The Role of Design Thinking in Big Data Innovations

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The Role of Design Thinking in Big Data Innovations

Abstract: Digital technologies are disrupting the way companies manage business. In today's society, where a plethora of different digital solutions are booming and the attention of both practitioners and scholars is growing, little is known about how to make the most of such technologies. Given the complexity of the phenomenon, this paper refers to a single digital technology, Big Data. It is commonly recognised that Big Data can represent a competitive advantage source for companies. However, there is still a lack of literature on how to exploit the opportunities provided by this technology, while the amount of data is so vast that their interpretation is complex. The focus on human centricity, iteration, and prototyping of Design Thinking brought the academic world towards the recognition that this approach could be valuable in steering and managing this technology. Thus, the paper investigates how Design Thinking can foster innovation based on Big Data technologies. It leverages three explicative case studies to shed light on a new set of hybrid practices. By comparing and contrasting cases, the four practices of (i) Cropping Big Data Landscapes, (ii) Reframing Big Data applications, (iii) Unveiling Big Data Opportunities, and (iv) Proving Big Data Releases are proposed. These hybrid sets of practices support both practitioners and academics in opening up the black box to interpret and value Big Data.

Keywords: Design Thinking; Big Data; Digital Transformation; Innovation; Open Innovation; Technology Development

Introduction

Digital technologies have disrupted the way managers do business. They are expected to provide benefits both to the companies that invest in them, and to society at large (Nambisan et al., 2017). Further reflections are needed to unfold how to manage them in order to improve people's lives, given the growing interest of managers and academics in the role that digital technologies play in companies and society (Danneels, 2004; Nambisan, 2017; Rippa & Secundo, 2019).

Technology *per se* is neither positive nor negative, but rather dependent on human choices and actions (Garud & Rappa, 1994, Adner & Levinthal, 2001). Academics are debating on the way digital technologies are enabling or hindering innovations (Tellis, 2008). Organizations leverage technological innovation to be competitive (i.e., IBM with Watson), but they also struggle in unfolding all the opportunities that are embedded in technologies (Verganti, 2011; Magistretti et al., 2020a). In today's world, numerous digital technologies change the way we interact with products, services, and people. Among these technologies, Big Data technologies are intensely debated in the academic and practitioner's world (Chen et al., 2012; Sivarajah et al., 2017). This technology holds greater importance, as it links with technologies such as the Internet of Things (IoT) – that can fuel Big Data – and Artificial Intelligence (AI) – that leverages Big Data to obtain more accurate outcomes. As a result, Big Data's main advantages comprise higher operational efficiency, higher service quality (real-time data), supported research through electronic communication, and access to a broader scientific community (Urbinati et al., 2020). On the other hand, Big Data raise new issues: vast amounts of data require new interpretation techniques (Erevelles et al., 2016). The speed at which data are generated is difficult to be mastered, and the exploitation of insights in a digital environment is becoming harder (Chen & Zhang, 2014).

Within the scope of such complexity, several organizations have realised the importance of design methodologies to ensure customer centricity and unfold the potentiality of Big Data. Among these companies, there are giants like McKinsey, IBM, LinkedIn, and Spotify. As declared by Karan Sachdeva, Sales Leader Big Data Analytics APAC, IBM merges IBM Design Studio and their Big Data platform with ‘the primary objective of leading a revolution for creating a human-centric design focused on Big Data applications for customers.’ LinkedIn has combined behavioural engineering, Design Thinking, and Big Data technology to create its network of strongly engaged users. According to Colette Kolenda, Senior User Researcher at Spotify, and Kristie Savage, Senior Data Scientist at Spotify, ‘Digital Interfaces have made data collection so easy that now our biggest challenge is not access to data, it’s the interpretation of it and deriving meaning from it that makes it a challenging task. Data science provides an insight into what is happening, and Design Research Methods helps us understand why those things happen and what should be done about them. By applying data in the design process, we amplify and not replace what designers do well already.’ (Peter, 2019). While organizations recognise the value of design methodologies and Big Data, many are missing out on the opportunity of their proper combination (Verganti et al., 2020). Organizations need to enable the two to effectively work in lockstep—in order to make the whole greater than the sum of its parts (Chabra & Williams, 2019). Within design methodologies, Design Thinking is recognised for its validity in shaping innovation, problem solving, and creativity, proving to be effective with business models and organizational challenges (Brown, 2009; Liedtka et al., 2013; Dell’Era et al., 2020).

Thus, scholars are starting to discuss the underlying potential of the combination of Big Data and Design Thinking. According to Sachdeva (2016), Big Data in combination with Design Thinking can be revolutionary by virtue of the value created for organizations. By embedding Design Thinking into big data use cases, organizations can unlock new opportunities, build empathy among users and pave the way to exceptional experiences—those experiences that are truly human-centred and create an emotional connection. Ensuring design in big data analytics projects from the initial stages can lead to the right blend of sensibility, technical feasibility, business viability and consumer needs (Deoras, 2017).

Despite many hints at the positive implications of the combined usage of Big Data and Design Thinking, few literature contributions specifically investigate their interplay. For this reason, this paper explores the role that Design Thinking can play in shaping Big Data-based Innovation Processes. These synergies are worth investigating to unveil the kind of impact that the human-centred approach has on the Big Data practices adopted in innovation projects. More specifically, the research question investigated by this paper is 'How does the adoption of Design Thinking practices shape the Big Data-based innovation?'

The paper investigates three explicative cases of the adoption of Design Thinking in Big Data innovation projects. By leveraging the insights gathered during the interviews and the comparison of the cases, the four practices of (i) Cropping Big Data Landscapes, (ii) Reframing Big Data applications, (iii) Unveiling Big Data Opportunities, and (iv) Proving Big Data Releases are discovered and discussed. These hybrid sets of practices support both practitioners and academics in opening up the black box to interpret and value Big Data. Indeed, blending design mindsets with more digital technological ones enables companies to explore Big Data technology opportunities and better develop solutions based on it. Thus, for managers, this helps in mastering projects on Big Data and for scholars in enriching the role that design and especially Design Thinking principles can play in digital technology development.

The remaining part of the paper is organised as follows. The subsequent section summarises the main contributions towards Big Data in innovation and Design Thinking practices. Then, we present an overview of our research methodology, and describe our empirical results. The final sections discuss the results achieved and offer some conclusions.

Theoretical Background

To properly address the aforementioned research problem, the theoretical background is organised into two main paragraphs: the first summarises the main literature contributions about Big Data in innovation, whereas the second provides an overview of the principal Design Thinking practices.

Big Data in Innovation

Big Data technology has been defined in many different ways by academics. Some scholars look at Big Data as what it is (Gandomi & Haider, 2015), others define it depending on what it does (De Mauro et al., 2016). There are differences in the definitions depending on the industry or the type of data (Martin, 2015). Despite this, there are some shared features, encompassed in the 3Vs model (McAfee, et al., 2012; Kaisler et al., 2013; Anshari et al., 2016) that highlight the role of Volume - huge amount of data, Velocity - continuous stream of data, and Variety - different kinds of data from different sources (Trabucchi & Buganza, 2018). Thereafter, the notion of the 3Vs was broadened to include the concepts of veracity - using reliable data and confident interpretations, variability - managing and interpreting the continuous stream of data and changes thereto -, and value - exploiting the value embedded in the data (e.g., Fan & Bifet, 2013; Del Vecchio et al., 2018).

The value residing in Big Data can consist of its possession, being a critical asset that possibly creates differentiation (Gonfalonieri, 2019), or in its potential to foster innovation, leveraging different data sources both internally and externally to the company (Sorescu, 2017). According to Urbinati et al. (2020), Big Data's main advantages comprise higher operational efficiency, higher service quality (real time data), support to research through electronic communication and access to a wider scientific community. Despite the identification of the main advantages generated, little is known in extant literature on how to gain these advantages.

Saltz and Shamshurin (2016) describe the critical success factors characterizing Big Data projects. In particular, the authors affirm that 'the data science maturity of a company describes how it effectively employs the tools, people and other resources to manage and analyse data for the purpose of informing business decisions. Organizations with a high level of maturity run their projects holistically, with checks, feedback loops and mechanisms for improvement.' Kopanakis et al. (2016) depict the process that leverages Big Data as being composed of five main phases: data management, data analysis, data-driven decision making, data-driven innovation and business performance. The data management phase encompasses tasks such as data acquisition & recording; extraction, cleaning & annotation; integration, aggregation & representation. Ensuring that the data collected is reliable, accessible, manageable, properly stored and secured is crucial (Oussous et al., 2017). The data analysis phase is about modelling and interpretation. Considering the challenges of high complexity and high dimensionality in Big Data, the more intuitions are recognised, the higher the chances of identifying potentially interesting patterns, correlations, or outliers (Shi & Wang, 2014). According to Waller and Fawcett (2013), data are widely considered as drivers of better decision making and improved profitability. The knowledge arising from the analysis of data leads to decisions that increase innovativeness and business performance. The benefits of Big Data exploitation contribute to business performance in terms of economic variables such as financial performance, innovative activity and performance (Brynjolfsson et al., 2011; Davenport & Dyché, 2013). Notwithstanding the extant literature, that shows the potential value of Big Data technology, scattered contributions reveal how to interpret that vast amount of data in order to create innovative solutions that are more valuable for end-users. Indeed, as shown by literature, vast amounts of data require new interpretation techniques (Erevelles et al., 2016). The velocity – speed – at which data are generated is difficult to be mastered, and the exploitation of insights in a digital environment is becoming harder (Chen & Zhang, 2014).

Thus, companies are still struggling to make sense out of the vast dataset (Hogart & Soyer, 2015; Verganti, 2020) and recognise valuable alternatives and patterns to design innovative solutions. Thus, research should focus on this gap and highlight how the interpretation of vast amounts of data can be appropriately conducted.

Design Thinking Practices

Digital technologies are permeating our society (Nambisan, 2017) and, due to their growingly complexity in adoption, are transforming business problems more and more into wicked questions. Hence, Design Thinking methodologies, given their foundations on wicked and ill-defined problems (Kimbell, 2011), yield a precious set of practices, mindsets and tools that can support problem solvers in challenging and making sense of such technological complexity, through the logical processes that they can be trained to put into practice (Liedtka, 2020). Among the practices, scholars debate about the role of abductive reasoning, for instance, as it is recognised by many authors as a logic, or way of Thinking, that is typical of Design Thinking and of its way of tackling problems (Dew, 2007; Hassi & Laakso, 2011; Micheli et al, 2019). Differently from induction and deduction, in fact, this third fundamental logical model relies not on observation, but on wondering, thus allowing the problem solvers to foresee what might be and to generate innovative solutions.

Within the Design Thinking literature many scholars debated over practices and mindsets useful for adopting such methodology for innovation (Carlgren et al. 2016; Elksbach & Stigliani, 2018; Micheli et al., 2019; Dell'Era et al., 2020). Despite this, little is known on the role that Design Thinking might have in the digital environment (Lynch et al., 2019; Magistretti et al., 2020a). Liedtka (2020) tried to unveil the potential of Design Thinking capabilities in the technological environment, by associating them with dynamic capabilities

(Teece, 2007). Nevertheless, more is needed to unpack the value that Design Thinking can have in digital complex environments.

Hereafter we review extant literature over Design Thinking and its practices. Liedtka et al. (2013) describe Design Thinking as a problem-solving approach characterised, among other aspects, by the generation of solutions through market research methodologies that are empathic, and user driven. Lockwood (2009) considers empathy with the user as the first principle that a firm needs to adopt to become design minded. Indeed, many scholars and practitioners ascertain that 'Empathizing with the Users' is a crucial practice in the Design Thinking methodology, since this is what makes it possible to put the people working on the project into the users' shoes and, therefore, to unveil surprising insights and needs that perhaps customers are not even aware of. According to Drews (2009) the more people get involved, the less likely it is that a crucial parameter will be missed or that the process will fail because a particular individual is too close to the problem. Hence, this practice represents a tangible way to validate the work with potential customers, as it evolves from idea generation to the launch phases.

The second set of practices are the ones related to problem framing: 'Challenge and reframe the initial problem to expand both problem and solution space' and 'Synthesis of research insights: finding patterns, framestorming (ideation to find alternative problem formulations)' (Carlgren et al., 2016). Beckman and Barry (2007) declare that the innovation process itself emphasises problem finding: identifying, framing, and reframing the problem to be solved are as important as solving the problem itself or finding an appropriate solution; it is also possible to frame the innovation process as one of storytelling and re-telling. According to Drews (2009), Design Thinking implies three main concepts: consumer-centricity, orientation toward the future, and challenging the norm (Magistretti et al., 2020b). In particular, the ability to challenge the norm becomes a true differentiator in rapidly changing environments. Human brains are extremely effective as pattern recognition machines (Dell'Era et al., 2008; Eliansen, 2019). According to Dew (2007), innovative ideas begin with novel hypotheses about the meaning behind the available information. Such information has to be deciphered, underlying patterns have to be guessed at, and plausible hypotheses have to be conjectured.

The following group of practices belongs to the visualization one: 'Make ideas and insights visual and tangible to externalise knowledge, communicate and create new ideas', 'Visually structure data', 'Do rough experimentations', 'Provide experiences to enable understanding' (Carlgren et al., 2016). According to Lockwood (2009), Design Thinking is essentially a human-centred innovation process that emphasises observation, collaboration, fast learning, visualization of ideas, rapid concept prototyping, and concurrent business analysis. Liedtka and Ogilvie (2011) describe the Design Thinking process as being made of four main questions: 'what is?' explores current reality; 'what if?' envisions a new future; 'what wows?' makes some choices; 'what works?' takes us to the marketplace; and visualization is a crucial tool that shows up in virtually every stage of the process. Indeed, they define visualization as the 'mother of all design tools', since it is a pervasive and thought unifying practice that permeates the whole Design Thinking process. Design Thinking focuses on providing experiences; for this reason, it attracts C-level attention, since it deals with experience and meaningfulness in ways and at levels that no other business disciplines do (Barry, 2017; Artusi et al., 2020).

The experimentation set of practices is composed of the following: 'Work iteratively (divergent, convergent)', 'Converge based on a diverse set of ideas', 'Prototype quickly and often to learn', 'Test solutions quickly and often: share prototypes with users and colleagues', 'Fail often and fail soon' (Carlgren et al., 2016). According to Liedtka and Ogilvie (2011), managers who want to think like designers should put themselves in their customers' shoes (empathy), view themselves as creators (invention) and view themselves as learners (iteration). The iterative rapid cycle prototyping shaped by IDEO does not just improve the artifact (Magistretti et al., 2020b). It turns out to be a highly effective way to obtain funding and organizational commitment to bring the new artifact to market (Brown & Martin, 2015). According to Drews (2009), early prototyping helps decrease the high-risk factor of new radical ideas and to eradicate early fears, as soon as people can start shaping and contributing.

The following four practices belong to the diversity cluster: ‘Create diverse teams and let everyone’s opinion count’, ‘Collaborate with external entities’, ‘Seek diverse perspectives and inspirations (variety of fields, broad research)’, ‘Take a holistic perspective into account’ (Carlgren et al., 2016). It is important to examine not only the specific issue or problem under consideration, but also how the issue relates to the environment or system in which it exists (Beverland et al., 2015; Micheli et al., 2019). Rose (2013) argues that a multi-disciplinary approach is able to connect different backgrounds (business specialists, aerospace engineers, software engineers, journalists, doctors, opera singers, and anthropologists) that can foster creativity (Ghezzi et al., 2020). Such diversity of thought demands a certain corporate culture. The hard part is creating an environment in which a diverse group of people can work together and having them get really good at building on each other’s ideas.

From the above bodies of literature one fact emerges, that both Big Data in innovation and Design Thinking practices fields are characterised by under-researched areas. In the former, the lack of understanding about how to interpret the vast amount of data to design solutions that are more in line with user requirements is quite evident. Conversely, the latter, highlights the absence of the technological dimension when discussing Design Thinking practices. Thus, by overlapping these research fields, an interesting gap arises, trying to answer the research question of how the adoption of Design Thinking practices might foster the adoption of Big Data solutions.

Research Methodology

Given the scope of the research and the question previously raised, the case study methodology appears to be the best approach to follow (Yin, 2011). The complexity of the phenomenon and the intersection between different fields, Big Data and Design Thinking, require a methodology that aims at exploration rather than confirmation (Stake, 1978). This paper aims to achieve a better understanding of how these two fields interconnect. Thus, we chose an explicative case study (Thomas, 2011) to investigate how Design Thinking practices shape the Big Data-based innovation process. Coherently, the authors adopted a multiple case study approach that leveraged three cases of companies developing Big Data innovations with a Design Thinking mindset. Indeed, the authors checked ex-ante with the informants that the Design Thinking mindset and principles were adopted during the implementation of the Big Data solutions within the company. More specifically, the cases of Math&Sport, TIM & Olivetti Solutions, and Neosperience were selected.

Data Collection and Analysis

Similarly to what was performed by Giudici et al. (2018), the authors collected the data from both primary and secondary sources *[see Table 1].* The primary source of data was collected through semi-structured interviews with key informants belonging to the three companies. In particular, the interviewees were the leaders of the Big Data project developed with a Design Thinking mindset. For each case, two rounds of interviews were conducted by one of the authors and two additional junior researchers. The first round of interviews aimed at exploring the broad description of the project and the overall approach. The second round delved deeper into the cases and into the process and practices adopted. This turned out to be an excellent way to collect more points of view, and around eight hours of recorded interviews, that were then transcribed and triangulated with secondary sources. The addition of the secondary sources, from archives made available to the authors, was crucial to consider the perspective of the human dimension and better discover aspects of the projects themselves.

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Data Analysis

Figure 1 shows how the authors analysed the data by transcribing the interviews and examining the data from each single case. The analysis was performed sentence by sentence, to search for significant concepts (Strauss & Corbin, 1998) that described how each company developed a Big Data project. This resulted in the generation of a dataset of both 'in-vivo' and constructed codes. Then, the authors iteratively organised the codes across the three cases and compared them to avoid redundancies and extract first-order categories (Gioia et al., 2013) of practices adopted for performing the Big Data project. Subsequently, the authors structured the first-order categories into second-order themes that were common to all the cases and furthered their aggregation into higher-level dimensions (Gioia et al., 2013). The data was manipulated to shed light on the process dimension. Thus, the authors individually looked at the data and then discussed the core evidence emerging from the process adopted within and across cases. This process reinforced the evidence gathered during the interviews and allowed the authors to unveil interesting aspects related to the research question previously raised.

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Empirical Results

To optimally grasp opportunities arising from the complexity of Big Data and deliver value to people means being able to master the processes correlated to the management of data. Across the three case studies, it emerged that four new practices were a key to the success of the innovation process involved in a big-data project. More specifically, the cases showed how these practices resulted from hybridization between innovation based on Big Data and a Design Thinking approach.

Math&Sport: Virtual Coach

The case from Math&Sport describes a project called ‘Virtual Coach’, an application developed by the Italian start-up in 2016 derived from the vision of the two founders a mathematician and an engineer. The case shows how starting from technology, they changed the meaning of football analytics: from describing to interpreting. They moved away from the mere statistical description of the events and provided an immediate interpretation of the matches based on the data collected and its conversion into actions to be undertaken.

The Virtual Coach project started around September 2018, inspired by the successful implementation of similar internal projects and the introduction of the 5G opportunity. Math & Sport was able to crop out the underlying insight from the data available in the football environment. More specifically, they recognised data of two kinds: positional data – plentiful, but raw, stemming from video tracking of activities – and scout data – scarce, but interpreted, stemming from the evaluations of the game. Math & Sport was able to foresee that the former could prove more valuable to meet needs that users were not fully aware of. In fact, they extrapolated the hidden need underlying scout data – thus, the evaluation and interpretation of the match performances – and amplified it by applying it to the greater dataset of positional data. As stated by one of the two co-founders:

> *Positional data are collected in all the main championships, from Serie A, to Premier League, to Bundesliga, to Ligue 1, to the Football World Cup, etc. commissioned by leagues, such as FIFA. However, they are used only for post-game analysis, or at most to provide the media with the number of kilometres run by the players, so that you can derive once and obtain the speeds, derive twice and get the accelerations. Our challenge instead was to create a product that would use this information in real-time to run a virtual coach.*

Despite recognizing the difficulty in managing positional data, Math & Sport challenged the limitation of their 'raw' nature and current use – limited to descriptive post-game analyses that only provided assessments of what had happened, rather than their interpretation. In fact, they reframed the application of positional data, as they turned the limitations into an opportunity to create a virtual coach that provided real time interpretation of positional data, thus defining the killer factor of their solution.

Math & Sport were able to unveil the valuable new application of the positional data thanks to new enabling technologies and collaborations that allowed them to experiment with their intuition. These enabling elements, together with a simpler visualization of data that allowed easy interpretations, led to unveiling functionalities that had not been possible before.

With a structured solution, Math & Sport developed two different types of prototypes to set the user experience criteria: one for the coaches and analysts, and one for the sport's enthusiasts, that only provided a subset of features. This implied the involvement of some football coaches, famous analysts and a limited group of supporters. All were fundamental to define the KPIs for the user experience and revealed the pain points for the future users that they would have intended to satisfy. Subsequently, a structured activity of end user validation took place. This activity included a market research on supporters, laboratory tests, a heuristic evaluation done by UX design experts, and on field user validation. After this, in September 2019 the beta version was released, marking the start of the product's iteration. This was also observed by the interviewee who stated:

> *Once we saw that the prototype was interesting, we carried out a validation activity with the end users' and 'We carried out the testing and design activities through laboratory tests, a heuristic evaluation by UX design experts, and user field validations.*

TIM and Olivetti: Smart Territorial Data

The second case describes the project from TIM – one of the major telco companies in Italy – and Olivetti. They collaborated on the Smart Territorial project when the theme of Big Data was still at its early stages in Italy and the value underlying telco data was still overlooked. It leveraged data collected by the TIM network to offer advanced cloud-based tools for territorial qualitative and quantitative analysis. It mainly targeted the Public Administration and businesses (local retails). What distinguishes this solution from the rest of the competition in the Italian market is the wealth of information, thanks to the integration of multiple data sources, and their perspective function.

The process started as Tim and Olivetti realised that telco companies had access to an incredible amount of data that had a high underlying potential. In an initial phase, the companies explored the horizon of possibilities in search of unmet needs that they could cover. As the Vice President of Olivetti Data Monetization Solutions, stated:

> *The project came from the idea and the need to be able to derive value from the data that a telco operator such as TIM had available.*
>
> *When we talk about telco data, we are talking about any phone call made, any message, any application used, any information about browsing, etc. So, the horizon of possibilities is quite broad.*

This meant challenging the initial understanding of telco data as a mere collection of customer information, to imagine a reframed and amplified use of them. To unveil the opportunities of the reframed data, Tim and Olivetti activated three research lines, carried out by three groups that investigated the technological, regulatory and competence creation aspects respectively. This step was needed in order to build the necessary internal competences, crucial to the successful extraction of value from the massive amount of data TIM could leverage. It was thanks to these acquired capabilities that the team was able to properly understand how to reap the true value of telco data by integrating them with data coming from other sources. As the informant also declared:

> *We start from telco data. Alongside this data, we can integrate other types of information, from open data to customer data. Then the information is stored within a data lake that is structured according*

to a classical Big Data infrastructure with Hadoop distribution. […] In addition to telco data, we also collect information on social networks to perform a sentiment analysis of an area and identify the hot topics. Then we can also integrate other types of information, like open data, which can provide an interesting contextualization of the environment under evaluation, thanks to information about the air quality, the weather, the average energy and gas consumption in a certain area, etc.

As soon as the hardware infrastructure was ready, an algorithm was developed, with the objective of obtaining correct data interpretation and the possibility of extracting the KPIs of interest. In this phase, data was reframed to better understand and unveil its meaning for people. As the Vice President stated:

The first usage of this data was a trivial heat map featuring the presence of people in some areas, then we upgraded the concept to a higher level, with a more sophisticated analysis of the clusters of people, which then evolved until we managed to identify the movements and flows of people through an area.

This part of the project required continuous adaptation. During the setup phase, validity data and the results obtained were tested. Then, the front-end development phase followed a more agile approach that provided continuous big data releases that helped them stir the solution towards continuous adjustments. As a manger stated:

We implemented an agile approach, in the sense that we tested the idea, we saw that the idea was well structured, we created a concept and then we scaled on that concept in terms of volume, gradually adding the parts of data sources, or algorithms, or interface features that we needed. […] There was certainly a gradual adjustment when we had to discuss terminology and abundance of data. We had overestimated our customers' reading skills, so we spent a lot of time and a lot of energy to get real-time data, when in the end it did not turn out to be very useful in the vast majority of cases. It was therefore useless to update information every quarter of an hour, so we decided to reposition a series of important indicators.

Neosperience: People Analytics

The third case describes the People Analytics project developed by Neosperience, a company that assists and supports organizations in their digital transformation, providing essential solutions to build better user experiences. Launched in February 2019, it aimed to converge the analytics of digital context with the physical world of retail, to gain more precise information on customers, on their flows and behaviours.

The innovation process started from the perception of the need of retailers to gain support in counteracting the diffusion of e-commerce. With that in mind, Neosperience leveraged the combination of data from physical and digital sources to carve out for themselves a specific position in the market providing empathy in technology. This was possible thanks to the technical department in Neosperience that researched existing technologies, solutions, algorithms and mathematical models in order to tackle the issue. Moreover, the multifunctional team challenged and reframed the existing technologies and solutions and held a generative session that unveiled a global vision of the technological solutions that could be delivered, combining skills in a different way and giving rise to more complete ideas. Hence, Neosperience accurately highlighted the value in bridging the physical and the digital spaces. Then, the company discovered the quality criteria for the user experience by involving expert clients – marketing and retail managers –in a focus group, as stated by a Product Marketing Manager:

> *The focus group was to comprise marketing managers and retail managers from eight different companies, in order to explain the idea to them, and ask questions to understand in which direction to focus more, what could be done to differentiate us, etc.*

Following the focus groups with the users, an internal meeting was held to reveal the pain points to tackle, as explained by the informant, expert in Marketing Strategies in Neosperience:

After meeting the users to discuss the idea, there was another internal meeting in which we arranged the suggestions that had come to mind. This activity was followed by an internal test with the people of the marketing and development departments to validate or reject hypotheses, to understand the strengths and weaknesses of the solution.

Then, the prototyping phase began. The prototype affected three different aspects of the solution – software, hardware and interface. The subsequent phase tested the solution. The tests were first performed internally and then externally as a proof of concept with five potential partners.

Cross Case Analysis

Across the three cases, four common practices emerged from the humanization of big data innovations that allowed the projects to reach a meaningful application of big data. In particular, Table 2 shoes how Math & Sport's Virtual Coach, TIM and Olivetti's Smart Territorial Data and Neosperience's People Analytics shared the practices of cropping big data landscapes, reframing their applications, unveiling their opportunities, and proving their releases. The cases showed the importance of selecting the most valuable data by recognizing their richness and framing it within a new solution space that could cover any untapped need. Moreover, they highlighted how questioning the status quo and advancing a new way of using data were paramount to reframe big data applications. Coherently, they were also able to unveil new opportunities by leveraging enabling technologies and diverse skills that supported continuous experimentation and exploration of new features for big data solutions. Finally, they all showed the importance of putting big data solutions to the test with iterative releases, allowing the three companies to first understand the user experience requirements and then test the big data solution experience against them.

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Discussion

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The cross-analysis of the three case studies highlights the recurrent use of four key overarching practices that result from the combination of the big data-based innovation process and Design Thinking. Indeed, despite being very different, the three cases show how they all presented recurring themes among cases that showed the impact of Design Thinking on big data-based processes in the Concept, Development, and Launch phases *[see Figure 2 for more detail].*

Cropping Big Data Landscapes

The term 'cropping' is usually referred to image processing as the selection of the relevant area from a photograph or an illustration. By transposing the cropping idea to the context of a Big Data project, the four cases exemplified this practice. Indeed, in the Virtual Coach case, Math & Sport was able to distinguish between types of data and select only the ones that implied an unmet value for the users. Indeed, they recognised in positional data the underlying potential that could manifest in objective interpretations of the events taking place in a football game. In the Smart Territorial Data case, TIM and Olivetti were able to recognise the value embedded in telco data. Moreover, they were able to select more heterogeneous sources of data that could be integrated with telco data. This allowed providing a wide-ranging and realistic analysis of territorial data. Similarly, the People Analytics case by Neosperience showed how they elaborated the intuition of customer needs, in order to select the most efficient and effective data sources and data types to achieve the ideated target.

Design Thinking was particularly suitable to identify the fundamental concept that should be developed throughout the project and, consequently, to select the most appropriate data to fulfil the objectives. Conceptualised as a human-centred approach that leads to innovation (Carlgren et al., 2016), Design Thinking drives the innovation process by identifying users' needs (Norman, 2005). The extant literature shows that this is usually achieved through empathy – the ability to adopt the perspective of another person, or recognise their perspective as their truth, being open to various inputs, suspend judgment, recognise other people's emotions, and communicate by mirroring back (Brown, 2009). The cases and the process show how seeing the wealth and the abundance of the perspectives provided by big data, it is fundamental to apply a user viewpoint in order to capture the enormous potential embedded in big data. Thus, closing the gap between the big-data centric innovation approach that usually is tech-centric (Saltz & Shamshurin, 2016) and the Design Thinking approach that not always considers technology (Magistretti et al., 2020b).

Reframing Big Data Applications

In the Development phase, instead, two patterns emerged. On the one hand there is a systematic recombination of the existing knowledge to find innovative solutions in terms of Big Data applications (Savino et al., 2017), and on the other hand there is the willingness to discover new technological opportunities through continuous experimentation (Verganti et al., 2020). Starting from the first hybrid practice, Math & Sport was able to challenge the existing use of data, by going beyond the initial use of positional data. On the contrary, they reframed the overall use of data in the sports environment, by proposing a real-time processing and result communication. At TIM and Olivetti, they challenged time, as they reframed the use of telco data, long before their competitors. This involved an intrinsic effort in framing and reframing the solution designed according to an appropriate perspective, that led them to the development of a complete algorithm base needed to build the solution with a precise objective, i.e., obtaining interpretation of the data of interest for future users of the application. At Neosperience, instead, they admittedly started from an overview of the existing solutions that were used to yield the type of service that they were targeting. They were thus able to rethink and combine the underlying technology in an innovative way, aimed at conveying their guiding vision, which is bringing empathy to technology. These approaches testify the tendency of the companies interviewed to apply Design Thinking together with Big Data practices as a way to promote 'Reframing Big Data applications.'

This is coherent with the reflection sustained in Design Thinking literature by Beckman and Barry about the fact that 'as we move into framing, we look for something new, extracting the important insights from the observational data' (Beckman & Barry, 2007). Design Thinking suggests exploring problems in innovative and different ways (Boland & Collopy, 2004; Sato et al., 2010) and thus, this a recognised value also in big-data projects. In other words, it is a cognitive model that is substantially different both from deduction and from induction: it is abductive, as it entails a divergent phase, i.e., unexpected ideas gathering, followed by a convergent phase, i.e., selection of promising ideas (Martin, 2009; Micheli et al., 2019). Designers are able to understand and consider the different perspectives and interests of internal and external stakeholders (including the users), to reframe the innovation challenge in a meaningful way and creatively combine the different perspectives in a new solution space (Beverland et al., 2015).

Unveiling Big Data Opportunities

In all the case studies, in fact, the companies 'used technology to change the meaning of offerings in a category. These companies were not necessarily the first to introduce a technology in the product category, but they unveiled a more meaningful and profitable form' (Verganti, 2011). Following this reasoning, the repeated reframing of the concepts and the ways to use technology is correlated with experimentation, which makes it possible to move to the considerations about the third hybrid practice discovered. Indeed, sometimes those experiments lead to the unveiling of new opportunities offered by the Big Data technology, such as the combination of 5G and positional data that allowed the Virtual Coach to support the game strategy, delivering real-time insights and suggestions. Likewise, Math & Sport were helped by a diverse team that allowed them to delve deeper in the analysis of functionalities, by following a series of experimentations to reframe the opportunities. Similarly, in TIM and Olivetti, the association of the different types of expertise of the Data Angels group allowed them to deploy their database not only for the analysis of the presence of people in Italy, but also of their mobility. Neosperience unveiled the right positioning of its solution, by undergoing rounds of experimentations with its users. For these reasons, it is necessary to highlight the presence of a hybrid practice that shapes the innovation process in its Development phase called 'Unveiling Big Data opportunities.'

The recent stream of literature concerning technology epiphanies provides insights into strategies that companies can adopt to gain value from applications based on new technologies (Verganti, 2009, 2011; Dell'Era et al., 2011). According to Verganti (2009), each technology is believed to embed a set of disruptive new meanings that are waiting to be uncovered. By revealing those quiescent meanings, a company may be able to seize the technology's full value (Magistretti et al., 2020a). Design Thinking can support unveiling the potentialities embedded in Big Data, exploring unconventional patterns and recognizing meaningful weak signals. This will also reinforce the view that technology can benefit by adopting an open innovation strategy (Chesbrough, 2003). Indeed, unveiling opportunities might reinforce the ability to foster an outbound strategy for companies (Bianchi et al., 2011).

Proving Big Data Releases

In the Launch phase, it is crucial to test the coherence between the technological features developed and the experience that is provided to the users through the solution. In the case of the Virtual Coach, this was achieved through the solution releases on the field, and observation of users' feedback and behaviour. The involvement of clients to test the activities allowed TIM & Olivetti to reposition a series of important indicators, deciding to select summary data representative of the context. When Neosperience was approaching the launch of People Analytics, they went through repeated tests that concerned verifications and refining steps on hardware, algorithms, and interface. This was crucial to control not only the way the respective parts of the solution worked, but also to achieve consistency throughout the technological and experiential aspects. These attitudes demonstrate the importance of mixing Design Thinking-oriented and Big Data-oriented approaches for these types of projects in order to keep 'Proving Big Data releases', i.e., proving the consonance between the characteristics provided by the Big Data technological infrastructure and those that teams are willing to deliver through the user experience.

In all four case studies, in fact, the companies tried to put the combination of the validity and reliability perspectives (Sato, 2009) into practice, where validity accounts for the benefits delivered to the customers and reliability accounts for the value obtained by the company itself by means of the technological knowledge acquired and the economic results achieved through the solution. Leveraging creativity, design thinkers can create breakthrough assumptions and use experimentation in the real world to assess whether they are coping with human problems (Johansson-Sköldberg et al., 2013)

Contribution to theory

The combination of the big-data innovation process with Design Thinking in a new process model to discover opportunities within this peculiar technology has a threefold contribution to theories. It contributes to (i) the growing debate on big data and digital transformation (Nambisan et al., 2017); (ii) the literature on Design Thinking (Carlgren et al., 2016; Micheli et al., 2019); (iii) and to enriching the discussion about the role that design can play in unveiling technological opportunities and in advancing our understanding of such a world (Verganti, 2009; Magistretti et al., 2020a; Verganti et al., 2020).

First, by unveiling a process model for coping with big data development, the paper contributes to the big data theory by showing a practical approach to master the 3V characteristics of big data (McAfee et al., 2012). Indeed, showing the value of cropping, reframing, unveiling, and proving it enriches the knowledge on the volume and variety of big data (Trabucchi & Buganza, 2018). The model also supports the academic claim that mastering the big data process is surely a maturity issue (Saltz & Shashurin, 2016). Still, it is also a matter of having a clear set of sub practices, in order to inform companies on how to manage the big data processes to foster innovation (Ervelles et al., 2016). Finally, the deep iteration presence in the model answers to the call of digital transformation on a process that can support companies in matching suitable interpretations of digital opportunities (Nambisan, 2017).

Second, the research unveils the role that Design Thinking can play in digital technology. Some initial reflection on the capabilities and practices needed in the tech realm are emerging (Magistretti et al., 2020z; Liedtka, 2020), but further investigations are needed. The paper illustrates a process deeply rooted on understanding user needs, iterations, and reframing, key pillars of the Design Thinking approach (Carlgren et al., 2016; Micheli et al., 2019), showing how they can support even high-tech projects such as big data. Thus, the paper expands the realm of Design Thinking application from product innovation (Brown, 2008) to technological innovation.

Finally, the paper contributes to the technology development literature (Magistretti et al., 2020a) by showing how Design Thinking with its human-centric approach toward user needs (Carlgren et al., 2016) can support companies in advancing their understanding of digital technologies' potentiality (Danneels & Frattini, 2018). The debate about the role that design can have in technology developments is still eager for contribution (Danneels, 2004). The paper contributes to the debate on technology development by showing how human-centricity and iteration can support the discovery of new opportunities in big data technology. The paper increases academics' understanding of the role of design in fostering meaningful innovation for humans by leveraging design principles (Verganti et al., 2020); this by showing a practical model and a combination of phases and practices that are enacted to unveil opportunities hidden within the big data technology (Verganti, 2009).

Contribution to practices

By illustrating the process model in Figure 2, the paper supports managers in developing big-data technologies in a more conscious way. Indeed, it is not just a matter of integrating the big-data mindset and tools in your organization; a more conscious approach is needed to exploit the value of such technology. The three phases (i.e., concept, develop and launch) can inspire managers in embracing the digital transformation by adopting more human big-data solutions. Indeed, the process model is a first attempt to give tangible proof of the steps that managers should follow to get the most out of the combination of traditional big data-based innovation processes and Design Thinking. The second level practices can even inspire managers on the skills and capabilities needed to boost innovation and be ready to launch on the market big data innovation. Finally, the iteration among the phases of concept, development, and launch shows how an agile mindset and approach toward innovation are strongly recommended to foster feedback loops and critical Thinking.

Conclusions

This paper discusses how Design Thinking can support companies in unlocking the potentiality of digital technologies such as Big Data. Leveraging three cases of pioneer adopters of Big Data for innovation, the paper shows how the adoption of Design Thinking practices reinforced the value generated in the digital transformation. The paper provides interesting insights for both academics and practitioners. Regarding scholars, the paper enriches the understanding of the Design Thinking practices also considering tech-based innovation projects. This is something that contributes to Design Thinking literature, to the recent call for making it more eligible as a theory (Micheli et al., 2019), and to the digital debate about how to make digital transformation more effective (Nambisan, 2017). Given the rising attention devoted to the dark side of artificial intelligence or other technologies, the paper highlights a process for Big Data that can support companies in considering the human side. With reference to practitioners, the hybrid set of practices proposed in Table 1, is an actual and tangible output that might help them navigate the complexity of Big Data processes. The rise of hybrid models is widely accepted in both theory and practice but is more and more relevant in a society that is evolving so quickly. Thus, by delving into the under-researched areas of Design Thinking and Big Data, this paper proposes a new way to interpret and manage them.

Notwithstanding this, the paper has some limitations. The qualitative nature of the study and the convenience sampling adopted might reduce the impact of such findings and the effectiveness of the hybrid set of practices proposed. Consequently, more research should be performed, and more studies on the role of Design Thinking in digital transformation are needed.

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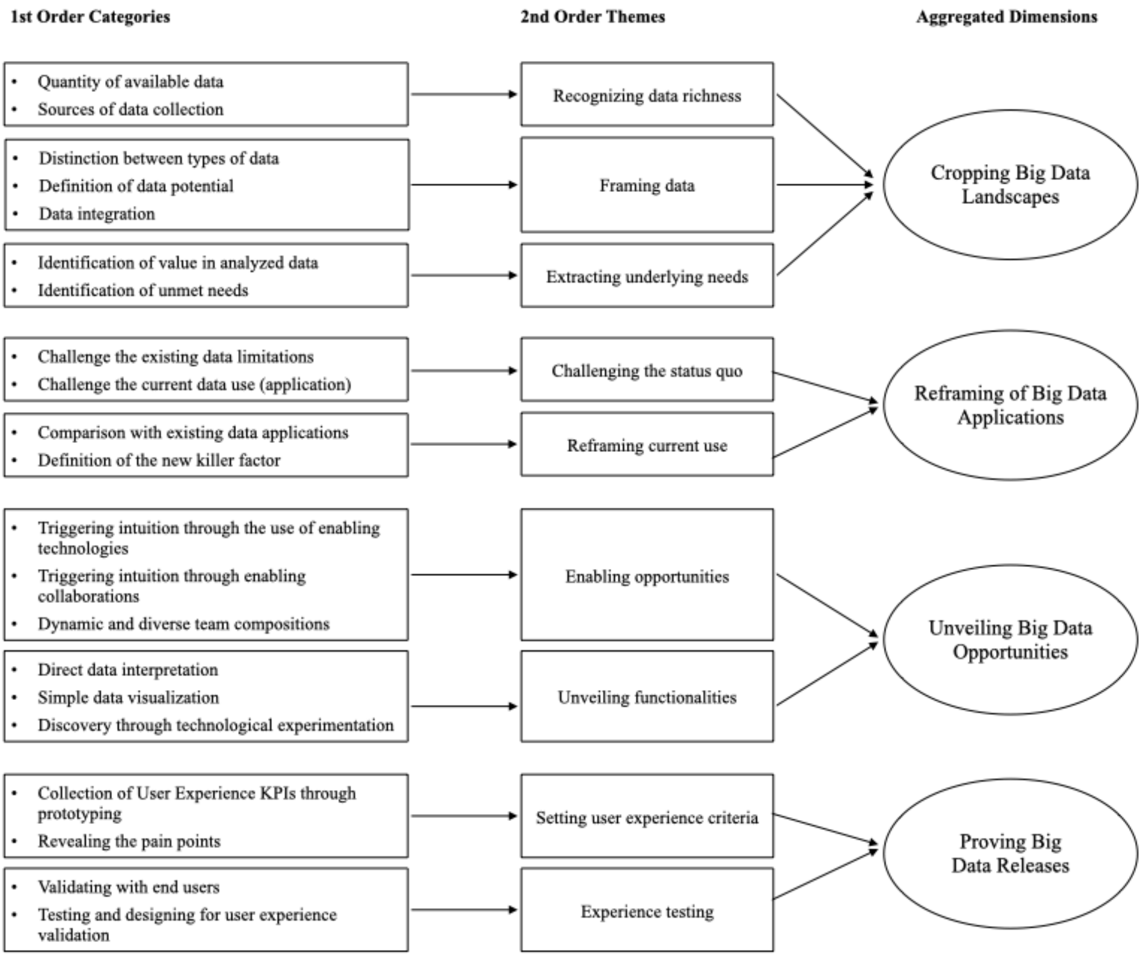
Figure 1. Data Structure



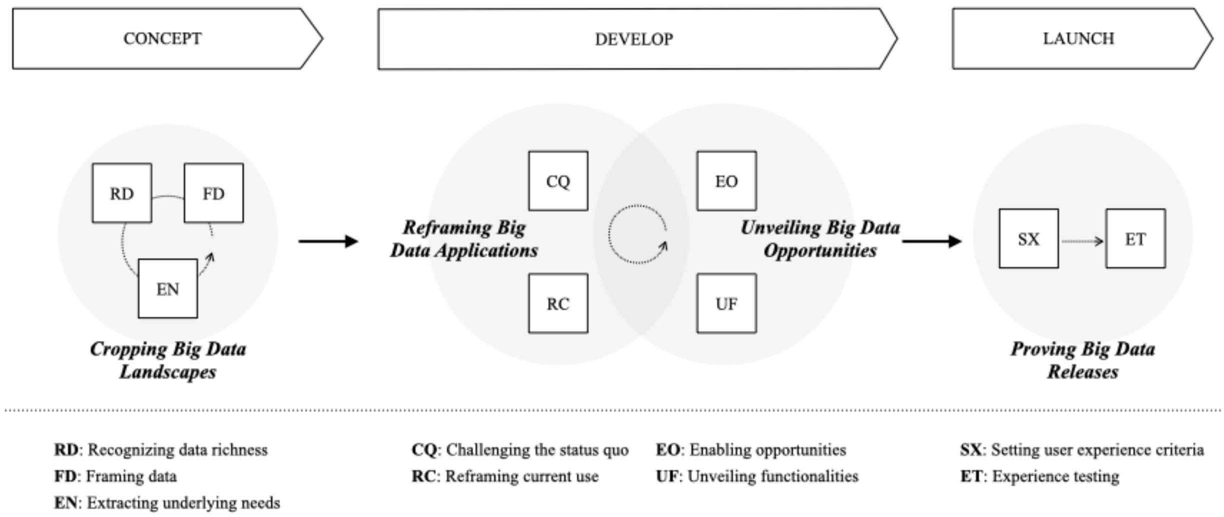


Figure 2. A process model combining big data-based innovation process with design thinking

Table 1. Main Data Sources and Use

DATA SOURCES	TYPE OF DATA	USE IN THE ANALYSIS
PRIMARY SOURCE SEMI-STRUCTURED INTERVIEWS	**First round** 4 Interviews with leaders from Big Data projects	Gathering data regarding the overall project, its contextual constraints and initial exploration of the cases
	Second round 4 Interviews with leaders from Big Data projects	Expanding the initial understanding of the project by delving deeper in the process and practices adopted.
SECONDARY SOURCE ARCHIVAL DATA	**Internal documentation** Presentations of the project	Triangulating data from interviews with project informants with facts and better understanding of the project
	Public documentation Information available online on the organization and project	Getting a general understanding of the organization and project

Table 2. Selected Evidence

Second-Order Codes	Selected Evidence on First-Order Codes
Aggregated Dimension: Cropping Big Data Landscapes	
Recognizing data wealth	*Quantity of available data*
	(Math & Sport) "There are lots of data in the world of football. The more abundant type of data is that coming from (2) the video tracking activity during matches. These are also called positional data, because they indicate the position (x, y, z) of the players and the ball every 40 milliseconds."
	(Tim + Olivetti) "The project came from the idea and the need to be able to derive value from the data that a telco operator such as TIM had available."
	Sources of data collection
	(Math & Sport) "Positional data are collected in all the main championships, from Serie A, to Premier League, to Bundesliga, to Ligue 1, to the Football World Cup, etc. commissioned by leagues, such as FIFA"
	(Tim + Olivetti) "When we talk about telco data, we are talking about any phone call made, any message, any application used, any information about browsing, etc. So the horizon of possibilities is quite broad."
	(Neosperience) "We collect images through cameras positioned in the stores and, using analytics algorithms for image processing, we identify the position of the person."
Framing Data	*Distinction between types of data*
	(Math & Sport) "It is necessary to make a distinction between this type of data (positional data) and data used by the media to describe the game (scout data). Scout data come from people's evaluations of the game."
	Integration of data
	(Tim + Olivetti) "We start from telco data. Alongside these data, we can integrate other types of information, from open data to customer data."
	Definition of data potential
	(Neosperience) "The image of the person is replaced by the skeleton of its cardinal points, according to which the trajectory of the subjects is reconstructed from frame to frame"
Extracting underlying need	*Identification of value in analysed data*
	(Math & Sport) "In that case (of scout data), in fact, there are people at the stadium who check and record if a player has run, if another one has sprinted, if one has shot a goal, etc."
	Identification of unmet needs
	(Math & Sport) "Those scout data are much less complete because they only tell you what is happening directly on the ball and not to all the players."
	(Tim + Olivetti) "In addition to telco data, we also collect information on social networks to perform the sentiment analysis of an area and identify the hot topics.
Aggregated Dimension: Reframing Big Data Applications	
Challenging the status quo	*Challenge the existing data limitations*
	(Math & Sport) "Why aren't positional data used instead? Just because they are "raw" position data, they don't directly tell you how many steps you've taken"
	(Neosperience) "The problem is that there are no precise data that refer to the physical shops, which have remained more or less the same for many years, such as the profitability index per square meter, the turnover, etc."
	Challenge the current data use (application)
	(Math & Sport) "However, they (positional data) are used only for post-game analysis, or at most to provide the media with the number of kilometres run by the players, so that you can derive once and obtain the speeds, derive twice and get the accelerations."

	(Tim + Olivetti) “So, the project has its roots around 2014-2015, when big data was not a top trend yet, especially not telco data”
Reframing current use	*Comparison with existing data applications* (Math & Sport) “Our challenge instead was to create a product that would use this information in real time to run a virtual coach” (Tim + Olivetti) “The first usage of this data was a trivial heat map featuring the presence of people in some areas, then we upgraded the concept to a higher level, with a more sophisticated analysis of the clusters of people” *Definition of the new killer factor* (Math & Sport) “Our killer factor is the ability to pull out objective and real time indications from data. We use data to interpret the event, because when I interpret data, I can control the phenomenon, simulate it and optimize it” (Neosperience) “ The idea behind People Analytics is to bring into the physical world of retail, a large amount of data that can be transposed from the analytics, to obtain much more precise traffic analysis, to monitor the behaviour, the flows and the hot spots inside the store”
Aggregated Dimension: Unveiling Big Data Opportunities	
Enabling opportunities	*Triggering intuition through the use of enabling technologies* (Math & Sport) “The intuition came when we had the possibility to use the 5G as enabling technology, which allowed a real-time analysis, while others do a descriptive post-analysis” (Tim + Olivetti) “We manage 51 billion information assets daily, so we needed to find the best technological solution both from a hardware infrastructure and from a software point of view” *Triggering intuition through enabling collaborations* (Math & Sport) “Math&Sport relies on the parent company Moxoff for the provision of the technological component. The two organizations are very close, this is the anomaly and the peculiarity of the case” *Dynamic and diverse team compositions* (Math & Sport) “The project has been carried out by a team of about 15 people working according to the agile methodology” (Tim + Olivetti) “To navigate the horizons of possibilities, we needed a team able to manage the technological aspect, the skills aspect, and the regulatory aspect of processing people’s data” (Neosperience) “The team is transversal to the company. There are experts for the technical side, for marketing strategies, and for communication and creativity”
Unveiling functionalities	*Direct data interpretation* (Math & Sport) “Now the Virtual Coach is able to exploit the information elaborated directly on the pitch, providing actionable insights” *Simple Data visualization* (Math & Sport) “It is objective thanks to our analytic model and representative thanks to data simplicity” *Discovery through technological experimentation* (Neosperience) “In this project there has been a reiteration of phases dedicated to technological experimentation and to user validation, which has certainly been useful in bringing about a solution that allows us to be positioned strategically unlike our competitors”
Aggregated Dimension: Proving Big Data Releases	
Setting user experience criteria	*Collection of User Experience KPIs through prototyping* (Math & Sport) “In February 2019 we had the first prototype for coaches and supporters to try. Their feedback is crucial to define our KPIs” (Tim + Olivetti) “The entire algorithm base started to be developed, focusing on the objective of obtaining the correct interpretation of the data available and extracting the KPIs of the experience of interest.” (Neosperience) “The focus group was to comprise marketing managers and retail managers from eight different companies, in order to explain the idea to them, ask questions to understand in which direction to focus more, what could be done to differentiate us etc.” *Revealing the pain points*

Experience Testing	(Math & Sport) “We have been carrying out trials on the field: it may seem stupid, but clicking a precise point on a tablet when it’s cold and there is tension involved could have revealed to be a pain point for the coaches” *Incremental testing* (Tim + Olivetti) “We tested the idea, we saw that the idea was well structured, we created a concept and then we scaled on that concept in terms of volume, gradually adding the parts of data sources, or algorithms, or interface features that we needed” (Neosperience) “Even when a product arrives on the market, it is never static because the competition goes very fast and technologies are more and more accessible, so we created for ourselves a plan of development and evolution for the product that is continuous, iterating cycles of checks and innovations according to the agile methodology” *Validating with end users* (Math & Sport) “Once we saw that the prototype was interesting, we carried out a validation activity with end users” (Neosperience) “We have identified five potential partners that were right for us by shop type, by size, through the contacts we had, to perform a proof of concept in store” *Testing and designing for user experience validation* (Math & Sport) “We carried out the testing and design activities through laboratory tests, a heuristic evaluation by UX design experts, and user field validation”