed at which data are generated difficult to master, but exploiting the insights in a digital environment remains difficult (Chen and Zhang, 2014). Thus, firms still struggle in making sense of vast data (Hogarth and Soyer, 2015; Verganti et al., 2020), identifying the valuable alternatives, and designing innovative solutions.

This brief review of the literature on data in innovation shows that although growing in number, the majority of studies (e.g., George and Lin, 2017; Maglio and Lim, 2016; Anshari et al., 2016; McAfee and Brynjolfsson, 2012; Del Vecchio et al., 2018; Fan and Bifet, 2013) refer to big data as a subject of innovation rather than a technology or means of supporting the innovation process at different times. Indeed, more research is needed to unveil how big data inform innovation processes.

2.2. Data in design thinking

As several scholars highlight (e.g., Cross, 1999; Dorst, 2011; Dorst and Cross, 2001), data are commonly adopted in design processes to nurture creativity, representing the "raw" or "semi-finished" material usually generated through the ethnographic observation of users in their context of use and/or complemented by, among others, videos, newspapers, and sketches that can serve as inspiration (Eckert and Stacey, 2000; Cillo and Verona, 2008). Thus, ethnographic techniques gathering qualitative data on the user context are often considered more reliable in providing potentially relevant qualitative insights (Micheli et al., 2019), or thick data (Geertz, 1973). Designers interpret this type of data as forms of experiential material: something that can be touched like a fabric, a visual pattern that can be found in nature, or any other kind of element that can inspire creative work. Data are consequently connected with tactile, aesthetic, and experiential learning processes aimed at sparking creativity in the generation of new product languages and signs (Dell'Era and Verganti, 2007; Stigliani and Ravasi, 2012; D'Ippolito, 2014). In a study developed in 2021, McKinsey researchers found that firms integrating "creativity, purpose and analytics", the so-called "triple-play companies", grow at least twice as fast as their peers (Cvetanovski et al., 2021). Furthermore, the use of data associated with creativity "resonates with customers in a deeper way" if linked to the firm's purpose. The underpinning logic they highlight is data granularity and analytics to unleash creativity in a more effective way, building personalized user interactions through testing-learning innovation approaches. According to Quiñones-Gómez (2021), design can "address data access by creatively and critically incorporating it as design material into professional practice". In other words, data create unprecedented opportunities for modeling and analyzing human behavior and use-dynamics through the array of methods that populate data science. Aiming to identify a "design knowledge space" where analytical skills meet creative and more intuitive skills, Quiñones-Gómez (2021) distinguishes structured from unstructured data, with the former more descriptive and able to provide structured patterns and trends linked to user preferences and (product-) system performance. Instead, the latter is deemed a more "predictive" form of knowledge mostly linked to user perceptions, and as such, able to inspire future use scenarios. According to Speed and Oberlander (2016), the relationship between design and data can be defined according to three main layers: design *from* data; design *with* data; and design *by* data. In design *from* data, systems are inspired by data referring to human features, such as user preferences, behaviors, opinions. In design *with* data, systems are supported by access to digital networks that continually generate huge amounts of data. Last, in design *by* data, "systems are designed by other systems", namely products and services designed by intelligent agents, such as machines, algorithms, and data-intensive technologies.

Design thinking is a creative method for dealing with wicked, complex, and ill-defined problems that do not have a single solution (Buchanan, 1992). Over the last two decades, design thinking has boomed among practitioners to the point that today it is widely recognized as a valuable creative problem-solving approach (Martin, 2009; Kolko, 2015; Carlgren et al., 2016; Dell'Era et al., 2020; Verganti et al., 2021). Different visualizations and interpretations have been proposed over the years. Adapting the Beckman and Barry (2007) framework, Dzombak and Beckman (2020) frame design thinking as a sum of four activities: observe and notice; frame and reframe; imagine and design; make and experiment. Similarly, Gruber et al. (2015) propose a framework of four activities: observe and learn; synthesize and frame; vision and opportunity; and solve and realize. In observe and learn activities, design thinkers harvest data from different sources to connect the macro- and micro-levels, fostering empathy with the context in which they are immersed (Carlgren et al., 2016; Beckman and Barry, 2007). In synthesize and frame activities, data are used to intercept the underlying structure that identifies specific preferences and behavioral patterns (Gruber et al., 2015; Dzombak and Beckman, 2020). Data are thus sorted, clustered, and organized using "visualization tools such as affinity diagraming and customer journey mapping to surface interesting patterns or findings". The widely recognized uses of data (Liedtka, 2015; Carlgren et al., 2016; Micheli et al., 2019) comprise unveiling insights about users, reducing the biases of mental models, and challenging the paradigms and widespread consolidated perspectives of the user problem. In the vision and opportunity activities, data are less relevant due to the divergent logics applied to generate novel ideas through rough sketches or visualization tools (Pham et al., 2021). Here the data and knowledge derived are crystallized in forms of ideas of new solutions or hypothetical scenarios (Magistretti et al., 2021b). In the solve and realize activities, concepts come alive in the form of prototypes where data is returned in the form of feedback from user testing activities (Granato et al., 2021).

Although the literature recognizes design thinking as a formal method to cope with ill-defined problems, introducing the human, empathy, and prototyping dimensions (Magistretti et al., 2022; Verganti et al., 2021; Garbuio and Lin, 2021; Gruber et al., 2015), little is known about how different types of data (big or thick) might contribute to the design thinking process. This opens interesting areas of investigation. First, when problems are ill-formulated, the role of data is unclear, questioning the value of a user-centered approach. Second, in considering the nature of big data, the literature generally looks at providing a definition and untangling the characteristics (Urbinati et al., 2019; Trabucchi et al., 2018), neglecting the existence of diverse types of data that differently inform innovation processes characterized by ill-defined problems. To bridge these gaps, we address the question of how different types of data can inform design thinking projects.

3. Research methodology

Consistent with the need to study the use of different types of data in the innovation process (Simsek et al., 2019), we adopt a grounded theory approach (Suddaby, 2006) based on a multiple case study (Yin, 2011), useful to obtain empirical evidence of complex phenomena and novel knowledge of value to the broader research community (Eisenhardt, 1989). Our empirical setting is the Italian ecosystem of consulting firms and corporations that adopt design thinking to face ill-defined problems in the digital transformation realm. Specifically, we investigate eight design thinking projects using both big and thick data (see Appendix A). This setting has been adopted and investigated in prior studies with relevant practical and theoretical implications (Cocchi et al., 2021; Magistretti et al., 2021b). We deem this setting appropriate, since this ecosystem (Dell'Era et al., 2020) has a deep understanding of design thinking, allowing us to obtain insights on the use of data in solving ill-defined problems. Moreover, the research team's involvement in several activities in these firms engendered trust and willingness to freely share insights and information.

3.1. Data collection

Our study analyses primary and secondary data from eight design thinking projects. We interviewed the informants in two rounds of semi-structured interviews, obtaining additional data from documents, videos, and institutional websites to integrate the primary data. We conducted the first round of interviews in June 2020 and the second toward the end of 2020, for a total 32 interviews lasting on average 90 min each and obtaining around 210 pages of verbatim transcripts. The main aim of the first round was to gather general information about the design thinking projects and start to explore the role that data played by interviewing project leaders, strategic, service, and UX/UI designers to gain a general overview of the project. In the second round, the aim was to delve deeper into the data utilization mechanisms, thus interviewing experts in the field of design thinking as well as the previous interviewees to confirm and expand our understanding of the use of different types of data along the process (see Appendix B, interview protocol and data collection). All the interviews were recorded, transcribed, and translated from Italian into English by two authors to ensure consistency and avoid language bias. Finally, these were merged and validated with the other authors to build a unique dataset (Siggelkow, 2007). We triangulated the interview data with videos, MIRO boards, material used in the projects analyzed, press releases, and other information available to the public (Table 1).

Table 1
Main data sources and uses.

Data sources	Type of data	Use in the analysis
Semi-structured interviews (210 pages; 80,000 words of transcript)	**First round (June–September 2020)** 7 interviews with project leaders, senior managers, and CEOs in innovation agencies. 9 interviews with creatives, service designers, data scientists, and technical experts working on projects using mixed datasets.	Collecting initial data and gaining an understanding of the different processes, methods, and tools with which innovation agencies use data. Exploring the different types of data used.
	Second round (September–December 2020) 16 interviews involving the same interviewees and additional innovation agencies belonging to the Italian design thinking ecosystem.	Expanding the sample and verifying the initial hypothesis on the use of mixed datasets and the lifecycle of data in the creative process. Triangulating facts and observations from interviewees and gaining a better understanding of the competencies involved.
Archival data	**Internal or public documentation** 15 presentations held in 2020 involving 15 different innovation agencies on their approach to data usage in their innovation practices (80 slides).	Supporting, integrating, and cross-checking interview-based accounts.
	Research report investigating the use of design thinking in digital transformation projects in 2020 and how this can help humanize new digital technologies, such as big data (227 pages/90,800 words with insights deriving from the direct involvement of 452 consulting organizations, 289 innovators, 279 start-ups).	Enhancing the validity of insights and better understanding the processes and scopes.
	Videos and articles downloaded from the internet or provided directly by interviewees (including articles published by companies, designers, innovators, technicians, and specialists, reports produced during project development). Overall, 23 written articles (151 pages/ 60,300 words), 3 lectures/public speeches held between 2020 and 2021 (3 h). The most relevant articles are included in the reference list.	Triangulating facts and observations to overcome the limitations of the study.

3.2. Data analysis

In accordance with qualitative rigor in inductive research (Eisenhardt, 2021), we adopted an exploratory multiple case study methodology. The data gathered in the design thinking projects were clustered and analyzed through *in vivo* coding. The longitudinal analysis (Langley et al., 2013) called for the empirical observation of projects over their evolution, linking the new insights from the observations with theoretical constructs. Coherently with this approach, the data analysis proceeded in a series of three intertwined steps to extrapolate the codes following the coding process of Gioia et al. (2013), Gioia and Chittipeddi (1991), and Gioia and Pitre (1990). First, for open coding, we searched for evidence emerging from the different interviews, iteratively consolidating the view by collapsing the codes into aggregate dimensions. Seeking a more theory-driven explanation (Strauss and Corbin, 1990), we constantly compared the first- and second-order codes with themes and practices in the design thinking literature. We iterated among different researchers, meeting several times to obtain the data structure shown in Fig. 1. The second step consisted in building the grounded theory model. Referring to Gruber et al.'s (2015) framework, we linked the aggregate dimensions with design thinking theory and the emergent set of practices related to managing data in design thinking projects. In the third step, to ensure the reliability of our findings, we had a series of interactions (32 interviews, Table 1) with panel experts in the Italian design thinking ecosystem. Their feedback helped us fine-tune the model and ensuring coherence with the data collected.

4. Empirical results

Our analysis suggests that the four design thinking activities of Gruber et al. (2015) are characterized by lower-level practices organized

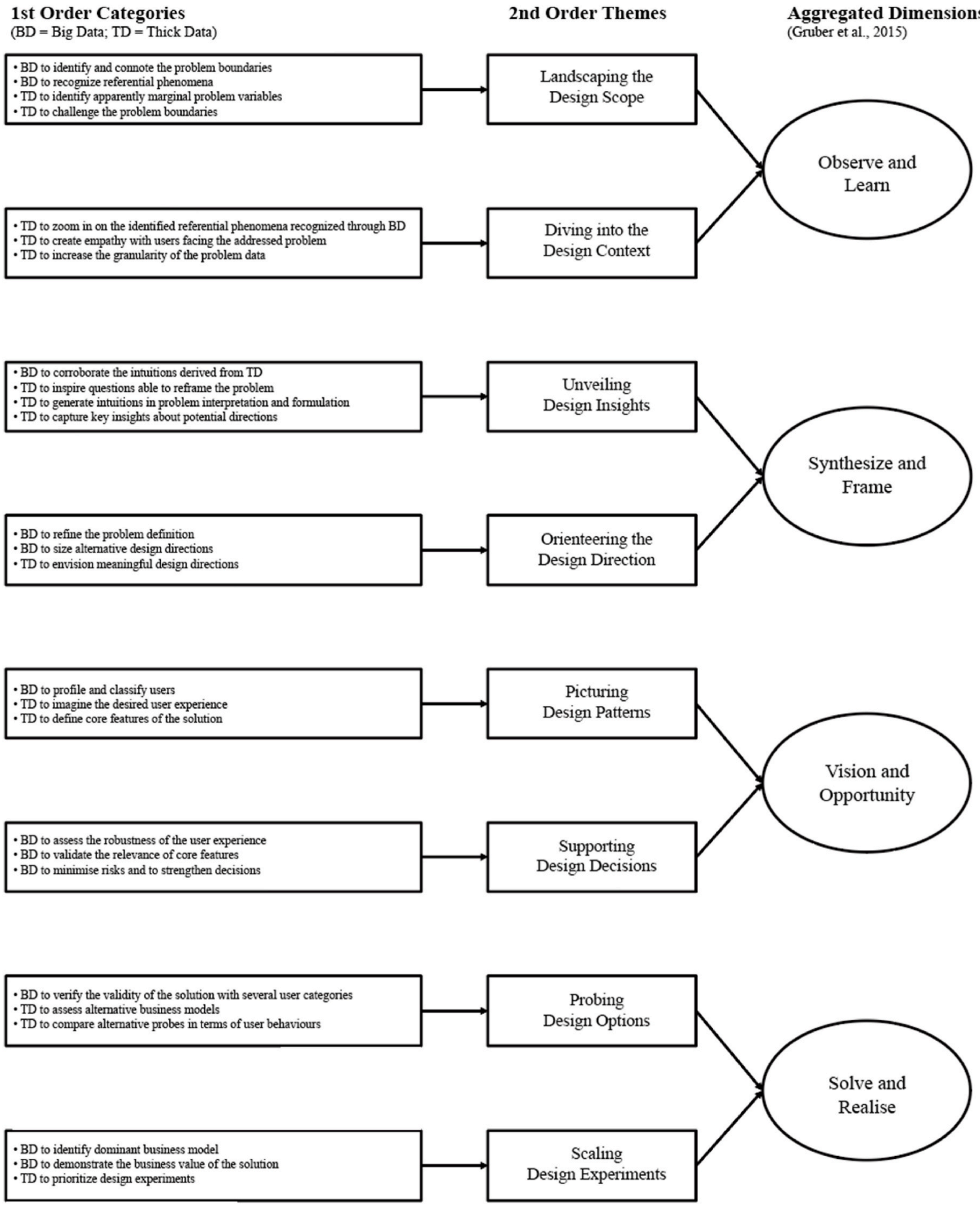

Fig. 1. Data structure.

and defined according to the type of data utilized in the process (see Fig. 2). We next present a narrative of the four aggregated activities to illustrate the effect of thick and big data on the design thinking process. While the temporal ordering partly overlaps, it is useful to distinguish these phases according to a discrete sequence that starts from the observation of users and the identification of the problem in line with the framing, visioning, and solving moments.

4.1. Observe and learn

Observation entails gathering data through observational or ethnographic research to properly explore the wicked problem addressed in the design thinking project. Big data are a fundamental source of knowledge to identify and connote the boundaries of the problem, particularly relevant for a panoramic overview of the project scope and related phenomena. While quantitative research can activate the scoping of the problem, identifying the most evident and consolidated phenomena, qualitative investigations allow assessing the relevance of the observed elements. Instead, thick data can enlighten apparently marginal variables that might help differently frame the challenge addressed, even suggesting the further collection of alternative data that can change the boundaries of the design scope (Table 2).

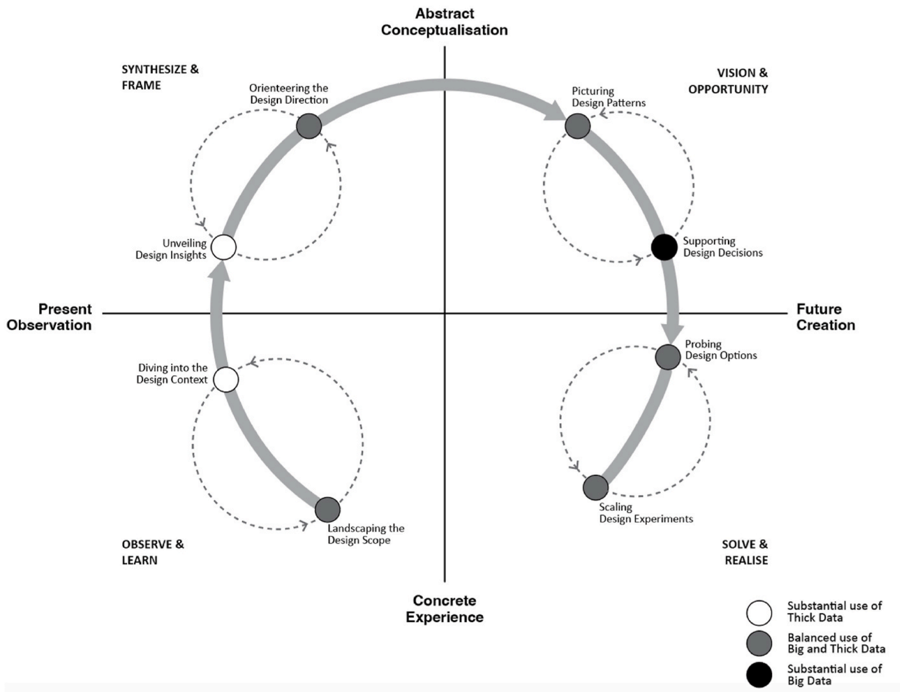

Fig. 2. A model of how big and thick data inform design thinking projects.

In particular, *landscaping the design scope* is characterized by the tight interplay between big and thick data, for instance:

> *"I seem to see these two models: exploring (the problem boundaries) with big data and challenging the results by conducting more vertical research (with thick data); identifying (the problem variables) with thick data and validating (the evidence that emerged) with big data."* (Researcher and Service Design Lead, Avanade)

The activities aimed at creating empathy with users, obtaining a more granular understanding of the available data and the problem, and zooming in on the observed phenomena exclusively use thick data. These activities allow giving a deeper meaning to the evidence collected, identifying the reason behind specific user behaviors, and making better sense of the available data. In these activities, the main role of data is providing insights, eliciting meaningful stories, and fostering greater awareness of people's real needs.

In *diving into the design context* (Table 2), design thinkers are not satisfied with accessing massive amounts of data but strive to zoom in on the stories behind the numbers to extract unexpected discoveries of the problem addressed.

As shown in Appendix A, this clearly emerges in the project conducted by Assist Digital aimed at reducing the number of drop-out calls and increasing the level of customer service satisfaction in a large telecoms company. Although the agency was able to access massive amounts of data and details on each call daily (e.g., hour, day, duration, location), no data the client provided explained the interaction between the customer service and users. The design team thus faced the limitations of numbers and the need to dive into each specific call to increase the granularity of data and create empathy with users:

> *"The bad thing (of not having thick data) is that you don't know why things happen. You can speculate, but since you don't see the users and can't ask directly, you don't know the reasons for their choices."* (Service Design and Anthropologist, Assist Digital)

In this case, the project team needed to understand the reasons why people decided to hang up at specific moments in order to propose meaningful solutions: Were their requests answered? What were the pain points? Therefore, the agency collected more granular information shadowing operators and directly listening to the calls. This provided the team with complete data needed to compile the personas and extract insights.

> *"We worked side by side (with the operators of the call center) listening to what happened in the calls and interviewing the call center operators (…) to understand the main reasons for contact. Obviously, they (big data) helped us to define which tests to conduct and analyze, and the flows to be proposed to users for testing (…) The big data advantage is that it is self-evident and clear. On the other side, you don't know the reason why of things. You don't know the real needs behind users' choices."* (Team Leader and Service Designer, Assist Digital)

4.2. *Synthesize and frame*

During problem-framing, our analysis identified the relevance of thick data for *unveiling design insights* (Table 3) supported by big data to corroborate the intuitions sparked by the qualitative investigations. As a deep and rich understanding of the situation is a driving force of the design process, evidence that is dense with socio-cultural meaning helps creatives define the relevant areas of focus, ask pertinent questions to reframe the ill-defined problem, and generate significant intuitions to interpret the problem. Big data help corroborate these visions, also acting as a measure to justify design choices (i.e., measuring the size of the interested user segment).

In *orienteering the design direction* (Table 3), big data becomes the driving force of the process, helping refine the problem formulation and alternative directions. In this second moment, thick data are a means of validation, supporting the envisioning of future directions by building on real needs, thus calibrating the significance of the project in real settings.

In the *synthesize and frame* activities (Table 3), the interpretation and corroboration of intuitions, inspirations, and insights can be augmented by the synergistic use of big and thick data. At least two of the projects analyzed (see Avanade and Oblo Design in Appendix A) reported

Table 2
Selected evidence on the aggregate *observe and learn* dimension.

Aggregate dimension: OBSERVE and LEARN	
Second-order codes	Selected evidence on first-order codes (BD=Big Data; TD = Thick Data)
Landscaping the design scope	*BD to identify and connote the problem boundaries* "Certainly, big data helped to position us at the beginning, trying to understand the significance and the domain of reference. In the next phase, big data will also have the role of confirming some assumptions related to the direction we want to take in the project." *Senior UX Designer, NTT Data* *BD to recognize referential phenomena* "Big data allow us to understand where there might be problems. They help us in figuring out who the customers are and in creating the various recruitment screeners for the tests and interviews." *Service Designer and Anthropologist, Assist Digital* *TD to identify apparently marginal problem variables* "I understood that it was very important to introduce a qualitative perspective, to understand how to read big data. The qualitative data served me as a map: I have all these quantitative indications, but the qualitative data open the directions on the map." *Service Designer, Twig* *TD to challenge the problem boundaries* "We started by interviewing stakeholders (…) It was strategic from our point of view because we (…) needed to explore the boundaries of the project." *Researcher and Service Design Lead, Avanade*
Diving into the design context	*TD to zoom in on the identified referential phenomena recognized through BD* "User needs were not given by big data but by qualitative interactions with the end users. Design can validate the evidence that emerged through analyzing quantitative data with qualitative insights." *Service Designer, Twig* *TD to create empathy with users facing the addressed problem* "The fact that we conducted qualitative research gave us greater awareness of what we wanted to achieve, which path to follow, and what people's real needs were. It is one thing to create a product that tells you if a face is recognized, but it is another to interact deeply with children's interpersonal communication." *Senior UX Designer, NTT Data* *TD to increase the granularity of the problem data* "When we analyzed only digital traces, there was no awareness of what that data could mean. It was very important to start a qualitative research phase. We didn't have the granularity to actually understand what the users needed and how to target the project." *Service Designer and UX Director, NTT Data*

blending both data types through the updated use of the *personas* tool.[1] Extracted from immersive investigations, personas often rely heavily on the creative team's personal intuition. In the processes studied, subjectivity is reduced through the use of quantitative data, as creatives explore the notion of *quali-quantitative personas* as a point of convergence in the data blending process.

One of the cases (see Avanade in Appendix A) had the goal of redesigning the intranet of an international bank to better connect local and global branches. The first step in the project was building basic knowledge of the context to frame the needs and ensure the wide relevance of the results. The design team began by conducting interviews and running workshops generating thick data in the form of preliminary knowledge and insights. This resulted in a *persona hypothesis* as a first assumption of who the final users might be. Big data were used to validate the evidence and the relevance of the hypotheses on a wider scale:

[1] Personas are archetypes exemplifying a group of people, such as customers, users, or employees (Stickdorn et al., 2018; Goodwin, 2011). They typically focus on types of user behavior and help in converging the creative team's knowledge for idea generation.

Table 3
Selected evidence on the aggregate *synthesize and frame* dimension.

Aggregate dimension: SYNTHESIZE and FRAME	
Second-order codes	Selected evidence on first-order codes (BD=Big Data; TD = Thick Data)
Unveiling design insights	*BD to corroborate the intuitions derived from TD* "The qualitative analysis was used to define our hypotheses, which we tested with big data. The results were statistically analyzed by means of clusters to make the qualitative data more robust." *Researcher and Service Design Lead, Avanade* *TD to inspire questions able to reframe the problem* "TD generated questions also on the basis of the initial evidence extracted from data analytics, and after a couple of weeks of work more questions (…) These questions helped us look at the problem from different points of view." *Head of Digital Analytics, Webranking* *TD to generate intuitions in problem interpretation and formulation* "There was an exchange of interactions between the team of data analysts and designers. Data analysts brought evidence to the designers who in turn offered intuitions, such as: it turns out that a lot of people are trying to do a certain action, or they are looking for a certain piece of information. Is it possible to investigate with big data whether there is evidence of this? If yes, it is considered in the design." *Head of Digital Analytics, Webranking* *TD to capture key insights about potential directions* "The second phase (in our project) was to interview (collecting qualitative evidence) the client's core group of chefs, not about the existing product, but about what the new one might be like: what trends they see, what their specific needs are, how they imagine they will use the new product. In parallel, we asked the same questions to R&D, marketing, and management. Combining all these answers, we obtained several insights on which we could build for project development." *Lead UX Designer, Studio Volpi*
Orienteering the design direction	*BD to refine the problem definition* "We started (the second phase of the project) by better understanding the pain points, developing text analysis with specific software. We took all the feedback from customer care and conducted a series of analysis to understand what was not working in the original service." *CEO and UX Designer, Fifth Beat* *BD to size alternative design directions* "In one of the projects, we were able to define the sample for the research thanks to statistical data we received from the client. On the other hand, in smaller projects, where the client does not have data to provide us with, we find it more difficult to understand who the target users are, and therefore which users to contact in order to make user tests to define design choices." *Senior UX Designer, NTT Data* *TD to envision meaningful design directions* "The main task I had (in the project) as a designer was to really understand what scenarios of use could be built around quantitative data: how to transform it from data to information by creating very concrete use cases, thus identifying real needs from real people." *Service Designer, Twig*

> *"Through interviews, focus groups, and workshops, we collected qualitative requirements. These then served to define our hypotheses, which we tested with a large survey."* (Researcher and Service Design Lead, Avanade)

Researchers statistically clustered the data collected and analyzed the socio-demographic data to validate the hypotheses.

> *"We analyzed the survey statistically through clusters to then arrive at the personas. The personas we built were quali-quantitative. They started from qualitative research used to construct hypotheses, and were verified through quantitative research."* (Researcher and Service Design Lead, Avanade)

This is an iterative process that moves several times from qualitative intuitions/hypotheses to quantitative validation until the team is sure about the correspondence and robustness of the profiles, both in terms of representativeness (quantitative socio-demographic data), and significance (qualitative interpretation). Personas were the main tool to collapse the qualitative and quantitative findings, while in the further development of projects, the two types of data were no longer separated:

> *"All the design decisions made after that were clearly the result of joint qualitative and quantitative research."* (Researcher and Service Design Lead, Avanade)

4.3. Vision and opportunity

When engaging in idea generation, designers adopt a generative approach traditionally dependent on "gut-based means" (Dzombak and Beckman, 2020). In our analysis, this area is linked to the *picturing design patterns* activity (Table 4). Here, the highly intuitive nature of design thinking that helps imagine and describe the user experience, as well as going in-depth to identify the core features of the solution, is integrated with logic-based critical thinking brought by big data. The latter is a fact-based resource to profile and classify users prior to conducting field observation.

One of the agencies interviewed (see Oblo Design in Appendix A) is a service design studio that combines ethnography, quantitative analysis, visual thinking, and participatory design. The agency analyses user behavior via digital data collected from social media and other platforms to describe and scope the problem. It then combines this analysis with ethnography-like investigations, directly including users and enquiring into their needs and desires. The project investigating the benefits and limitations of remote learning environments that emerged after COVID-19 employed big data at the beginning:

> "[As] *an accelerator of knowledge creation. The possibility to do this kind of scraping and to very quickly obtain an overview of some topics (i.e., user preferences and profiles), allows us to set up more targeted qualitative research protocols, which already go to deepen a series of topics (…) instead of having to discover them from scratch*". (Information and Service Design, Oblo Design)

In this project, the agency created an initial map of topics and expectations to profile a wide category of users (university students in the US) that could not be explored quickly with other methodologies. With these profiles, they were able to use thick data to boost imagining the desired user experience and investigate with relevant users the best features for remote learning environments. This included two specific activities: the collection of digital diaries for students to describe their experience (current and desired), and interviews with around 50 people. Here, the profiles created through big data were central to project effectiveness:

> "*Instead of interviewing 10 students recruited according to a set of criteria, but who we do not know, (…) it becomes 10 students who we already know because we come from 10 previous steps of which quantitative analysis is a crucial one. The activity becomes much more effective from our point of view.*" (Information and Service Design, Oblo Design)

As the agency reported, this "self-adapted methodology" starting from personal interest and experimentation aimed at refining the objectives of the qualitative investigation using a list of relevant topics for a category of users obtained from the analysis of digital traces.

> "*The experiment was to see if we could get more granular user profiles from these large mappings, and thus facilitate design sessions inspired by these enriched stories. That was a bit of an enlightenment for us, as we realized that this could give us some great ideas when we put it into the service and product design contexts (…) from our point of view, this is an original approach. Originality does not only come from the intersection of diverse types of data, but from the craft work that we do on top of it. This means that, since the quantitative dataset is often built by us, we reflect on it qualitatively. It's a bit like doing field research, but in this case, the field is the map generated by big data analysis.*" (Information and Service Design, Oblo Design)

In supporting *design directions* (Table 4), big data is a source of evidence to assess the robustness of the user experience proposed, and validate the relevance of core features. Thick data help minimize risks and strengthen decisions by creating meaningful connections between user needs and the solution. Design thinkers do not make choices based exclusively on statistical/numerical evidence. As one of the creatives reported:

> "*Thick data are a tool to explore the design context, user desires, and customer expectations. In our projects, it is one key component to inform the design process (…) The product design sector is still strictly related to ethnographic research and more qualitative approaches. Big data is a potential future investment toward using data to keep track of product/service use and design better informed functions.*" (Lead UX Design, Studio Volpi)

Table 4
Selected evidence on the aggregate *vision and opportunity* dimension.

Aggregate dimension: VISION and OPPORTUNITY	
Second-order codes	Selected evidence on first-order codes (BD=Big Data; TD = Thick Data)
Picturing design patterns	*BD to profile and classify users* "Quantitative data are used to understand who the customers might be. It is a common process for us. Big data are useful, for example, to understand geographic areas, age clusters, habits etc. This is something we do together with a series of interviews." *Team Leader and Service Designer, Assist Digital* *TD to imagine the desired user experience* "The main problem is to refine the huge mass of data, often raw (provided by BD) by choosing only those that go in the right direction. By balancing this with the qualitative dimension, it is possible to work out which data to give more credibility to. Dealing with the people who will use the product is essential to calibrate the user experience." *Senior UX Designer, NTT Data* *TD to define core features of the solution* "As the initial qualitative research revealed, chefs have many different levels of expertise. There are those who experiment and create recipes, and there are those who just need a button to make it (the product we are designing) reach −40° as quickly as possible. This initial phase allowed us to understand how to structure the product and what information to give the user in order to use it at its best." *Lead UX Designer, Studio Volpi*
Supporting design decisions	*BD to assess the robustness of the user experience* "Usually, we try to collect insights with qualitative techniques, and then we try to weigh them with quantitative measures, going to see if something is said by one person or is more representative." *CEO and UX Designer, Fifth Beat* *BD to validate the relevance of core solution features* "Big data are useful in several parts of the design process: to profile users and recruit them for tests on specific features, and to understand where the most important points of interaction are. Big data also provide evidence to understand the relevance of the imagined features, and act as validation of the solution being proposed." *Team Leader and Service Designer, Assist Digital* *BD to minimize risks and to strengthen decisions* "Big data were especially useful in measuring the benefits produced by the solution introduced. Integrating them allowed us not only to design services that would give added value to users, but also to monetize the data and make informed decisions about the related policies." *Service Designer and UX Director, NTT Data*

4.4. Solve and realize

In the solve and realize practice (Table 5), ideas become physical and

Table 5
Selected evidence on the aggregate *solve and realize* dimension.

Aggregate dimension: SOLVE and REALIZE	
Second-order codes	Selected evidence on first-order codes (BD=Big Data; TD = Thick Data)
Probing design options	*BD to verify the validity of the solution with several user categories* "The best way to explore a context is usually qualitative data. At that point, given the verticality and constituency of the research, it makes sense to expand it to the wider population with big data. Generalizing with big data helps to confirm what we had collected, enlarging the dataset to all relevant user categories." *Researcher and Service Design Lead, Avanade* *TD to assess alternative business models* "We started with the data on the interactions to better understand what information we could extract from the dataset, knowing that many things were hidden. Once we understood the value we could extract, we relied on our intuition, because in Twig we are used to asking questions that - to those who are more vertical in a field - seem absurd or stupid. We then went on to validate our intuition about the value of the solution and its business potential using qualitative methods, directly involving those with the appropriate vertical expertise." *Executive Advisor, Twig* *TD to compare alternative probes in terms of user behavior* "After making some assumptions and because we had no vertical knowledge on the project topic, we held a series of meetings with our client, who was also our user and - unlike us - had hyper-vertical knowledge of that world. We worked together to understand whether the assumptions we had made would match the needs of our end users. We then went back to the (big) data to see if we could improve the assumptions we had made." *Service Designer, Twig*
Scaling design experiments	*BD to identify dominant business model* "Big data has informed design decisions by providing hints on how to monetize the data and the service, while also making informed decisions about other contextual elements that were influenced." *Service Designer and UX Director, NTT Data* *BD to demonstrate the business value of the solution* "The difficulty with qualitative data is making the client understand certain concepts. To make them understand that a usability test done on 5 users gives you 80% of cases, if you don't have this kind of training, and if you're not open to this approach, becomes a stumbling block to overcome. However, when you present a decision that has quantitative data behind it, it is easier to present and defend it." *Service Designer and Anthropologist, Assist Digital* *TD to prioritize design experiments* "To draw out some opportunities for improvement (as this is a product that already exists), we created 'how might we … ' questions and sketched out some ideas, then immediately prototyped them and used them for testing and extracting qualitative data. This allowed us to prioritize a number of opportunities and define a number of key results." *CEO and UX Designer, Fifth Beat*

are tested through specific protocols for experimentation (i.e., A/B testing). Here, diverse ways of using big data and algorithms are more common, including automatic user/usability tests. In our analysis, two main activities emerged (Table 5): (1) *probing design options* with the prevalent use of thick data to assess alternative solutions and compare probes in terms of user behaviors, however, big data remain important to verify the validity of a solution with several user categories; (2) *scaling design experiments* uses mainly big data to define the most relevant solution and demonstrate the business value, thus driving decisions on investment and scaling. Instead, thick data help to envision future directions for development, allowing the team to identify key elements for improvement based on the feedback from the tests.

One of the projects analyzed (see Twig in Appendix A) aimed to develop a data analysis platform to support business managers in the beauty sector to make better business decisions. The project team was asked to analyse existing data from an online beauty portal owned by the client to create a service and provide evidence to place business managers in the best position to make strategic choices. The initial dataset contained a huge amount of data about user buying patterns, reviews, and interactions with different brands and products. However, the main challenge for the creative team was identifying meaningful ways to aggregate this data and provide a useful tool for managers. What knowledge might they want to receive? In what format? About what specific consumption characteristics? This led the team to define data aggregation scenarios, first exploring the possibilities offered by the available data, then validating the hypothesis of use through direct interaction with final users.

After initially acting as input, the role of data changed along the process: once the aggregation scenarios had been created, the data were used as support and inspiration. To test and experiment the ideas developed, the team defined diverse user journeys proposing alternative ways to keep collecting and interpreting data through the service and then monitor user activities. These were rendered as low-fidelity prototypes and tested with the client and end users, thereby generating thick data to prioritize the relevance of diverse experiments and compare alternative design options. The feedback received helped improve the service and final output.

> *"(We tried to) define the user journey of the service, defining how to display the right data, with the right perspective, easily interpretable and usable by users (…) Doing this, we also introduced the perspective of creating a dynamic service that could grow with use, laying the foundations for creating a system that can be scalable and intelligent, and that can also validate the needs we identified at the beginning."* (Executive Advisor, Twig)

In addition to processing, the big data available had several other functions. They helped formulate metrics to understand the business value of certain data and identify the best business model for the platform. Here, the interviewees identified one of the important meeting points between big and thick data that emerged during the project:

> *"For our client, we also needed to prioritize the information, for example on different brands, and give the latter different relevance in the platform. We therefore created a parameter that would consider the data in a way that was not totally mathematical. The aim was also to give authority to the service by creating a dedicated internal rating system. This created an important connection between quantity and quality."* (Executive advisor, Twig)

This process led to a virtuous feedback loop in the collection, analysis, and interpretation of data and the design of the service that reframed the value of data from an input to an output that can create additional value.

5. Discussion

Our qualitative analysis sheds light on the phenomenological dimension of data use in design thinking projects. In particular, we identify new and thus far unexplored activities in the design thinking process when dealing with data, and eight practices that underpin these activities.

In so doing, our study responds to recent calls from innovation management scholars to investigate the dynamics of big data in facing ill-defined problems (Simsek et al., 2019). Here, our findings advance current understanding of when and how different practices might be adopted to effectively manage different data sources (Urbinati et al., 2019). In addition, our study contributes to the design thinking field by showing how different types of data can support firms in dealing with ill-defined problems, enlarging the set of practices underpinning the design thinking activities envisioned in the literature (Micheli et al., 2019; Magistretti et al., 2021a). Furthermore, we contribute to the ongoing management debate about the tension between the ontological and phenomenological view by envisioning a temporal view of the use of data. In particular, our study proposes a phenomenological perspective where different practices dynamically coexist and evolve (Teece, 2007; Felin et al., 2012; Cloutier and Langley, 2020) in the integration of different data types in innovation processes.

In addition, in qualitatively exploring the eight design thinking projects, our empirical results highlight that big data are not enough to steer innovation projects dealing with ill-defined problems. While acknowledging the role of big data in supporting various stages of the innovation process (Chen et al., 2012; Sivarajah et al., 2017; Trabucchi and Buganza, 2019; Urbinati et al., 2020), our findings provide evidence of their shortcomings in going deeper into the user context to explain some of the underpinning reasons for user preferences, habits, and unmet needs. Descriptive, predictive, and prescriptive big data analytical methods look for recurring patterns within huge data sets (Sivarajah et al., 2017). Although widely acknowledged in the literature, our study highlights the need to enrich data analytics with qualitative data on the context (i.e., thick data), often more effective in opening new design pathways, imagining new scenarios, or reformulating design questions in alternative ways. Moreover, our model (Fig. 2) aims to increase current understanding of the logic (how) and role (when) that data play in design thinking processes and projects when the problem is ill-defined.

We also enrich the design thinking literature with empirical results (Micheli et al., 2019; Magistretti et al., 2021) through identifying the eight practices that differently use big and thick data. Fig. 2, building on Gruber et al.'s (2015) framework, shows how big and thick data usage varies across the four different design thinking activities.

In particular, thick data are substantially used in the *observe and learn* and *synthesize and frame* parts of the process. A plausible explanation is that ill-defined problems (Buchanan, 1992) require using data to build empathy (Brown, 2008) and gain relevant insights (Magistretti et al., 2021). This is coherent with the design thinking literature (Carlgren et al., 2016; Micheli et al., 2019) stressing that human-centeredness and empathy are central to discovering user needs and defining the problem to be solved. Indeed, dealing with ill-defined problems implies different challenges. As Einstein and Infeld (1938) state: "The formulation of a problem is often more essential than its solution […] To raise new questions, new possibilities, to regard old problems from a new angle, requires imagination" (p. 83). These challenges call for specific practices in the discovering and defining activities (Fig. 2), and our empirical evidence shows that these practices should substantially rely on thick rather than big data. Thus, ambiguous problems are subject to inquiry and entail detailing the problem before being able to solve it (Getzels, 1975; Unsworth, 2001). In other words, innovations dealing with ill-defined problems rely heavily on anomalies, paradoxes, and outliers (Mednick, 1962). This is especially the case when recalling the literature asserting that extreme or lead-user experiences are a relevant source of inspiration for innovation (Urban and Von Hippel, 1988; Lüthje and Herstatt, 2004; Brown and Katz, 2011).

In terms of *vision and opportunity* and *solve and realize*, thick data become less relevant, with a more balanced or even substantial use of big data. A possible explanation is the reciprocal role that big and thick data play in validating the evidence vs intuitions. The substantial presence of big data in these latter practices is coherent with the literature affirming that big data help in decision-making and converging (Urbinati et al., 2019). Our empirical results show that it is not sufficient to have big data. In particular, in ill-defined problems and situations involving multiple stakeholders, solutions need to be designed through a plurality of iterations and a more balanced use of big and thick data. Inspired by the design culture that looks at the integration of analytical reasoning with intuitive reasoning (Martin, 2009), a more design-oriented perspective is needed in dealing with big data innovation. Indeed, thick data can inspire new questions and insights that nurture envisioning potential and future meaningful scenarios (Sestino et al., 2020). In other words, the complementary use of big and thick data can mitigate the presence of biases embedded in both data categories (Crawford, 2013; Hargittai, 2015; Janssen and Kuk, 2016). Thus, our findings enrich the design thinking literature by informing scholars that different practices are needed when dealing with data and technologies (i.e., the eight practices reported in Fig. 2) in design thinking processes and activities (Gruber et al., 2015), thereby enriching prior systematizations of practices in the new product development and innovation literature (Carlgren et al., 2016; Micheli et al., 2019).

Finally, by proposing a dynamic and evolutionary perspective of the use of big data in response to ill-defined problems, our findings contribute to a phenomenological view of big data. Distinct types of data are used in different design thinking activities (i.e., substantial use of thick data, balanced use of thick and big data, substantial use of big data). The management literature provides several definitions of big data in an ontological perspective (Trabucchi et al., 2018; Urbinati et al., 2019), considering and defining the characteristics as a *unicum* in a process. By unveiling the eight practices and twenty-six different roles of big and thick data across the four design thinking activities, our empirical analysis proposes a phenomenological view (Teece, 2007; Felin et al., 2012; Cloutier and Langley, 2020) of data (big and thick) that has at its core their different uses in the innovation process. This might lead the way to further explorations of this phenomenological view and the interactions of big data in innovation processes, in line with the recent call of Gong and Ribiere (2021).

6. Conclusions, implications, and limitations

Our study highlights that different types of data are employed in different design thinking activities when the scope of the project has ill-defined boundaries and problems. The eight practices inform managers on how they can effectively utilize either thick or big data in response to ill-defined problems, adopting design thinking as a method to develop solutions.

Although based on an interesting empirical analysis, our study has some limitations. First, as our exploratory analysis was conducted in a specific geographic context (Italy), the limited area of investigation may have influenced both the data collection and analysis by introducing bias in the translation of concepts from Italian to English, as well as cultural bias resulting from the nationality of informants and their use of data in the projects. In addition, the projects analyzed involved the presence of at least one consultant, which could suggest that some data use practices are guided by the legitimization and concertation of certain choices and approaches. Moreover, the information asymmetry of consultants, above all in the initial phases, leads to a more intensive use of data in the pre-comprehension and problem finding/framing phases. Second, client companies were not included in our data collection, which could raise questions regarding our findings. Finally, in proposing a phenomenological view of data use in innovation processes, we do not consider data as an innovation objective. Thus, our empirical evidence does not contemplate the opportunities deriving from the availability of new data (i.e., data collected from sensors, use of digital platforms, data generated automatically by products, etc.), instead focusing on the value that the integration of different types of data (old and new, big and thick) might bring to the design thinking process. Although the availability of new data may have considerable effects on the innovation processes studied in the long run, our results highlight that the mere availability of data is not a sufficient condition to sustain the innovation process when dealing with ill-defined problems. Rather, a human component (linked to intuitive thinking) is a necessary ingredient to unveil the pathways to innovation. In particular, our study untangles the relation between thick and big data but does not look at how these data are generated and collected. Therefore, future studies might integrate our investigation by studying how data are generated, and thus the impact of old and new data on innovation processes.

In addition, to strengthen the results of our study, future research could enrich the sample from a geographic point of view and include other key parties (e.g., client companies) who in this research are merely passive receptors. Geographic diversity could illuminate how different industries and cultures leverage intuitive or analytical cognition, and the relative use of big vs thick data. The inclusion of client companies could instead enrich our general understanding of the crucial role that data play in decision-making.

Last, all the projects analyzed in our study concern new service development. Future studies that include new product development projects – with more material friction and constraints – could pave the way to defining new interpretative uses of data and their role in creative projects and innovation.

Declaration of competing interest

None.

Data availability

The data that has been used is confidential.

Appendix A

Table A1
Overview of the cases.

Consulting Firm	Client industry (anonymized for privacy)	Project objectives	General data types used	Project duration (months)	Project team (mainly provided by the consulting firm)
Avanade A joint venture between Accenture and Microsoft Corporation. Global leader in the provision of innovative digital services, offers digital transformation solutions in several business sectors from banking and insurance to health and retail	Banking (multinational company operating worldwide)	Redesign the digital workplace (intranet system) of an international bank to better connect international branches	Analytics (i.e., digitized archival records, streaming data, transmission logs), surveys, demographics, interviews with employees	5	1 Researcher 2 UX Designers 1 Visual Designer 1 Creative Director
Assist Digital A Europe-wide consulting firm that aims at merging AI and human intelligence to build the future customer experience. It offers a wide range of digital services to accompany digital transformation, combining experts in CRM, big data, and design	Telecoms (multinational operating worldwide)	Increase the level of customer service satisfaction by reducing the number of drop-out calls	Analytics (i.e., digital records, transmission logs), interviews with employees, transcription and textual analysis of phone calls, customer satisfaction surveys	12	3 Designers (UX and Service) 2 Developers
Digital Entity, NTT Data NTT Data is a global IT innovator and 6th largest IT service provider in the world offering a wide range of services focused on innovation and cutting-edge technology to meet the challenges of a constantly changing market. Digital Entity is its service design studio in Italy	Self-commissioned	Design an AI-based system to support the learning process of children with autism	Data collected from sensors (i.e., live data and streaming data on use) Self-reported data on use	12	1 UX Designer 1 Communication Designer 2 Data Scientists
Fifth Beat An Italian-based consulting firm working on innovating the digital experience for worldwide clients	Real Estate (based in USA)	Redesign the digital user experience (including all digital touchpoints) of a real estate company	Web analytics (i.e., click tracking, scroll depth, live visitors, frequency of visit, page views, pathways taken) Demographics and statistics on population, sentiment analysis (topic modeling), interviews, user tests	3	1 Head of Design 1 UX Designer 1 UI Designer 1 User Researcher 1 Information Architect
Oblo Design A service design studio supporting organizations in their innovation journeys. It offers a mix of competences to enhance the service design practice in real business contexts	Education (based in USA)	Develop scenarios to improve remote learning for young students in the US after Covid-19	Demographics and statistics on population, sentiment analysis (topic modeling), interviews, user tests	3	1Product Designer 1UI/UX Designer 1Communication 1Designer 1Ethnographer
Twig A digital strategy consultancy based in Milan. Through design, communication, and marketing, it positions and promotes brands, products, and services, guiding more than 30 multinationals, SMEs, and public administrations in their digital transformation journey	Beauty (multinational operating worldwide)	Design a B2B service for beauty business managers and operators using the data collected in an existing platform	Web analytics (i.e., click tracking, scroll depth, live visitors, frequency of visit, page views, pathways taken), interviews, focus groups, user tests	6	1 Service Designer 1 Executive Advisor 2 Developers
Studio Volpi A strategic innovation and design agency experienced in design concepts, technology, and engineering, UX and UI development, branding and communication. It integrates engineering, art, communication, design, and digital technologies to develop winning solutions and products for tomorrow's market	Food (Italian company)	Design a new generation of IoT blast chillers for professional chefs	Data on use collected from sensors (i.e., live data and streaming data on use), sentiment and behavioral profiling, Interviews, focus groups	4	1 Product Designer 1 UX Designer

(continued on next page)

Table A1 (*continued*)

Consulting Firm	Client industry (anonymized for privacy)	Project objectives	General data types used	Project duration (months)	Project team (mainly provided by the consulting firm)
Webranking A digital agency with partners and clients worldwide. It helps companies improve their digital experience with a mix of competences ranging from communication to technology and knowledge management	Finance and insurance (multinational operating worldwide)	Design a new digital platform to integrate all services offered in one place	Web analytics (i.e., click tracking, scroll depth, live visitors, frequency of visit, page views, pathways taken), interviews, focus groups	3	1 UX/UI Designer 1 Communication Designer 1 Data Scientist 1 Software Developer UX Researcher 1 Art Director 1 Content Manager

Appendix B. Semi-structured interview questionnaire

Before the interview, each organization was contacted individually via e-mail. This initial contact was useful to provide details on the research project and guidelines on the selection of the project proposed for the study. This was followed by several exchanges (always via e-mail) during which interviewees provided archival material and initial details on the context and project. After this initial interaction, two rounds of interviews were conducted (see Table B1).

The questionnaire was then administered through direct interaction with interviewees. The interview sessions were held in Italian and mainly via digital platforms (Teams and Zoom), then recorded, transcribed, and translated by two authors who checked for discrepancies. In case of doubts, they directly consulted the interviewees.

The interview protocol was structured in two main sections. The first section comprised a standard set of questions (Section 1-4 of Table B1) aimed at gaining a general understanding of the project, the context in which it was developed, the team involved, the client, the objectives, the sources and types of data used. The second section (Section 5-7 of Table B1) comprised a variable set of questions adapted to each project, taking advantage of the conversation, and aimed at diving deeper into the potential topics emerging from each interview. In this part, further reflections were elicited (when necessary) on the impact that big data had in the development of the project (i.e., considering differences with other projects that did not have such data). Further details were asked on the iterative use of big and thick data and their integration, eliciting, for example, the description of new tools and methodologies created to blend the two types.

Table B1
Overview of the interview protocol in the two rounds.

First round of interviews	Archival data provided by companies	Use in the analysis
Section 1 Focused on collecting information on the project, mainly indicating the name, the year(s) of development, the type of client, and a brief description of the main objectives. Details were also collected on the team involved, their expertise, and role.	Brief provided by the client, existing reports used to understand the project context.	Collecting initial data and gaining an understanding of the different processes, methods, and tools with which innovation agencies use data. Exploring the different types of data used.
Section 2 Focus on data to understand what data were used and the origin i.e. from the client or external sources, data collected anew during the project or already existing. For data collected anew, a focus was on how this was collected (from which sources) and why collecting these data was important for the project.	Datasets used in the project either provided by the client or collected by consultancy, presentations and internal reports.	
Section 3 Focus on big data to dig into the process enacted to analyse big data and the advantages/disadvantages of using this in the design process, the software used, the specific types of data. This part of the interview also investigated the use of big data in each different project development phase.	Sources of data, datasets used, indication of software used. Where relevant, sharing visualizations/diagrams and reports produced.	
Section 4 Focus on thick data to dig into the process enacted to analyse thick data, the advantages/disadvantages of using this in the design process, and the specific types of data. This part of the interview also investigated the use of thick data in each different project development phase and the possible interplays with big data.	Sources of data and specific outputs produced, including maps, personas, reports, client presentations.	
Second round of interviews		
Section 5 Aimed at further understanding the consulting firms' approach to the use of data, also focusing on the data types (big and thick) the organization is used to working with.		Verifying the initial hypothesis on the use of mixed datasets and the data lifecycle in the creative process. Triangulating facts and observations and gaining a better understanding of the competencies involved.
Section 6 Aimed at checking with interviewees the initial hypothesis that emerged during the first round of interviews.		
Section 7 Aimed at better understanding the professional profiles involved in the project.		

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Marzia Mortati is Associate Professor in Service Design at the Design Department of Politecnico di Milano. She is Vice-Director of the International Master in AI for Public Services and one of the Executive Directors of the European Academy of Design. Her research focuses on the Design Process, Service Design, Public Sector Innovation and new technologies. To develop research on these topics, she has worked on numerous international research projects collaborating with researchers and practitioners all over the world. She has authored several articles in academic conferences and international scientific journals, including Design Issues, Design Management Review, The Design Journal, Policy Science, International Journal of Entrepreneurial Research and Behavior.

Stefano Magistretti is Assistant Professor in Agile Innovation at the School of Management, Politecnico di Milano, and a senior researcher in the LEADIN'Lab, the Laboratory of LEAdership, Design, and INnovation. Within the School of Management, he also serves as Director for the Observatory Design Thinking for Business. He has published conference articles and chapters in edited books, as well as articles in journals such as Journal of Product Innovation Management, Industrial Marketing Management, Long Range Planning, Technological Forecasting and Social Change, Industry & Innovation, Business Horizons, Creativity and Innovation Management, Journal of Knowledge Management, Research Technology Management, and Technology Analysis and Strategic Management Journal.

Cabirio Cautela is Full Professor of Strategic Design at Politecnico di Milano – Design Department and Phd in Business Management. He was Visiting Scholar at Stanford University – CDR (Center for Design Research) in 2012. His research topics deal with the strategic role of design, design management processes and how design generates new business models and new ventures. His last articles were published by journals as Technovation, Creativity and Innovation Management, International Entrepreneurship and Management Journal, Design Issues, International Journal of Entrepreneurship and Innovation Management, Design Management Review.

Claudio Dell'Era is Professor in Design Thinking for Business at the School of Management - Politecnico di Milano, where he serves also as Co-Founder of LEADIN'Lab, the Laboratory of LEAdership, Design and INnovation. He is also Director of the Observatory "Design Thinking for Business" of the School of Management –Politecnico di Milano. Research activities developed by Claudio Dell'Era are concentrated in the areas of Design Thinking and Design Strategy. He has published more than 100 chapters in edited books and papers published in conference proceedings and leading international journals such as Entrepreneurship Theory and Practice, Journal of Product Innovation Management, Long Range Planning, Industrial Marketing Management, Technology Forecasting and Social Change, R&D Management, International Journal of Operations & Production Management, Industry & Innovation, Creativity and Innovation Management, Business Horizons, and many others.