Design Principles Supporting Data-driven Decisions Platforms

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Abstract

The digital transformation of organizations and societies and the increasing availability of big data and analytics make decision-making more complex and dynamic. This challenge is likely to continue and accelerate. Therefore, there is an urgent need for a new scientific approach to facilitate decision-making based on evidence from data. Quite recently, organizations have begun relying on machines to make decisions. So, this leaves us astray about designing data-driven decision platforms to enable humans and machines to collaborate toward organizational decision-making. Incorporating data and algorithms into decision-making addresses existing challenges and brings new ones. Therefore, to enable data-driven decisions, data-driven platforms are needed. However, existing platforms need the principles that ought to exist to foster insight-driven choices in organizations. We argue that a consolidated normative theory must be required for designing data-driven decision platforms. This is problematic because it hinders the ability of organizations to become data-driven concerning how they make decisions. Accordingly, we have posited and evaluated a set of design principles to support data-driven decision platforms, following design science research methodology. Our overarching purpose is to present the posited design principles and the preliminary results from their qualitative evaluation and to contribute to developing design principles, enabling researchers and practitioners to augment them into instantiations of various data-driven decision platforms.

1. Introduction

The challenges facing organizations nowadays are increasing, including competition (local and international), resource optimization, customer experience, governance and compliance, sustainability, decision-making quality, etc. At the same time, the sheer amount of big data available nowadays not only presents an opportunity to address such challenges but also brings about new ones. This work addresses one of the challenges facing organizations, namely, decision-making. Even when using big data and AI algorithms, data-driven decisions (DDD) have harmful and unintended consequences for organizations (Rinta-Kahila et al., 2022). The study of decision-making has attracted considerable scientific attention from many disciplines, including psychology, economics, sociology, political science, biology, neuroscience, and different areas of business administration. Hence, if we know how people make decisions, we can help them make better ones. However, the study of decision-making is subject to significant difficulties (Hogarth, 2010). In the past, such a challenge –making decisions– could have been studied in purely social terms since the decision maker used to be a solo human making decisions based on their intuition and insights. These days, decisions are being made with evidence from data and analytics. Such a contemporary decision-making paradigm, which is based on machine learning (ML) and AI running on top of big data to provide insights to decision-makers, has been reflected in several recent publications, e.g. (Elgendy et al., 2021; Gröger, 2018; Shrestha et al., 2019; Vaccaro & Waldo, 2019). Towards that end, Shrestha et al. (2019) identified several ways to make decisions: solo-human, solo-machine, or via collaboration between humans and machines.
Therefore, addressing the organizational decision-making challenge requires a sociotechnical approach. Organizations are complex socio-technical systems requiring a sociotechnical approach to address them. Organizationally, a sociotechnical system is an approach to complex organizational work design that recognizes the interplay between social components, human and societal, and, on the other hand, technology. Both humans and machines are necessary to make any technology work as intended (Selbst et al., 2019). The term denotes the interface between society's complex infrastructures and human behavior. Contemporary organizations rely on technology and humans; this has given way to a more holistic approach grounded in sociotechnical theory, where the concentration is on the human, the technology, and the interplay that unfolds. Allen Lee explained that information systems (IS) research studies further than the technological system, the social system. IS sometimes explores both technology and social elements, society or humans, side by side. The unfoldings that emerge when the two interact within IS scholarship, too. The nature of IS research sets it apart from the other related disciplines. In line with that, the IS reference disciplines do not adequately represent it because they focus either on technology or the organization but not on the emergent sociotechnical phenomena that unfold. Therefore, some see such disciplines as contributing disciplines rather than references (Lee, 2001).

Previous research argues that a successful digital transformation positively affects firm performance. It can create a competitive advantage, so companies across industries engage in digital transformation efforts (Klos et al., 2023). Organizations nowadays focus on launching digitalization strategies to cope with the digital age (Skhiri & Duverne, 2020). Accordingly, and since data is considered the new oil, there needs to be more design principles for a decision-making platform that aims to provide insights from data to managers and decision-makers, thereby facilitating the enactment of modern decision-making theory at organizational levels. Therefore, we strive to address this problem by answering the research question: What design principles govern the design and implementation of data-driven decision platforms?

We aim for the proposed set of design principles to help organizations address their decision-making challenges to combat or reduce the unintended and negative consequences of data-driven decision-making (DDDM) when used without guiding principles, such as discrimination, which was reported in cases where government agencies put DDDM in use for welfare decisions (Rinta-Kahila et al., 2022). We, additionally, want to help organizations utilize big data and AI algorithms towards decision-making to remain in control over an out-of-control AI spread (Mikalef et al., 2022).

This paper is organized as follows: We present the research methodology, then explain and discuss the theoretical foundations, such as datafication and platformization. We then address the state of DDDM and the challenges it encounters. Finally, we introduce DDDM platform design principles and evaluate them qualitatively.

2. Design Research as the Methodology
Information systems (IS) are concerned with the design of artifacts (Orlikowski & Iacono, 2001). Accordingly, it has become one of the field’s main research points (Baskerville et al., 2018). Venable and Baskerville (2012, p.141) define design science research (DSR) as research that develops a novel, useful artifact to address a broad category of a problem and assess how well it works to resolve that problem. A focus point of DSR is to develop design knowledge, which could be represented in different forms and at various levels of abstraction (Cronholm & Göbel, 2018), such as constructs, models, methods, design principles, or design theories (Chandra et al., 2015; Gregor & Hevner, 2013; Gregor & Jones, 2007). This paper focuses on conceptualizing design principles since design principles constitute a joint research contribution within the IS domain. Gregor and Jones (2007) explained that design principles define the structure, organization, and functioning of the designed product, method, or artifact. Furthermore, design principles could be generalized to solve a class of problems rather than a specific set of system features to solve a particular issue (Hevner et al., 2004; Sein et al., 2011; Walls et al., 1992;).

2.1 Importance of design principles

In DSR, we create artifacts using design principles. According to Gregor and Jones (2007), eight components make up design theories: structures, principles of form and function, artifact mutability, justificatory knowledge, principles of implementation, explanatory instantiation, and purpose and scope. Furthermore, rather than referring to something that naturally occurs, the term "artifact" describes something humans made or created (Simon, 1996). Additionally, Gregor & Jones (2007) clarified that as the study of information systems lies at the intersection of human behavior and the characteristics of physical objects, information systems design theories can differ from those in other fields. In this work, we put out design principles for data-driven platforms, or the artifact, which includes human decision-makers and analytics algorithms. The rules guiding the creation of the specified artifact are called the set of design principles (Gregor & Jones, 2007). According to Venable et al. (2012), the implementation principles may also help assess the artifact in DSR. Sein et al. (2012) state that the design principles of the artifact—referred to as the platform—should be theoretically grounded but practice-inspired. We therefore propose that the design principles of the data-driven decision-making platform will contribute to the literature on data-driven decision-making and data-driven enterprise (digitalization). The design principles represent the inputs to the artifact’s design in DSR. They may also represent the artifact’s output in terms of knowledge produced by design. This has been defined in several DSR-theorizing articles. For instance, Gregor and Hevner (2013) described the various categories of IT artifacts at knowledge contribution abstraction levels that vary based on the maturity of problem and solution domains. Consequently, a particular DSR project could produce novel artifacts on one or more of the following three levels: distinct instantiation of the kinds of products and services; broad contributions, including creating models, constructions, design concepts, and technology regulations in design theory; or moderate design theories related to the phenomena being studied.

This paper contributes to level two design principles. The design principles represent nascent design theories or knowledge as operational principles (Gregor & Hevner, 2013). DDD platforms would then be able to incorporate our proposed DPs into platform design functions (DFs) (Meske & Bunde, 2021).
Including design principles in design science knowledge sets it apart from other types of knowledge. They represent prescriptive phrases that guide accomplishing a particular objective (Gregor et al., 2020).

We conclude this discussion by saying that even though frameworks for developing design theory or design knowledge have been suggested, The development of design concepts has not received the attention it deserves (Chandra et al., 2015). We conceptualize the design principles as per the following figure.

### 2.2 Generalizability

Generalizability is essential in IS and design-oriented research (Lee & Baskerville, 2003; Sein et al., 2011). For the platform to be generalizable, we incorporate Sein et al.’s (2011) levels of generalized outcomes due to their relevance to the study of design principles. While the platform addresses the decision-making problem and provides a solution, both the problem and solution need to be generalized. Such movement from the specific and unique to the generic and abstract is a critical platform component. Accordingly, we augment Sein et al.’s (2011) three levels of generalizability:

1. Generalization of the problem instance: the challenges facing organizations discussed in the paper, e.g., opacity, accountability, defensive decision-making, etc., are generic to all organizations and various organizational decision-making contexts.
2. Generalization of the solution instance: the aimed-for DDD platform could be used in various organizational contexts.
3. Generalization of design principles: the design principles posited by the paper are generic in that various organizations and decision-making contexts could accommodate them.

The platform’s generalizability will enable it to be used in several domains and for various decision-making purposes. We want to conclude this section by emphasizing that practitioners and researchers could exploit design principles (Kolkowska et al., 2017).

### 3. Related Theoretical Foundations

In the following sections, we will introduce the developing design principles we posit. The DPs rest on examining relevant literature studies to support our proposition, as well as the practice of reviewing existing decision-making platforms. When writing this manuscript, the design and implementation of the DDDs’ platform were lacking. Searching on Google Scholar, ACM DL, or IEEExplore revealed research relevant to platforms (Farshidi et al., 2020; Broekhuizen et al., 2021; Gröger, 2018; McAfee & Brynjolfsson, 2017; Tura et al., 2018); design principles (Hermann et al., 2015); and DDDs (Bean & Davenport, 2019; Elgendy et al., 2021; Kar & Dwivedi, 2020; Mandinach, 2012; Provost & Fawcett, 2013). However, no research provides the insights the DPs need to design and implement a DDD platform.

The DPs in this paper rested on three kernel theoretical foundations: datafication, platformization, and contemporary decision theory. According to Markus et al. (2002), a kernel theory underlays a design
theory (Göbel & Cronholm, 2016). Further, Kuechler & Vaishnavi (2008: p. 489) added that kernel theories “frequently are theories from other fields that intend to explain or predict a phenomena of interest”.

Our argument to inscribe knowledge from datafication is the sheer amount of data available nowadays for analysis and decision support (Elgendy & Elragal, 2016; Elragal & Klischewski, 2017). Additionally, the European data economy continues to proliferate to reach an estimated EUR 829B by 2025 (OPENDEI, 2021). The argument for selecting platformization is motivated by the fact that big data and analytics algorithms require building blocks in the form of a platform to support effective data acquisition, pre-processing, sharing, and analytics (OPENDEI, 2021). Other research also focuses on specific platform features, e.g., blockchain platforms (Farshidi et al., 2020). Lastly, the argument for selecting contemporary decision theory owes to the nature of developments that have taken place in decision theory, accumulating research into not only decision-makers but also analytics and data, shaping a new form of decision theory (Elgendy, 2021). In the following subsections, we briefly describe the kernel theoretical foundations and related work that have informed our DP design.

3.1 Datafication

A recent article by Gröger (2021) confirmed that there is no AI without data, where data preparation and quality are crucial to analytics and digitalization efforts, including DDDs. We datafy many events to make better decisions and become more efficient. Datafication is the process by which subjects and objects are transformed into digital data. Influenced by the upsurge of digitalization and enabled by big data, datafication is exaggerated as further dimensions of social life happen in the digital space. Datafication has enabled the digital world we live in. Baskerville et al. (2020) explained that an information system is traditionally understood to reflect and represent physical reality. However, such a conventional view—that digital technologies both produce and affect physical reality—is becoming less and less relevant; that is known as the ontological reversal.

We take the notions of datafication and the digital-first to DDDM by introducing the DDDM platform, which will aim at utilizing digital data and integrating both worlds, the digital and physical, to enhance the quality of decisions. Datafication is revolutionizing the world in several ways, whereby big datasets are analyzed using advanced analytics tools to turn data into meaningful insights and, after that, support decision-makers. The DDDM platform is bringing datafication to the decision world. When applied successfully, datafication brings organizations under the dominion of data-driven enterprises.

3.2 Platformization

Platforms that support decision-making are created to to store, process, integrate, manage, and analyze datasets in order to enable a data-driven environment. The aim is to develop a system, a platform, that is useful for a more significant number of organizations and stakeholders, including decision-makers. The proliferation of platforms, i.e., platformization, came as a consequence to the big data era. Big data need to stored and maintained under one integrated roof to generate value to business. Accordingly, decision-makers need constant access to it via a DDDM platform. Business models based on such platforms
have an extreme competitive advantage over competitors (Sharma & Kumar, 2023). Additionally, platforms accelerate communication and collaboration amongst decision-makers intra and inter-organizations in a way that leads to better-quality decisions and pave road for innovation. Platforms enable cross-company decisions coordinated at the macro, meso, or micro levels. DDDM platforms act as the underpinning of an ecosystem of data and insight sharing. Tura et al. (2018) asserted that the design choices related to the various aspects of a platform are critical to ensure value creation. Therefore, we will use this as a motivation to address the design principles needed to design and implement a DDD platform.

The analytics paradigm spreads across many different roles and responsibilities, such as those of the data engineer, data analyst, and data scientist, and the world is suffering from a shortage of these roles. It would have saved businesses time and money if they could use analytics technologies with basic skills where they needed no or minimal code writing. Luckily, such technology exists nowadays, called low-code (aka no-code) platforms. Indeed, it would be beneficial if a person who knows business requirements and objectives had access to a DDDM platform where they could perform basic operations in data science-related roles without prior coding or data engineering knowledge. Alsahref et al. (2022) highlighted that building ML models requires domain knowledge and advanced ML programming skills. However, there is tremendous difficulty in finding skilled ML experts in the labor market. This is how no-code and low-code ML platforms come to exist. Low-code and no-code approaches help rapidly build ML models, automate data pipelines, and visualize the results. In the low-code platform, decision-makers with basic analytics skills can use existing building blocks, e.g., libraries, and still have the flexibility to customize the required task. With no code, however, it is mainly meant for decision-makers with expertise in a field or function but minimal to no prior software development knowledge. No-code enables users to drag-and-drop process objects to perform analytics tasks with minimal effort or programming skills and a great deal of flexibility to customize. While low-code ML platforms can be used by different personas like data scientists and ML developers, no-code services, e.g., AutoML, could be used by decision-makers with solid business or domain knowledge. Di Sipio et al. (2020) have underlined the importance of emerging low-code cloud platforms and their vital role in digitalization.

3.3 Contemporary Decision Theory

The study of choices to make decisions is known as decision theory (Elgendy et al., 2021). However, in many decades of multidisciplinary research, decisions and the theories surrounding them have been subject to a high degree of complexity and debate (Hansson, 1994). Decisions are by no means easy. The decision problem is a scenario in which a decision-maker selects an action from a range of options that are impacted by uncontrollable events and have varying consequences with either positive or negative payoffs (Peterson, 2011). As a result, decision theory typically concentrates on means-ends rationality or the results of decisions as assessed by preset criteria (Hansson, 2011). In addition, decision theories are typically classified as descriptive or normative. According to Peterson (2011), normative decision theory provides guidelines for what decision-makers should or must do. Hence, a normative theory of decision-making focuses on the criteria that must be met to arrive at a rational
decision (Hansson, 1994). An empirical field called descriptive decision theory seeks to describe and forecast how to make decisions (Peterson, 2011). Empirical experiments demonstrating how people's conduct defied normative theories were the impetus for developing descriptive decision theories. It focuses on the reasons behind people's thoughts and behaviors rather than attempting to change, sway, or elevate them. Additionally, descriptive decision theory assumes that real-world decisions can be rational and non-rational (Bell et al., 1988). Accordingly, normative and descriptive decision theories are distinct disciplines with the potential for interaction or lack thereof (Peterson, 2011). Research has attempted to extend the concepts of game theory, information theory, decision theory, systems theory, etc., by applying them to intelligent machines and agents motivated by the rise of big data and artificial intelligence (AI). The emphasis has been on how machines make decisions and how to train them. According to Simon's (1977) theory of AI, information processing algorithms and human thinking are comparable. They looked for patterns in the data, memorized them, and then used them to draw conclusions or extrapolate. As such, several programs can mimic or even outperform human judgment or problem-solving skills (Frantz, 2003). However, more research is still needed to determine the degree of cooperation between the two and how it affects decision-making.

Furthermore, although traditional decision theories rely on a numerical depiction of a decision process, real-world situations may call for clarifying numerical terms (Grabos, 2004). While progressively developing, the instruments of conventional decision theory have not shown themselves to be entirely sufficient to back attempts to automate AI decision-making, particularly in more complex and realistic scenarios involving unexpected preferences or decisions or in scenarios where the underlying assumptions are subject to modification (Doyle & Thomason, 1999). This has spurred research on several AI frameworks and functions and directed attention toward qualitative decision theories or qualitative theoretical foundations of decision-making (Grabos, 2004). By creating qualitative and hybrid representations and methods that enhance and supplement the quantitative decision theory's capacity to handle the entire spectrum of decision-making activities, qualitative decision theories seek to enable automation (Doyle & Thomason, 1999).

4. Embryonic Data-driven Decision Platforms

Technology platforms are becoming increasingly popular (Tura et al., 2018). DDDM will, therefore, be made available through a no-code platform. Analytics support has been provided by platforms (Gröger, 2018; Ismail et al., 2019). A DDDM platform aims to include big data analytics (BDA) in decision-making. BDA is a technique for using sophisticated analytics algorithms to analyze large datasets. It makes it possible to produce actionable and valuable insights for various goals, such as DDDM assistance (Wamba et al., 2017). As a result, advanced analytics can significantly enhance decision-making and uncover insightful information that would not have been possible otherwise (Elgendy & Elragal, 2016). According to Elragal & Klischewski (2017), BDA is a theory-driven toolkit that facilitates the elucidation of information in a suitable and interpretable format and produces theoretical contributions.
In this work, the DDDM refers to a situation where (big) data analytics techniques are used to analyze (big) datasets and generate insights to support DDDs. A no-code DDDM platform should focus on all the elements of contemporary decision theory as per Elgendy et al. (2021): decision-maker, decision, decision-making process, data, and analytics. However, the current analytics platforms are not explicitly geared towards DDDM but rather to analytics in an ad-hoc and insular fashion (Gröger, 2021), as exemplified further in the paper.

In the following paragraphs, we examine how some state-of-the-art DDDM platforms fail to address these challenges, leading to the need for new developments. Consequently, we devise a set of design principles (DPs) that organizations designing and implementing DDDM platforms should utilize.

We look at some platforms that introduce themselves or are listed as offering DDDM. We provide insights on how they address the organizational challenges and highlight current shortcomings, reflecting the need for new, holistic design solutions requiring a novel set of DPs. In doing so, we encounter a couple of concerns:

- **Listing & evaluation of decision-making platforms**: a few listings of platforms and tools offer organizations DDDM capabilities. On the other hand, lists and rankings exist for other technologies such as business intelligence, AI, data mining, enterprise systems, dashboards, etc. (for more information, please visit Gartner's Magic Quadrant lists). However, the closest listing is the one provided by Gartner under the title "data and analytics service providers" (Gartner, 2022). That being said, the list includes the leaders who offer help to organizations about DDDM. The report consists of an evaluation of several consulting providers, system integration, and managed services, e.g., Accenture, Atos, Capgemini, Deloitte, EY, IBM, KPMG, PwC, Wipro, etc. It is to be noted that the criteria are based on: business acumen, business process transformation, business change management, technology enablement, asset-based services, analytics and BI service expertise, data management service expertise, AI/ML service expertise, D&A governance expertise, and D&A as a service. The ten capabilities focus more on the supply side than the demand side. That is, the terms “decision” and “decision-making” were each mentioned once in the criteria, with “decision” as part of the D&A governance expertise, whereas “decision-making” is part of the asset-based services criteria. The Gartner report, however, does not discuss the design principles of the DDD platform posited by this paper in the following section (such as human-in-the-loop, collaborative rationality, the evaluative nature of outcomes, openness, multi-species analytics, and explainability), which are set to address challenges facing organizations. Accordingly, we believe a new set of DPs, as proposed in this paper, is necessary to help organizations address the currently unaddressed DDD challenges.

- **Delineating DDD platform providers**: listing DDDM platform providers is one side of the problem. The other side is the criteria for inclusion rather than for evaluation. For example, in the Gartner report, leading consulting companies include Accenture, Atos, Capgemini, Deloitte, EY, KPMG, and PwC. Added to this list are large IT companies offering consulting services, such as IBM, Wipro, and
Cognizant. IT companies also focus on consulting and systems management, e.g., Infosys. Lastly, companies focusing on data and innovation exist, e.g., NTT Data.

Outside the Gartner report, companies profile themselves as decision-making platforms. Examples are:

Table 1

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<thead>
<tr>
<th>Company</th>
<th>Country</th>
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<tbody>
<tr>
<td>decisionlabs</td>
<td>Sweden</td>
<td><a href="https://decisionlabs.se/en/">https://decisionlabs.se/en/</a></td>
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<tr>
<td>decisionlab</td>
<td>UK</td>
<td><a href="https://www.decisionlab.co.uk">https://www.decisionlab.co.uk</a></td>
</tr>
<tr>
<td>The decision lab</td>
<td>Canada</td>
<td><a href="https://thedecisionlab.com">https://thedecisionlab.com</a></td>
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Looking at those examples as well as others such as Board (board.com), GiniMachine (ginimachine.com), Intelligence2day (intelligence2day.com), TDP (decisionplatform.io), Sword (sword-group.com), and Pyramid (pyramidanalytics.com), etc., reveal the following:

- Companies such as Board offer dashboards, cloud-facilitated and linked to several data sources, e.g., databases, data warehouses, big data, IoT data, or flat files. This type of platform may serve BI and data management more than decision-making.
- Another class, such as GiniMachine, focuses on a no-code platform on which users could upload data and run AI/ML algorithms on top to enable automated decision-making. However, the role of the human decision-maker and how to interact with the output of AI/ML algorithms needs to be sufficiently addressed.
- A class of platforms, such as Intelligence2day, promises to turn big data into actionable insights. However, this is done without addressing the challenges organizations face.
- Another class, such as TDP, offers DDD via a platform. They enable real-time data-driven action via the platform. The platform, however, focuses mainly on data and analytics with little attention to human-machine collaboration and the issues that unfold, e.g., accountability, human-in-the-loop, explainability, and openness.
- Other platforms, such as Sword, focus more on data and analytics algorithms and less on decision-making or the decision-making process.
- Lastly, some platforms, such as Pyramid, focus on several aspects of data warehouses, preprocessing, business analytics, data science, and AI self-service. The platform permits decision-makers to make faster decisions. It offers quick access to data and allows for using AI algorithms as a self-service. While the platform focuses on data management and analytics, it also oversees the interaction between human decision-makers and algorithms and the associated organizational challenges that unfold accordingly.
Thus, each company listed above focuses on only part of a DDD platform. Some focus on the data, others on the dashboards, and a third category focus on the analytics algorithms. They only address parts of the challenges facing organizations. Such characterization calls for a data-driven-oriented platform, for which we need to have the design principles guiding its design and implementation. Therefore, this research is motivated by that gap. We believe inadequate attention to organizational challenges when making DDD could cause organizational and human (decision-maker) difficulties. Accordingly, the research on the design principles comes to the scene. It provides the required support, which has the sought-after utility for organizations and humans, both making decisions and being influenced by them.

5. Conceptualizing the Challenges

DDDM has penetrated several parts of our lives and societies. It will continue to do so shortly. DDDM has been used in transportation, healthcare, banking, security, legal, and other domains. Data-enabled algorithms enable the automation of cognitive, discretionary, and decision-making tasks previously performed solely by humans (Gronsund & Aanestad, 2020). Nowadays, decision-making is not exclusive to humans! Decisions are often taken by algorithms, humans, or both. The question about how the interplay between humans and machines unfolds is shaped by polarization. That is, some tend to recognize a replacement setup in which jobs are taken over by intelligent machines (McAfee & Brynjolfsson, 2017), while others emphasize interrelation and augmentation (Bailey & Barley, 2019), where humans and algorithms interact to perform a task. Some of the previous research focused on certain types of decisions to support rather than being generic, such as R&D decisions (Calafut et al., 2023). Generally, the automation of a human worker's tasks may result in replacing the human worker. Still, limited automation exists for specific tasks, resulting in a situation in which humans and technology collaborate, where novel tasks emerge and ensure a continued need for the human worker (Gronsund & Aanestad, 2020). Such tasks bring about several challenges, which problematize the need for a new solution. In the below pointers, we explain the key challenges:

- **Human-machine collaboration**: Elgendy et al. (2021) outlined that the partnership between humans and machines towards decision-making could be more complex. Such collaboration needs a framework of reference. To illustrate, decision-makers will face obstacles when inferring information from a machine learning algorithm's output. The problem could be illustrated as follows: both the decision-maker and the ML algorithm might be conceived as experts. Yet they have been trained and reason differently. As far as the decision-maker is concerned, this is problematic once we consider situations of peer disagreement. Peer disagreement is when two similarly competent peers disagree concerning a domain-related activity. When making a well-informed decision, the weight assigned to the algorithms should be discussed. Should the decision-maker be required to call a senior decision-maker for an additional opinion? Or, would the senior decision-maker be rightfully mad, given that the algorithm provided a precise diagnosis? Addressing the human-machine collaboration is, therefore, a key pointer.
• **Opacity:** ML analytics and other statistical methods have the potential to improve decision-making accuracy, but this comes at the expense of opacity when trying to assess the reliability of a given diagnosis (Grote & Berens, 2020). Therefore, we plan to make our platform explainable to the decision-maker rather than to the data scientists whenever we provide alternative decision choices.

• **Defensive decision-making:** the participation of ML analytics algorithms challenges the epistemic authority of decision-makers. It also stimulates defensive decision-making, which might come at the expense of various stakeholders, such as the organization, the decision-makers, and society. In such a way, decision-makers anchor their decisions to those made by the algorithms to escape the embarrassment of being wrong.

• **Accountability:** Those who make decisions are held responsible for them. When necessary, they can defend their decisions. Furthermore, a decision-maker may be held accountable for reckless behavior if they injure someone due to a decision error. The best available evidence should be considered when deciding to reduce those risks. The decision-maker is aware of the differences in the decisions made by the algorithm and their own. However, the algorithm does not give the decision-maker a rationale for its judgment. The decision-maker may possess some higher-order proof regarding the overall accuracy of the method. It is understandable why the decision-maker would be tempted to give in to the algorithm, provided the overall accuracy is relatively high. However, suppose the decision-maker clings to their original theory, and their diagnosis proves incorrect. In that case, they may be seen as acting irresponsibly because they disregarded the data that the algorithm offered. An additional unintended consequence could be that the decision-maker is inclined to interpret the data in a way that supports the algorithm's conclusions. As a result, the interaction between ML algorithms and decision-makers may jeopardize the decision-maker's long-term skill set and undermine the importance of accountability.

• **Algorithmic aversion:** some decision-makers can augment algorithms’ outputs into their decisions, but some cannot. Therefore, decision-makers must be more careful with algorithmically generated insights in DDDM. When decision-makers cannot decide when and when not to augment analytics output into decisions discriminately, they are averse to using algorithms. Aversion happens for different reasons, e.g., cognitive incompatibility, decision autonomy, and lack of incentives (Burton et al., 2020). This is particularly exemplified in organizations that need a data-driven culture, leading to a hindrance in transforming data into actionable insights, which would have otherwise been a strategic asset for informing the data-driven decision-making process or the organizational members (Yu et al., 2021).

• **Resource scarcity:** contemporary organizations are data-driven, which means they can access data. However, their market position is influenced by their ability to utilize the data to derive valuable insights. To take a competitive edge over rivals, efficient transactional systems are needed; it has become essential to analyze historical data promptly and propose necessary actions for the business to take. Researchers (Brynjolfsson & McElheran, 2016) have highlighted the significance of DDDM and their potential to realize values over gut-based decisions. Provost & Fawcett (2013) pointed out that understanding the data is critical, and data science is the discipline that helps
expand the knowledge about available data and generate insights from it. Provost and Fawcett (2013) explained that data science helps to attain DDDM. The data science paradigm spreads across various roles and responsibilities, including data engineers, data analysts, and data scientists, and it also has dependencies with external roles such as product owners, business analysts, etc. A person in a particular persona does not need to be a champion in other trades and have a cross-functional skillset. However, it would be beneficial if a person who knows business requirements and objectives had a platform where they could perform the basic operations of data science-related roles without prior coding, analytics, or data engineering knowledge. On the other hand, Alsharef et al. (2022) argued that building an ML model requires domain knowledge and advanced ML programming skills. They (Alsharef et al., 2022) pointed out the difficulty in finding skilled ML experts; hence, automatic ML is perceived as an asset that crosses the gap between data science and the need for appropriate analytics resources.

6. Nascent Design Principles

The literature studies associated with each DP below have been utilized in other contexts. Still, they are found to be relevant to the DDDM platform. Subsequently, they have been brought together to address the DDDM challenges and open doors for organizations to foster digitalization initiatives about DDDM. The set of DPs that should be considered when developing the DDDM platform is explained below. It is to be noted that the relationship between challenges and design principles is many-to-many. The human-in-the-loop concept and the collaborative rationality design principles address the first challenge of human-machine collaboration.

Moreover, the explainability and openness design principles can address the challenges of defensive decision-making, accountability, and algorithmic aversion. The no intermediaries design principle addresses the challenge of opacity. Furthermore, certain non-functional design principles, such as the data integration and governance design principles, do not correspond directly to a specific challenge but rather govern how the platform will be designed and implemented.

- **DP1-Human-in-the-loop**: Although there are many instances where machines can reduce human mistakes, recent cases from businesses and government agencies have demonstrated the grave repercussions of doing away with human decision-making (Hirschheim, 2020; Smith, 2020). This is significantly amplified where the decision-maker is what is known as a knowledge worker or when the decision has some critical implications, in which cases the inclusion of experienced humans and practicing executives play a significant role (e.g., in strategic decisions) and is necessary for decision-making (Gupta et al., 2021). Thus, this platform will always maintain a human decision-maker in the loop; hence, it is a contemporary decision-making platform rather than an automated decision-making platform (Gronsund & Aanestad, 2020).

- **DP2-Collaborative rationality**: Bounded rationality is supported by a large portion of the decision theory and the relevant body of knowledge. It is the opposite of unbounded rationality. The concept of bounded rationality was developed by Herbert Simon (Simon, 1997). Conversely, being
unbounded indicates a person who knows everything, can compute everything, and can remember everything, but perhaps not a human can do that! Many models in the social sciences are classified under bounded rationality. In this platform, we tend to offer an approach whereby humans and machines (analytics) collaborate, i.e., collaborative rationality (Elgendy et al., 2021), towards making decisions to reduce the impact of bias and human-alone bounded rationality. Thus, the analytical capability of AI and the psychological and emotional elements of experts and decision-makers can be combined to lead to more accurate decisions (Gupta et al., 2021).

- **DP3-No intermediaries:** DDDM platforms without intermediaries are anticipated to promote accountability (Diakopoulos, 2016). The platform requires an interface independent of designated technical competencies frequently held by a few managers to align to serve various organizations and decisions. Given that decision-makers from different disciplines have varying degrees of competence, the platform must be made to be later adopted by them (e.g., self-service or democratized platforms). Platforms should not be designed exclusively for data scientists or engineers; instead, decision-makers of all levels and skills should be the primary users of such platforms. Therefore, such platforms should aim to increase users' self-efficacy with technology (La Torre et al., 2023).

- **DP4-Explainability:** Though they lack explainability and interpretability, which leads users to wonder why a particular recommendation is made, ML and AI algorithms have great success in elucidating valuable insights from data to support decision-makers in a particular decision situation (Du et al., 2020; Lipton, 2018). Since analytics techniques are supposed to be interpretable and explainable, this DP seeks to ensure that the platform is outfitted with the necessary tools and techniques to make analytics understandable and interpretable to its intended users (Lipton, 2018).

- **DP5-Multi-species analytics:** Regarding various decision-making scenarios and situations, the platform should remain impartial regarding statistics, machine learning, and other AI techniques. To achieve this, we want to use Gröger's (2018) definition of analytics approaches, which includes business intelligence, big data, machine learning, artificial intelligence, and advanced analytics. The platform—a kind of information system—should be able to handle all of these.

- **DP6-Evaluative nature of outcomes:** Regardless of the process followed and the techniques utilized, all decisions must be reviewed; however, many companies find this process onerous, which hinders their ability to learn from past mistakes (Bouyssou et al., 2000; Janssen et al., 2017; Keegan & Rowley, 2017). Businesses still need to comprehend how analytics enhances effectiveness and influences decision-making. To realize value, one must assess the degree to which a data-driven decision produces the intended results (Cao et al., 2015). Thus, to evaluate decisions based on contextual multi-criteria, such as efficiency, cost, impact, etc., the DDDM platform ought to have a variety of metrics.

- **DP7-Openness:** It provides others with the technical means to access the platform's main features. The platform's openness facilitates connections with other service providers. Since the primary interfaces of open systems are typically made public, the interface used to access the decision platform would also be made public. To facilitate external transactions between suppliers and
distributors, platforms need to make their operations accessible to external users. Platforms need to offer an architecture that supports these interactions to generate value for its users and appropriate value for themselves (Broekhuizen et al., 2021). The platform's openness supports the idea of (open) innovation.

- **DP8-Data Integration**: The platform should be able to collect, clean, and integrate data and its history of all varieties—structured, semi-structured, and unstructured—from all sources and in all formats to provide the foundation for further analytics (Gröger, 2018). When data is not integrated or within reach, users tend to copy and aggregate without any standard procedure (Skhiri & Duverne, 2020), influencing the analytics outcomes and, after that, the decision quality. The platform should be able to handle multidimensional data with speed and accuracy since the lack of required information leads to a lack of insight generation (Gupta et al., 2021).

- **DP9-Governance**: In the era of big data, governance continues to represent one of the critical challenges. Therefore, the platform needs to ensure that roles, decision rights, and responsibilities for efficient and compliant use of data and analytics techniques are preserved. This includes many things, including data ownership and stewardship (Gröger, 2021; Tura et al., 2018). The importance of data governance has been studied inclusively. For example, Bhatia & Kumar (2022) identified data governance as one of the most important critical success factors for Industry 4.0.

- **DP10-Low-code platform**: No-code and low-code platforms come into the picture to address the resource scarcity challenge. Low- and no-code platforms help rapidly build analytics models, automate data pipelines, and visualize insightful results. However, they differ significantly in terms of what type of audience will use this service. With the low-code approach, developers can use existing building blocks and libraries and still have the flexibility to customize the task as required. When it comes to no-code, it is mainly meant for domain experts with minimal to no prior software development knowledge (Li et al., 2021). With the no-code approach, users can use drag-and-drop functionality to perform the desired task with minimal to no flexibility to customize. Different personas, like data scientists and ML developers, can use low-code ML platforms. Additionally, no-code AutoML services can be used by persons with solid business or data domain knowledge, such as data engineers, analysts, business analysts, or decision-makers. Di Sipio et al. (2020) have highlighted the importance of emerging low-code cloud data platforms and their vital role in speeding up digitalization.

The fact that companies address DDDM from just a single perspective is also reported in previous studies such as Provost and Fawcett’s (2013, p.51): “There is a confusion about what exactly data science is, and this confusion could lead to disillusionment as the concept diffuses into meaningless buzz … One reason is that data science has intricately intertwined with other important concepts also of growing importance, such as big data and data-driven decision making”. Accordingly, we believe in the value of our posited design principles as a path for companies offering DDDM to address organizational challenges comprehensively.

### 7. Qualitative Evaluation of the Design Principles
The overall design of this case study is exploratory due to the relative novelty of the phenomenon and the limited body of literature available. The purpose is to evaluate the set of proposed design principles in a real-life context, with attention to the acceptance and relevance of the DPs. Phenomenon-driven research is suitable for exploring phenomena and capturing and extending knowledge by facilitating conventional understanding, which is helpful for both academics and practitioners in the field (Schwarz & Stensaker, 2014). Thus, to evaluate the design principles qualitatively through interviews, we have conducted case study research with a group of data science experts from an analytics and business intelligence company. To preserve its identity, we disguised its name as Edge. The company has been in the business intelligence business for approximately 20 years and recently spun off an independent legal entity focusing on low-code ML platforms. The company, Edge, operates in three geographical regions: Europe, Africa, and Asia. Edge, about business intelligence, offers its clientele off-the-shelf solutions from various vendors, such as SAP, Microsoft, Tableau, and Salesforce. Approximately five years ago (2017–2018), the company Edge decided to focus on ML and AI, according to their management, by introducing a proprietary data-driven low-code platform, which we refer to as Bridge, a disguised product name. The company serves various clientele in various industries, such as retail, automobile, construction, and healthcare.

The reasons we have selected Edge for our case study are multi-fold: 1. they operate in multiple regions; 2. the company serves various customers; 3. have off-the-shelf and proprietary products; 4. own a dedicated team to ML; and 5—experience with the design and use of low-code data-driven platforms.

The researchers contacted the company, explained the nature of the research, and asked for the possibility of interviewing experienced data science and ML team members who have contributed to the design and use of their low-code data-driven platform, Bridge. The company, Edge, has approved the engagement with the research and designated their CTO to organize the interviews. The interviews were conducted by one of the researchers at Edge's headquarters. Five respondents were interviewed, whose metadata is described below:

<table>
<thead>
<tr>
<th>Item</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>3 male, 2 female</td>
</tr>
<tr>
<td>Title</td>
<td>Senior Developer; Senior BI Consultant; Data Science Team Lead; CTO &amp; Innovation Manager</td>
</tr>
<tr>
<td>Average experience</td>
<td>10 years</td>
</tr>
<tr>
<td>Experience with analytics</td>
<td>All have at least 4 years of experience with data science and ML</td>
</tr>
</tbody>
</table>

Interviews lasted approximately 5 hours, one hour with each respondent. In the end, the researcher sent out the results via email for confirmation and as a means of research transparency. During the interview, the researcher presented the challenges of DDDM and the proposed design principles via PowerPoint,
administered a Q&A session on the material presented, and then asked the respondents for their feedback on the design principles.

The responses were helpful not only for us as researchers but also for the respondents and Bridge. Towards that end, we found:

- All respondents have positively perceived all ten DPs as needed and necessary. They have used the terms “needed” and “important” to describe the design principles.
- The team initially considered combining DP7 and DP8 but ultimately decided to keep them separate because DP7 concerns portal openness, whereas DP8 focuses on data.
- Concerning DP9 Governance, the respondents suggested putting security and privacy under governance.
- The team suggested adding scalability to the list of DPs as a non-functional principle. From a market and customer standpoint, the platform should scale up and down as and when needed.

Overall, the set of posited DPs from this research has gained the confidence of those interviewed. What was interesting for us as researchers is that the CTO, supported by all other respondents, came up with the idea to evaluate their product, Bridge, against our posited DPs. The discussion focused on how they could apply the design principles to their product. Findings of that discussion are reported in the table below, where the respondents’ evaluation of their product, Bridge, against the DPs is represented as weak, moderate, or high (a solid circle in the below table means all respondents agree; a half-solid means half the respondents agree; etc.).

In the previous table, in the column Design Features (verbatim), we listed the features per the respondents’ words, i.e., verbatim descriptions. We believe the design features in Table 3 are expected to help those who wish to implement the proposed DPs into their decision-making platforms.

After the above evaluation of Bridge against the proposed DPs, the team CTO decided to have internal follow-up meetings to level up their platform to meet the proposed design principles. This has been a relatively fast utility for our research. Additionally, the proposed design features associated with each design principle give way to the possible instantiation of the proposed design principles.

### 8. The Value and Requirements to Implement the DPs

Should the above-listed DPs have been incorporated into a DDDM platform, the value such a platform could bring is multi-fold. The key to digitalization is data. The platforms make sure that pertinent data is gathered, processed, and dispersed at the appropriate time and location. It is then utilized in day-to-day operations for business automation and support, as well as model building. Digital transformation happens when all of this takes place concurrently with organizations’ and business models’ adaptation to new circumstances and opportunities. Furthermore, DDDM has been shown to offer clear advantages (Larsson and Wallin, 2020). In a study on the impact of DDD on firm performance, economist Erik
Brynjolfsson and his colleagues from MIT and Penn's Wharton School created a DDD metric that ranks companies based on how heavily they use data to make decisions throughout the entire organization (Brynjolfsson, Hitt, & Kim, 2011). It was demonstrated that, statistically speaking, a firm's productivity increases with its level of data-drivenness; even after accounting for a wide range of potential confounding factors, the differences are statistically significant, and an increase in productivity of 4–6% is correlated with a standard deviation higher on the DDD scale.

Additionally, there appears to be a causal association between DDDM and higher returns on equity, market value, asset utilization, and return on assets. According to Dahiya et al. (2021), BDA solutions utilizing publicly available data and vendor-based (non-customized) applications would not produce firm-specific knowledge and, as a result, would not give an advantage over competitors! Their research, however, indicated that BDA applications and solutions need to be customized. High-level firm-specific information can be obtained by integrating proprietary (big) data with external or open data, which may also produce a long-term competitive advantage.

On the other hand, for the DPs to be implemented, the following requirements, listed in the table below, ought to be met:
<table>
<thead>
<tr>
<th>DP Number</th>
<th>Design Principle</th>
<th>Requirements</th>
</tr>
</thead>
</table>
| DP1       | Human-in-the-loop             | ☑️ Provide easy navigation  
|           |                               | ☑️ Allow different forms of outputs in various formats  
|           |                               | ☑️ Compare between analytics models  
|           |                               | ☑️ Provide customized dashboards summarizing model results  
|           |                               | ☑️ Capture human judgement  |
| DP2       | Collaborative rationality     | ☑️ Make available analytics algorithms  
|           |                               | ☑️ Provide the outcomes of analytics algorithms in the form of insights  
|           |                               | ☑️ The platform should enable the decision-makers’ feedback on the decisions made  
|           |                               | ☑️ Keep a decision log  
|           |                               | ☑️ Enable matrix to compare between analytics models  
|           |                               | ☑️ Regulate the relationship between human decision maker and algorithms e.g., who makes which decisions and how to resolve conflicts  |
| DP3       | No intermediaries             | ☑️ Design the platform to allow for direct use by decision-makers, without data scientists or developers  
|           |                               | ☑️ Enable low-threshold improvements to add data and run algorithms  |
| DP4       | Explainability                | ☑️ Support explainability out-of-the-box as there is a clear need for human decision-makers to understand the basis for ML recommendations, since the black box is not trusted  
|           |                               | ☑️ Provide outcomes with simple explanation  
|           |                               | ☑️ Visually represent the outcomes  
|           |                               | ☑️ Model illustration screens  |
| DP5       | Multi-species analytic        | ☑️ Select the most appropriate analytics libraries, get them configured, and trained  
|           |                               | ☑️ Algorithms in the library need to belong to versatile background  
|           |                               | ☑️ Enable expandable analytics i.e., new algorithms to be added  |
| DP6       | Evaluative nature of outcomes | ☑️ Define evaluation metrics  
<p>|           |                               | ☑️ Blended metrics ought to be prepared and used in case of collaborative decisions  |</p>
<table>
<thead>
<tr>
<th>DP Number</th>
<th>Design Principle</th>
<th>Requirements</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP7</td>
<td>Openness</td>
<td>Ensure that the platform is based on open specifications</td>
</tr>
</tbody>
</table>
| DP8       | Data integration       | Ensure that the platform allows free access to data and marketplace components developed externally  
|           |                        | Permit different types of data and data providers and engines                   |
|           |                        | Allow for seamless data integration                                            |
| DP9       | Governance             | Allow for the possibility to define and monitor policies in data acquisition, processing, and analysis |
|           |                        | The possibility for decision-makers to participate in data acquisition and sharing transactions |
|           |                        | The possibility for decision-makers to participate in insight sharing transactions |
|           |                        | Permitting several platforms to connect and exchange data without losing control |
|           |                        | The platform should satisfy the legal requirements                           |
| DP10      | No-code                | Allow for processing the data, analyze it, interpret results and visualize the insights generated, without having to write any piece of code |

We have also defined the building blocks that must be developed to implement the DPs. The building block is either functional or technical. A **building block** is a software component that can be configured to fit an application purpose, i.e., the platform. It enables the delivery of the DDDM platform services. Building blocks consist of functional features and technical components. A **functional feature** defines how the platform or application acts or behaves but does not have direct communication with the end-user or does not extend the services of the platform but enables rendering them. A **technical component** interacts with the platform end-user, i.e., decision-makers, to facilitate its purpose and services. See below table:
<table>
<thead>
<tr>
<th>DP Number</th>
<th>Design Principle</th>
<th>Building Blocks</th>
</tr>
</thead>
<tbody>
<tr>
<td>DP1</td>
<td>Human-in-the-loop</td>
<td>Functional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Easy navigation</td>
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<tr>
<td></td>
<td></td>
<td>Technical components</td>
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<tr>
<td></td>
<td></td>
<td>· Dashboard designer (component)</td>
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<tr>
<td></td>
<td></td>
<td>· Model comparison</td>
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<tr>
<td></td>
<td></td>
<td>· Human judgement Capturing</td>
</tr>
<tr>
<td>DP2</td>
<td>Collaborative rationality</td>
<td>Functional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Decision metadata</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Technical components</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Algorithms libraries’ acquisition</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Decision definition</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Feedback capturing</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Human-algorithm weight and sequence</td>
</tr>
<tr>
<td>DP3</td>
<td>No intermediaries</td>
<td>Functional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Easy upload of data</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Easy run of analytics algorithms</td>
</tr>
<tr>
<td>DP4</td>
<td>Explainability</td>
<td>Functional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Understandability</td>
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<td></td>
<td></td>
<td>· Simplicity</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Technical components</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Model explainability</td>
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<tr>
<td></td>
<td></td>
<td>· Graphical representation of models’</td>
</tr>
<tr>
<td>DP5</td>
<td>Multi-species analytic</td>
<td>Technical components</td>
</tr>
<tr>
<td></td>
<td></td>
<td>· Analytics engine</td>
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<td></td>
<td></td>
<td>· Algorithm training</td>
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<tr>
<td></td>
<td></td>
<td>· Algorithm configuration</td>
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<tr>
<td></td>
<td></td>
<td>· Algorithm parameter optimization</td>
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<tr>
<td>DP Number</td>
<td>Design Principle</td>
<td>Building Blocks</td>
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<tr>
<td>DP6</td>
<td>Evaluative nature of outcomes</td>
<td>Import new algorithms</td>
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<td></td>
<td></td>
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<tr>
<td>DP7</td>
<td>Openness</td>
<td>Technical components</td>
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<tr>
<td></td>
<td></td>
<td>Evaluation matrix builder</td>
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<td></td>
<td></td>
<td>Link evaluation matrix to decisions’</td>
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<tr>
<td>DP8</td>
<td>Data integration</td>
<td>Functional</td>
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<tr>
<td></td>
<td></td>
<td>Data marketplace services</td>
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<td></td>
<td>Data agreements</td>
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<td></td>
<td></td>
<td>Technical components</td>
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<td>Data exchange API’s</td>
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<td></td>
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<td>Data models and formats</td>
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<td></td>
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<td>Metadata discovery</td>
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<td></td>
<td>Data workflow engine</td>
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<tr>
<td>DP9</td>
<td>Governance</td>
<td>Functional</td>
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<td>Data policy</td>
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<td>Security policy</td>
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<td></td>
<td></td>
<td>Regulatory compliance</td>
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<td></td>
<td></td>
<td>Technical components</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Identity management and access control</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Encryption and anonymization</td>
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<td></td>
<td></td>
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<tr>
<td>DP10</td>
<td>No-code</td>
<td>Functional</td>
</tr>
<tr>
<td></td>
<td></td>
<td>No-code</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Technical components</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Code environment, pre-production</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Code hiding tool, post-production</td>
</tr>
</tbody>
</table>
Future research studies need to implement the building blocks into a data-driven decision-making platform, distill the lessons learned through updates to the design principles and interactions between the building blocks, or define new ones.

9. Conclusion

In design science research, formulating generalized and intelligible design principles that can be reused in new contexts is an essential outcome (Cronholm & Göbel, 2018). In this paper, we have posited design principles and evaluated them in an organizational context. The contribution of this research is multifold:

- It addresses organizations' decision-making challenges by introducing platform design principles on which humans and algorithms collaborate to make data-driven decisions.
- It opens doors for forthcoming research on how such design principles could be implemented and evaluated in a longitudinal organizational context.
- It brings organizations, decision theory, and AI into common ground, opening the door for cross-disciplinary research.
- It utilizes and informs design theory.

In this research, we have explained the decision-making challenges facing organizations recently due to the sheer amount of data available and the direction businesses and governments take to cultivate the value of data and analytics. Such developments need a different approach to decision-making, that is, DDDM. Therefore, we suggested using a DDDM platform set out to be used intra- and inter-organizationally in a generalized manner to accommodate the needs of several decisions. Through case study interviews, we proposed and evaluated a set of design principles meant to help organizations address their decision-making challenges and combat the unintended and negative consequences of DDDM when used without guiding principles. We aim to help organizations utilize big data and AI algorithms for decision-making while remaining in control of AI.

We presented a usable and normative approach to inform practitioners and researchers about the design principles supporting DDDM platforms. Those DPs were posited to present a generic framework for the shared problem of lacking guiding principles.

They could be instantiated as a prototype implementation and tested in several case study organizations. We believe instantiation and testing will generate knowledge to help us scrutinize and enhance the design (theory). According to Gregor and Hevner (2013), our research can be classified as an improvement. This categorization is justified because we have proposed a set of DPs that can be described as developing design theory. In the future, we plan to evaluate them empirically in multiple evaluation cycles to test their reusability (Gregor & Hevner, 2013). After that, they can be mapped to design functions and incorporated into DDD platforms. Therefore, we have developed conceptualizations for the DPs that address DDDM platform challenges as a form of applicable prescriptive design
knowledge focusing on DDDM. This knowledge can be used as input knowledge and potentially extended by future research, especially by researchers focusing on developing DDDM platforms and related concepts (Meske & Bunde, 2021). Testing and developing the DPs in various organizational and decisional contexts would increase their generalizability.

**Declarations**

**Author Contribution**

Both authors worked on the manuscript. AE wrote the main sections. NE worked on the theory part. All authors reviewed the manuscript.

**Data Availability**

As part of the qualitative study conducted to evaluate the design principles posited in this paper, we have administered evaluation interviews with respondents. The interview scenario was based on the main author presenting the design principle and seek input, questions and evaluation by the respondents. Responses were then aggregated and reported in Table 3 in the paper. Responses are anonymized.

**References**


Table 3

Table 3 is available in the Supplementary Files section.

Figures

![Diagram showing the relationship between Design Science Research (DSR), Design Knowledge, and Design Principles (DPs)](image)

Figure 1

*Design Principles Conceptualization*
Figure 2

*The Mapping of Challenges to Design Principles*

**Supplementary Files**

This is a list of supplementary files associated with this preprint. Click to download.

- [Table3.docx](#)