Data-driven Culture: A Transformational Framework

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Abstract

In the context of digital transformation, having a data-driven organizational culture has been recognized as an important factor for data analytics capabilities, innovativeness and competitive advantage of firms. However, the current literature on data-driven culture (DDC) is fragmented, lacking both a synthesis of findings and a theoretical foundation. Therefore, the aim of this work has been to develop a comprehensive framework for understanding DDC and the mechanisms that can be used to embed such a culture in organizations as well as structuring prior dispersed findings on the topic. Based on the foundation of organizational culture theory, we employed a Design Science Research (DSR) approach using a systematic literature review and expert interviews to build and evaluate a transformation-oriented framework. This research contributes to knowledge by synthesizing previously dispersed knowledge in a holistic framework, as well as, by providing a conceptual framework to guide the transformation towards a DDC.

Keywords: Data-driven culture, data culture, digital transformation

Introduction

In recent years, organizations have faced an imperative to grasp and articulate the intrinsic meaning and value of data in their decision-making processes. This is particularly crucial within contexts marked by disruptive advancements driven by digital technologies like the Internet of Things (IoT), leading to the creation of various interconnected products (e.g. Porter and Heppelmann 2014). While data analytics capabilities have increasingly been recognized as an important factor for organizations' long-term survival, innovativeness and competitive advantage (Bange and Lorenz 2022; Brynjolfsson and McElheran 2016; Duan and Cao 2015), the literature refers to data-driven organizations (DDO) as a more comprehensive concept. For instance, Hupperz et al. (2021) usefully conceptualized that a DDO comprises several key elements such as data-driven business models, data-driven innovation, data analytics as well as data science and digital transformation. They also refer to a data-driven culture (DDC) as a key aspect. In this context, various studies have shown that establishing a DDC plays a crucial role for the success of data analytics as well as innovation and performance of firms (Gupta and George 2016; Halaweh and Massry 2015; Hassna and Lowry). DDC has been defined as "patterns of behaviors and practices by organizational members who share beliefs that having, understanding, and using certain kinds of data and information plays a critical role in the success of their organization especially related to decision-making practices that impact organizational performance" (Campbell et al. 2021; Kiron et al. 2012).

Despite the growing importance of DDC, survey data report that only a minority of firms already have an established DDC (New Vantage Partners LLC 2021). In the academic sphere, prior work on this topic suffers from two main shortcomings. First, the literature is fragmented, lacking a clear overall theory or structure of the topic, and providing no comprehensive overview. Second, there is a lack of theoretical foundation or connection to existing theories. Therefore, a critical research gap exists in our understanding of how DDC can be effectively cultivated and maintained in organizations.

This study aims to address this gap by providing a comprehensive framework for understanding the different aspects of DDC and the mechanisms that can be used to embed such culture in organizations as well as structuring prior dispersed findings on the issue. In essence, such a framework provides important guidance for organizations in a complex and vague field by distilling the very core factors to implement and foster a DDC. While there is research that usefully summarizes enabling factors of a DDC (e.g. Berndtsson et al. 2018), our framework especially supports the cultural transformation toward a DDC, so that organizations are enabled to harness the potential of their data and value creation is supported.

To do so, we used a DSR methodology (Hevner et al. 2004; Hevner 2007; Peffers et al. 2012; Venable et al. 2012, 2016). Our research design consisted of a systematic literature review (SLR) (Kitchenham 2004; Webster and Watson 2002) as an input to build the artifact as well as semi-structured interviews (Patton 2015; Recker 2013) to evaluate the framework. Moreover, we use seminal work from the field of organizational culture (Hogan and Coote 2014; Schein 1996, 2004) as our theoretical fundament and research lens to amend the DDC literature with known underlying principles and mechanisms that drive the transformation of culture within organizations.

Our research makes an original contribution to knowledge by synthesizing dispersed knowledge about DDC, as there is no previously published SLR, to the best of our knowledge. Additionally, we provide a theoretical, conceptual, and practical contribution by presenting a novel framework and integrating the topic DDC with Schein's (2004) theory of primary embedding mechanisms of organizational culture. By conceptually linking DDC aspects to the embedding mechanism, our framework gives guidance on how to establish a DDC in organizations.

Theoretical Background

Data-drivenness and Data-driven Culture

Within the scholarly and practitioner debate on digital transformation, data and data analytics and related phenomena have been identified as one of the most promising and relevant competitive success factors for companies (Bange and Lorenz 2022). Strongly related to that are data-driven decisions, which can be seen as a sub-area of evidence-based decision-making. This means that decisions are made on facts and information, represented by data rather than on intuition, experiences, hierarchy, and so forth (Barends and Rousseau 2018; Stobierski 2019). Based on the continuously increased availability of various forms of data and data sources, insights and findings can be derived objectively using machine-based algorithms and data models, even leading to autonomous decision-making processes, frequently seen as consistent in various different decision-making situations (Pranjić 2018). Such approaches are associated with superior decision-making, resulting in several benefits, such as increased firm performance in general, identification of new and valuable business opportunities, or a higher probability of identifying changes and risks in dynamic contexts (Brown et al. 2011; Chaudhuri et al. 2021).

The literature indicates considerable terminological vagueness around the phenomena of data-drivenness. Anderson (2015) understands data-drivenness as the development of resources, capabilities and in particular a specific type of culture that acts based on data. From a terminological point of view, it must be distinguished between data-informed, data-driven, and data-centric. Data-informed indicates, a rudimentary usage of data in the sense that an organization systematically collects and stores data and that decision-makers are principally aware of that data. However, data are not the main driver within decision-making processes (Connor 2020). In contrast, data-driven refers to experts guiding the data organization process, but, more importantly these experts organize the analysis of such data-based on advanced technologies and in relation to the needs of decision-makers. Moreover, data-driven requires that an intense use of data in decision-making is accepted and implemented company-wide across various hierarchical levels (Connor 2020; Treder 2019). Big data and big data analytics are key components of data-drivenness (Svensson and Taghavianfar 2020). Data-centric refers to organizations whose business model is based on data and data itself is part of the value creation process within products or services (Connor 2020), such as Google.

As indicated by Anderson (2015), culture seems to play an important role within data-drivenness, as culture ultimately determines what happens in organizations. An initial understanding of data-drivenness in relation to organizational cultural considerations may consist of a generally accepted idea that not intuition and hierarchical positions should be the base for decisions but instead findings based on data (Karaboga et al. 2019) and a shared corporate understanding that a DDC can lead to discovering new insights (Dremel 2017). As a consequence, the role of management (Dar et al. 2021; Korherr and Kanbach 2021; Medeiros et al. 2020; Zareravasan 2021) and all other members of an organization are important within a data-driven approach (Campbell et al. 2021; Chatterjee et al. 2021; Shao et al. 2022; Sheng et al. 2021). Finally, technologies, such as data analytics, are the operational base for a data-drivenness (Bag et al. 2021), and the overall attitudes in relation to the willingness to learn or a positive attitude to failures and failure acceptance seem to be relevant (Berndtsson et al. 2018; Medeiros and Maçada 2022).

Organizational Culture and Primary Embedding Mechanism

Organizational culture as shared ways of perceiving, thinking, and reacting is, based on Edgar Schein (1996), “one of the most powerful and stable forces operating in organizations”. Most organizational culture definitions include common values, beliefs, and norms (Caldwell and O'reilly 2003; Hogan and Coote 2014). In addition, Schein (2004) states that organizational culture is a learned pattern of corporate assumptions to solve problems sufficiently well to be generally accepted within a given entity. Thus, the true meaning of shared assumptions is laid upon guiding and anchoring behavioral routines and decision guidelines. As a consequence, the organizational culture can be perceived as a subtle mechanism of management to influence and regulate employees without the negative consequences of static regulations (Hogan and Coote 2014). While various theories on organizational culture exist (e.g. Allaire and Firsirotu 1984; Denison and Mishra 1995; Schein 1990, 1996, 2004), we have chosen Schein’s theory of organizational culture, as it is a comprehensive and well-established theory specifically addressing the dynamics of organizational culture and change, which are especially relevant in the context of DDC due to the profound changes initiated by digital transformation.

The model of organizational culture distinguishes between three different levels of cultural phenomena based on their visibility (Schein 2004): artifacts; espoused values; underlying assumptions. Despite their interdependencies, Schein identifies delimiting factors for distinct characteristics:

- Artifacts represent visible or tangible elements of organizational culture. At this level, the organization’s specific features are easy to recognize and even to monitor their adherence, however not inevitable to understand (Schein 2004). The derivation of an organizational culture based exclusively on artifacts holds certain risks of misinterpretation.
- Espoused values focus on the organization's aspirations and intended behavior. These values might represent the organization’s projection of an intended future. Individuals within the organization that disobey generally accepted espoused values, risk to be excluded. Nevertheless, these values are not static and can change, if their underlying premises fluctuate or dissolve. If established rules of behavior lack positive consequences within specific and replicable settings, the underlying value-based behavior can change, especially if maintaining these behaviors is resource intensive.
- Underlying assumptions stand for tacit, deep convictions, which lay the basis of our behavior patterns. Within an organization, the set of shared basic assumptions is unconsciously embedded. These assumptions are perceived as a self-evident reality, which are repeatedly subjectively proven right. As a consequence, these are hard to recognize as an organizational subjective truth from within an organizational construct. This common ground creates a strong mutual identity within an organization.

To transform values within organizations, Schein (2004) defines six "Primary Embedding Mechanisms" (EM). These mechanisms enable managers to anchor their assumptions within the corporate culture. Through managers' conscious and unconscious behavior, cultural change is customized and enforced in different ways:

EM $_1$: *What leaders pay attention to, measure, and control on a regular basis*: Management's attention, questioning and monitoring efforts lead the employees' focus within the organization. This effect is enforced when executives consequently follow the same standards within their own work.

EM $_2$: *How leaders react to critical incidents and organizational crises*: The willingness of employees to undergo behavioral change increases in critical situations. As a consequence, the reactions from leaders within a crisis offer a strong potential for cultural influence, either by a change of routines or by consciously remaining on course.

EM $_3$: *How leaders allocate resources*: Management decisions on releasing projects and assigning budgets have a direct influence on employees. In doing so, the organizational level of focus and freedom is directly and quantifiably restricted or widened.

EM $_4$: *Deliberate role modeling, teaching, and coaching*: Executives' behavior is closely monitored by employees, especially in situations when they are informally interacting with subordinates. In accordance with Schein (2004), if leaders highlight and demonstrate that hierarchy and status play a subordinate role, employees are encouraged that good decisions and innovations can arise independently from hierarchy levels.

EM $_5$: *How leaders allocate rewards and status*: Corporate gratification systems should be in line with corporate culture. In particular, when unsatisfactory behaviors arise, executives should consider whether these outcomes were encouraged by the existent reward system and if this was intended.

EM $_6$: *How leaders recruit, select, promote, and excommunicate*: "One of the most subtle yet most potent ways in which leader assumptions get embedded and perpetuated is the process of selecting new members" (Schein 2004). Including the organizationally desired attitudes of an employee into job requirements and promotion criteria will continuously influence corporate culture.

Methodology and Research Design

Methodology

Our research is grounded on the DSR methodology (Hevner et al. 2004; Hevner 2007; Peffers et al. 2012), which has been established as a well-recognized distinct paradigm in Information Systems research within the past two to three decades. Due to the nature of our research that intends to develop an artifact in the form of a framework, DSR is considered a suitable methodology. Frameworks are types of artifacts that have previously been developed with DSR (e.g. Doyle et al. 2016).

Our research design has been developed based on Hevner's (2007) Three Cycle View of DSR. According to Hevner, there are three cycles of activities: A Relevance Cycle that inputs requirements from the environment and returns artifacts for field testing; a Rigor Cycle that provides theories, methods and expertise from a knowledge base, and finally; a Design Cycle for the construction and evaluation of artifacts. Figure 1 shows how Hevner's framework has been customized to the specific context of our research.

As shown in the visualization, we use a combination of a systematic literature review (SLR) and semi-structured interviews as our main methods. The 'build' activity of the framework has largely been based on a synthesis of results from the SLR as an inductive element, with organizational culture theory as a deductive element. However, also our evaluation method has been "tightly coupled with design itself" (Venable et al. 2016) by iteratively refining the framework that was initially developed. A particular emphasis in DSR should be placed on the proper evaluation of artifacts which is a key activity in any DSR project (Peffers et al. 2012; Venable et al. 2016). In prior DSR, there has been a large variety of evaluation methods, including logical argument, expert evaluation, action research and prototyping (Peffers et al. 2012). According to Venable et al. (2012), various contextual aspects have to be considered when designing an evaluation strategy. Based on the nature of our artifact and resource limitations, we have decided to deploy an 'artificial ex-ante strategy' (Venable et al. 2012). Method-wise, we have chosen an expert evaluation in the form of semi-structured interviews as an evaluation method. As Peffers et al. (2012) have shown based on an analysis of papers in ten well-regarded journals, there is an observable association between types of artifacts and evaluation methods. Their analysis shows that expert evaluation has previously been used to evaluate frameworks in high-profile research and can thus be considered as being appropriate for our purpose.

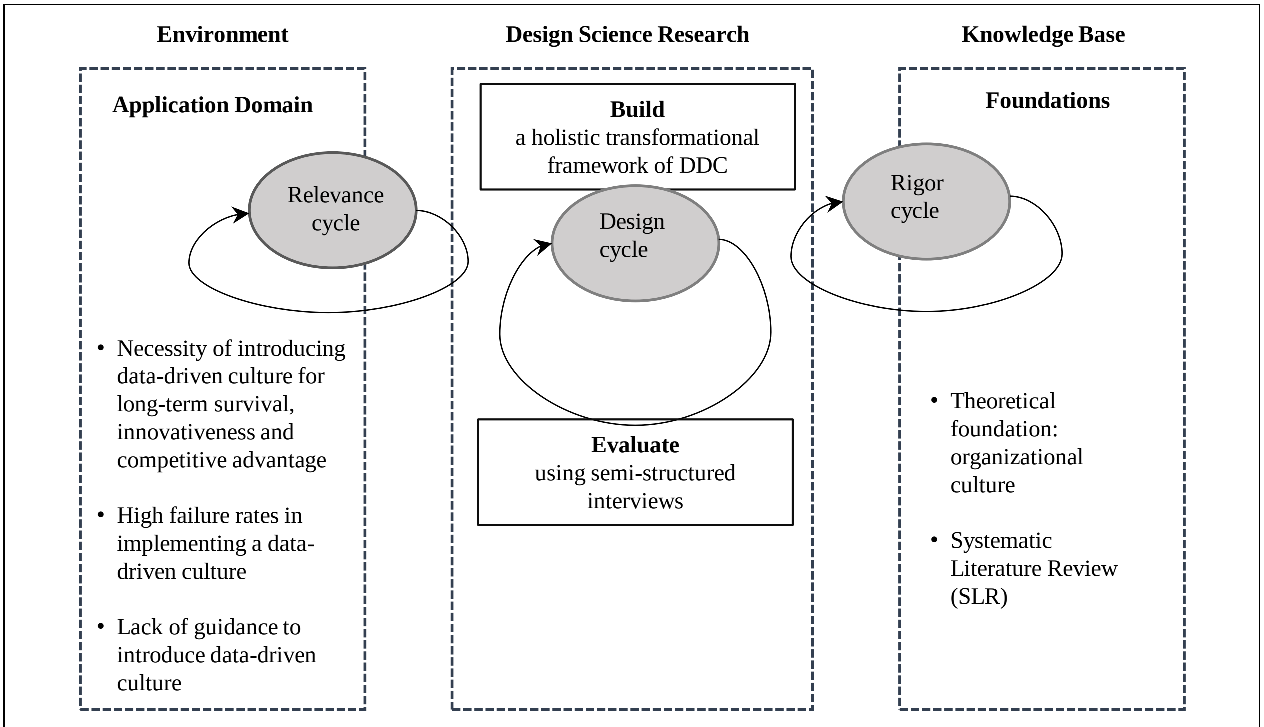

Figure 1. Research Design. Own Illustration Based on Hevner (2007).

Systematic Literature Review

The SLR was conducted based on established procedures in the Information Systems discipline (Kitchenham 2004; Webster and Watson 2002). To steer the selection and review of the literature, the following guiding questions have been formulated.

Guiding question 1: What benefits result from DDC?

Guiding question 2: What success factors should be considered in establishing a DDC?

Guiding question 3: What problems and challenges are known when establishing a DDC?

The literature review was conducted between March and June 2022. The selection of articles was based on four systematic steps that are visualized in Figure 2.

i. Choice of databases: We have used several relevant databases to maximize search results. Besides databases with high indexing standards (Web of Science, WoS), we have used Google Scholar in order to include grey literature, the Association of Information Systems electronic library (AISeL) due to its outstanding importance in the discipline as well as Emerald Insights as an additional source of journal articles.
ii. Search string: In order not to restrict the results too much, we have used the simple search string "Data-driven" AND "Culture". Depending on the database, different search fields were addressed to balance the comprehensiveness of results and feasibility in terms of the number of results to be manually filtered. Due to the lack of options to restrict the search to title and abstracts in Google Scholar, the search was restricted to the title only, while in the other databases, the abstracts were

also included. In WoS, the so-called "topic" was selected, which includes title, keywords and abstract (see Figure 2). No other filters such as publication data or discipline were applied.

iii. After removing duplicates, 687 articles were screened according to the inclusion and exclusion criteria (see Figure 2). Grey literature, i.e. sources such as white papers that have not been formally published in academic settings (Garousi et al. 2019), has also deliberately been included in order to broaden the scope of sources and identify practice-relevant insights.

iv. Finally, a backward search (Webster and Watson 2002) was conducted on the remaining 35 relevant articles based on the paper titles in the references section of the articles, resulting in 7 additional papers. Considering time and resource constraints, we prioritized conducting a backward search to identify important groundwork and landmark studies that have significantly influenced the development of the field over conducting a forward search. The complete list of papers and their contribution to the guiding questions, can be found in the appendix.

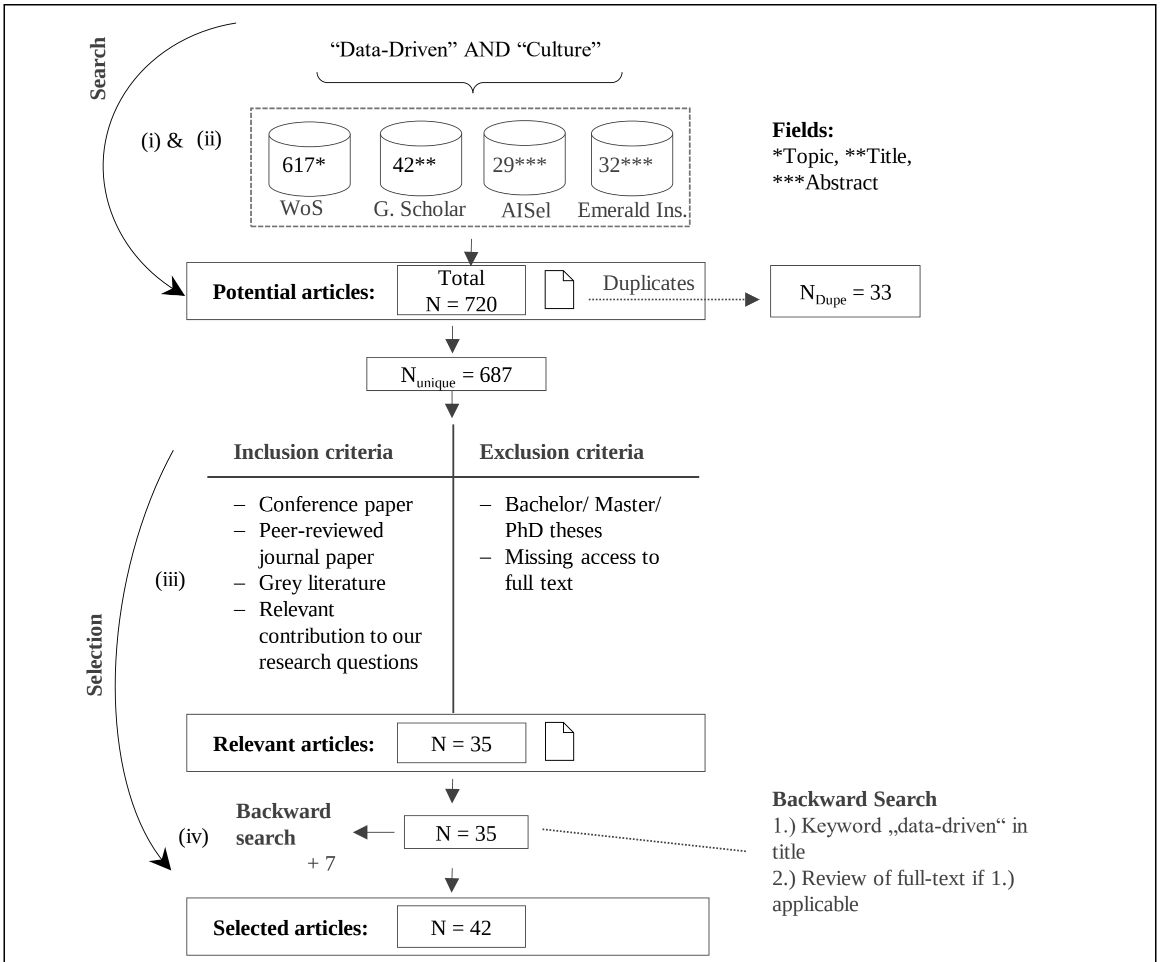

Figure 2. Search and Selection Process of Systematic Literature Review.

Expert Evaluation

To evaluate the framework, we have used semi-structured interviews (Oates 2006; Patton 2015; Recker 2013; Saunders et al. 2007). For the purpose of this work, this type of interview has been suitable because it can be used both, to confirm prior findings, and to identify new aspects (Recker 2013).

We have developed an interview guide to structure the evaluation of the artifact. Besides the formal procedures of opening and closing the interview, the guide consists of three major phases. Firstly, we rather openly addressed the personal background of participants as well as the concepts of data-drivenness and DDC. Secondly, we presented the framework artifact and initiated elaborations of the participants regarding the structure, completeness, comprehensibility, and clarity of the artifact. Thirdly, we asked for concrete practical recommendations for action in relation to the success factors and the embedding mechanisms of Schein (2004). We have applied a purposeful sampling (Patton 2015; Saunders et al. 2007) of participants based on theoretical and content-related considerations to gather information-rich and meaningful data. More specifically, we have included participants with heterogeneous functions in their organization and representing different industry sectors. Additionally, the participants were selected from firms that have a considerable experience in projects concerning data-driven approaches. In essence, criteria to be considered as an adequate expert for artifact evaluation are: (i) affiliated to a firm that is well known for data-driven projects, and (ii) sufficient personal, professional experience in several data-driven projects. An overview of the participants can be found in Table 1. All interviews took place in September 2022. Due to the evaluative nature of the interviews and the perception of data saturation (Corbin and Strauss 2008), the recruitment of additional interview candidates was discontinued after five interviews. The sample size can be considered as appropriate taking into account that several consultants were part of the sample, that have insights into a larger number of client organizations and thus can be seen to represent several cases. The interviews were conducted using a video conferencing software and, with the consent of the participants, transcribed and subsequently coded to extract relevant findings in a structured manner. We applied an iterative, flexible thematic coding approach (Braun and Clarke 2006), primarily of inductive nature, which allowed us to extract the relevant information from data to evaluate the artifact. Intensive reading of the transcripts and coding was initially done by one author and afterwards checked for accuracy by all other co-authors.

	Position	Experience	Degree	Industry sector	Duration
E1	Manager –Operational Excellence/ Change Management	> 20 years	Ph.D.	Consulting	40 min
E2	Principal Consultant Predictive Excellence and Head of Insights & Analytics	> 15 years	M.Sc.	Telecommunications/ IT	40 min
E3	Consultant – Web Analytics	< 5 years	B.Sc.	Online marketing	25 min
E4	Cloud Consultant und Administrator	> 10 years	B.Sc.	Software and consulting	30 min
E5	SAP Consultant	< 5 years	B. Sc.	Software and consulting	17 min

Table 1. Interview Participants for Artifact Evaluation.

Results and Discussion

Overview of Framework

In this section, our final framework as depicted in Figure 3 is presented. The framework describes the transformative process that an organization is undergoing to achieve a DDC. Within this fundamental transformation, several success factors exist, that can be categorized in the overall themes of Leadership & People, Technology and Organization. This structure has emerged from inductive categorization and theory-building (Saldaña 2009). To support the concrete practical realization of the transformative process, the individual success factors for a DDC are implemented by leveraging the primary embedding mechanisms introduced by Schein (2004). Meanwhile, an organization is confronted with many challenges that impede the transformation and hence also the implementation of a DDC. We understand them as phenomena that are underlying the whole transformative process. Based on a detailed review of challenges in various pieces of literature, we decided to use the logic of organizational change failure causes toward

DDC introduced by Esteller-Cucala et al. (2020) to structure these underlying challenges. After successfully completing the transformative process, the organization can benefit from the outcomes of DDC, which we have inductively categorized into Profitability, Innovation, and Performance Management. The elements of the framework will be discussed in detail in the following sections.

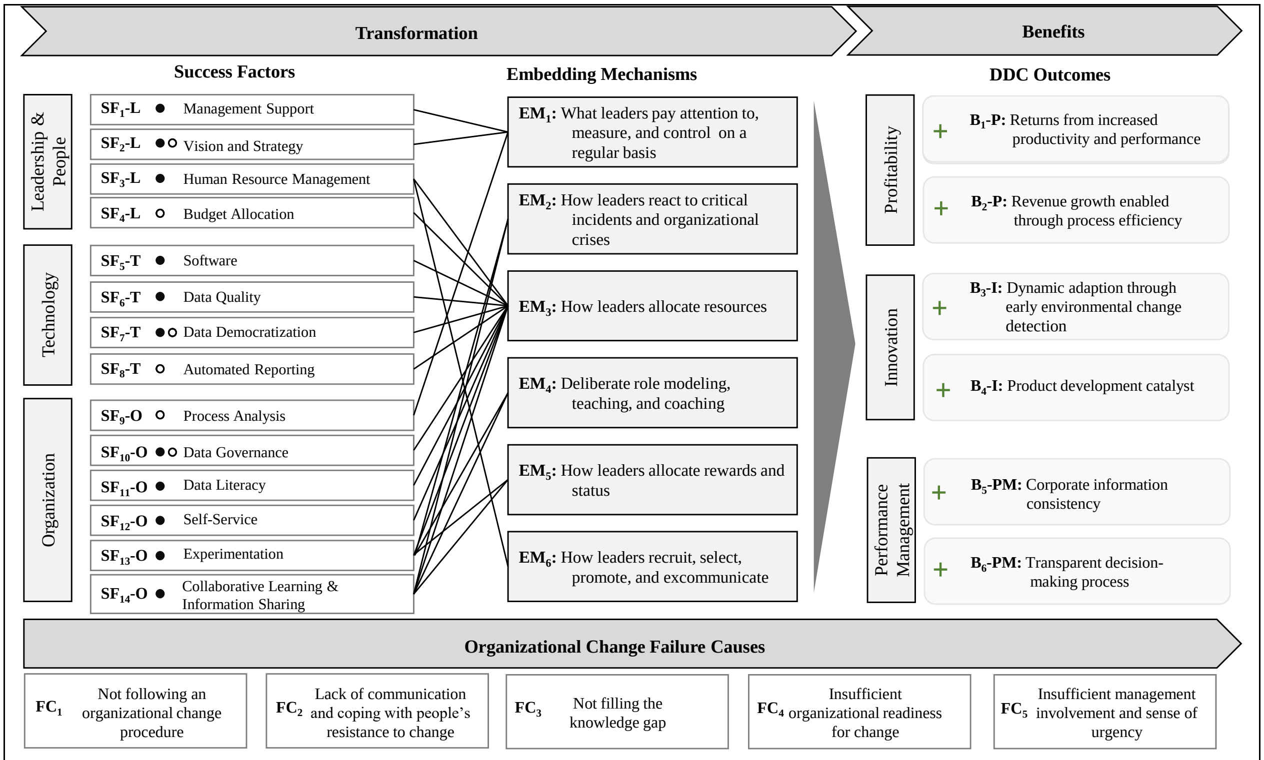

Figure 3. Conceptual Framework.

Success Factors

With regard to establishing a DDC, 14 success factors (SF) were identified. We define SF as factors that are likely to have a positive impact on the successful implementation of DDC (adapted from Audet et al. 2012). It is crucial to make a clear distinction between factors that contribute to success and those that lead to failure, as a factor that causes failure may not necessarily be a factor that promotes success, and vice versa (Gargeya and Brady 2005). Although these relevant factors individually contribute to a sustainable and lasting DDC transformation, there are complex synergy gains from combining them. The success factors are subsequently clustered into three focus areas: Leadership & People (L), Technology (T), and Organization (O). Eleven of these result from the SLR; these are marked with an ●. Additional three SF arise from the expert interviews, marked with an ○. Factors resulting from the SLR and which are further confirmed through the experts are marked with an ●○.

SF_1-L: *Management Support* is critical for all cultural change (Berndtsson et al. 2018; Medeiros et al. 2020). Repetitively explaining the advantages, providing resources, leading by example, and anchoring a DDC within relevant decision processes are management tasks (Anderson 2015; Gökalp et al. 2021; Windt et al. 2019). Positive recognition of data-oriented behavior, even if this involves additional risks, is supporting this progress (McCarthy et al. 2017; Storm and Borgman 2020). Finally, executives need to excel in data-based analysis and methods of hypothesizing themselves (Berndtsson et al. 2018; Windt et al. 2019).

SF_2-L: *Vision and Strategy* need to provide clear, congruent, and actionable reasons for the desired DDC (Anderson 2015; Dremel 2017; Ronka et al. 2015). Specific instructions through real-life applications and exemplary cases lay the blueprint for employees to apply the announced overriding principles (Chatfield et al. 2015; Windt et al. 2019).

SF_3-L: *Human Resource Management* ensures that the required skills are acquired and developed through experts but also among the existing workforce (Gökalp et al. 2021; Johnson et al. 2019). Aside from data-science experts, this requires contact persons to bridge the gap between analytics and business model related applications such as business analytics translators, data analysts or data stewards (Dremel 2017; Halper and Stodder 2017; Henke et al. 2016; Liakh 2021).

SF_4-L: *Budget Allocation* for trainings, workshops, and external consultants is a critical and success determining factor. Based on the expert interviews, an appropriate part of the overall budget should be attributed to data analytics, e.g. visualization software and management tools (E1).

SF_5-T: *Software* is an essential hygiene factor. All required software tools should be available to access, analyze and visualize data (Shaji et al. 2021).

SF_6-T: *Data Quality* refers to accurate, complete, consistent and relevant data to minimize poor decision-making (Kline and Dolamore 2020; Medeiros et al. 2020; Pugna et al. 2019). The acceptance of DDC from shareholders and executives strongly depends on a high perceived data quality (Chatfield et al. 2015; Ronka et al. 2015).

SF_7-T: *Data Democratization* ensures a high accessibility for all entitled employees (Agyei-Owusu et al. 2021). This should go way beyond IT or BI departments, which generate monthly reports or handle ad-hoc-requests. To crack open project- or silo-based data access, employees from all departments need to access data directly and be provided with an easy-to-understand gateway (Berndtsson et al. 2018; Dremel 2017; Kline and Dolamore 2020; Ronka et al. 2015).

SF_8-T: *Automated Reporting* in terms of providing standardized reports automatically, fosters the acceptance of DDC. The low-threshold and straightforward availability of various data reports reduces additional work for employees to gain data insights (E2).

SF_9-O: *Process Analysis* covers the early assessment of corporate process landscape readiness (E4). The results of this ongoing evaluation provide clarification to what extent the organizational structures are sufficient for DDC.

SF_{10}-O: *Data Governance* regulates the effective and efficient administration of data, representing a key element of DDC (Berndtsson et al. 2018; Chatfield et al. 2015). This ensures, on the one hand, the shared and risk-free usage of data throughout its entire lifecycle within the organization, while on the other hand securing ethical and regulatory boundaries (Halper and Stodder 2017; Kline and Dolamore 2020; Liakh 2021; Medeiros et al. 2020; Pugna et al. 2019).

SF_{11}-O: *Data Literacy* includes all capacities necessary to appropriately apply data-based decision-making (Abdul-Majied et al. 2018; Anderson 2015; Ronka et al. 2015). Aside from mathematics, statistics and coding, strong analytic skills are required (Carillo et al. 2019; Storm and Borgman 2020). Nevertheless, data literacy is typically distributed in a heterogenous way within the organization; as a consequence, a strong communication and cooperation between employees is critical (Chatterjee et al. 2021; Shao et al. 2022; Vanhoof and Mahieu 2013; Wisdom et al. 2006). Straight-forward and low-threshold training opportunities should be provided (Berndtsson et al. 2018; Chatfield et al. 2015; Windt et al. 2019).

SF_{12}-O: *Self-Service* enables more and uncomplicated ad-hoc analysis of data. The required tools typically increase predictive data investigations by trial and error (Berndtsson et al. 2018).

SF_{13}-O: *Experimentation* provides new knowledge and supports behavioral change toward DDC, especially if accompanied by clear goals (Storm and Borgman 2020). Executives should resist making accusations even when small projects turn to failure but provide reference points for new routines (Berndtsson et al. 2018).

SF_{14}-O: *Collaborative Learning and Information Sharing* between departments reduces silo mentality and fosters DDC (Anderson 2015; Korherr and Kanbach 2021; Omar et al. 2019). Ideally, data scientists proactively approach different business units and share advantageous data analytics routines (Almeida and Low-Choy 2021; Esteller-Cucala et al. 2020).

Primary Embedding Mechanisms

While identifying success factors is an important element in the transformation, mere knowledge about the factors does not lead to change, yet. We use Schein's (2004) primary embedding mechanisms to integrate the necessary transformational nature into our framework. By linking Schein's generic mechanisms to the specific success factors of DDC, we show how leaders can actively influence organizational change toward a DDC. Due to space restrictions, we refer to Figure 3 for a complete overview of the links between DDC and embedding mechanisms. In this section, some examples of the recommended actions are illustrated using statements from the expert evaluation.

Referring to Schein's first factor (*what leaders pay attention to, measure, and control on a regular basis*), leaders should communicate their general support of the transformation, and elaborate a clear DDC-oriented vision and strategy that includes all departments and employees. As E1 points out, it is crucial that this strategy can be operationalized to lower levels so that "employees specifically understand what data-driven behaviors are expected from them". When it comes to *reacting to critical incidents and organizational crises*, leaders should make sure to also rely on data to solve the crisis and not fall back into old emotionally-driven patterns due to the exceptional situation. *How leaders allocate resources* can address most of the success factors, as allocating financial and other resources is an important prerequisite for change. In terms of *deliberate role modeling, teaching, and coaching,* several interviewees have mentioned the importance that leaders behave in a data-driven way themselves, for example when it comes to strategic decision-making. *How leaders allocate rewards and status* can be adapted for the transformation toward a DDC by increasing extrinsic motivation through targeted bonus systems, but also by intrinsically motivating people by appreciating and praising success that was achieved based on data-driven activities. With regard to the question, *how leaders recruit, select, promote, and excommunicate,* it is important to both, increase the level of data literacy of the existing workforce, and consider this aspect as a minimum requirement in recruiting (E2).

Organizational Change Failure Causes

Cultural change is not a one-time expense, but a continuous process, in which organizational structures, established routines, and technologies need to be questioned and reviewed (Esteller-Cucala et al. 2020). This is only successful if the employees' willingness to change is constantly promoted (Berndtsson et al. 2018; Gökalp et al. 2021). Based on Esteller-Cucala et al. (2020), we define "organizational change failure causes" as various factors or reasons that contribute to the unsuccessful implementation of organizational transformations, particularly those focused on becoming data-driven. These failure causes (FC) are primarily related to five critical areas from the domain of change management (adapted from Esteller-Cucala et al. 2020):

FC_1: *Not following an organizational change procedure*: An organizational transformation requires a specific roadmap, which explicitly highlights the strategic alignment between data-science, and industry-specific business strategies (Gökalp et al. 2021; Hassanin and Hamada 2022). It is critical, that corporate vision provides tangible recommendations of actions and explains how business analytics adds value on shopfloor level (Berndtsson et al. 2020; Pugna et al. 2019; Windt et al. 2019).

FC_2: *Lack of communication and coping with people's resistance to change*: An effective and recipients-oriented dialog lays the foundation for employees that are capable and motivated enough to transfer their working procedures (Esteller-Cucala et al. 2020; Windt et al. 2019). Workforce resistance arises, if employees cannot imagine themselves within the new organizational structure (Berndtsson et al. 2018; Storm and Borgman 2020). To minimize the risks of an unsuccessful organizational transformation, employees should be provided with different tools to give input and feedback to influence the desired DDC (Wisdom et al. 2006).

FC_3: *Not filling the knowledge gap*: Even with a high transformation commitment, the skillsets of the employees need to be addressed by on-the-job training and comprehensive documentation (Esteller-Cucala et al. 2020). Keeping a high transparency on change and skill-level progress while fostering knowledge sharing assists the transformation to DDC (Gökalp et al. 2021).

FC_4: *Insufficient organizational readiness for change*: The clear conviction within the organization is that a data-driven mindset includes new norms, values, and behaviors derived from the corporate vision

(Esteller-Cucala et al. 2020; Korherr and Kanbach 2021; Svensson and Taghavianfar 2020). Providing sufficient data quality and data consistency is required, to establish trust in DDC (Hannila et al. 2022; Henke et al. 2016; Pugna et al. 2019; Storm and Borgman 2020).

FC_5: *Lack of management involvement and sense of urgency*: To avoid tardiness and ignorance of the above-mentioned points, executives need to motivate and pay great attention to employees' engagement (Berndtsson et al. 2018; Pugna et al. 2019). The urgency of DDC is underlined by sufficient resource allocation, budgets for required tools and infrastructure as well as a high display of priority from management level (Lorente-Martínez et al. 2022; Windt et al. 2019).

Benefits

DDC can result in a number of benefits for organizations. The areas of empirical or practical advantages through DDC can be distinguished into aspects of Profitability (P), Innovation (I), and Performance Management (PM):

B_1-P: *Returns from increased productivity and performance:* Several references stress the competitive advantage (Chatterjee et al. 2021; Medeiros et al. 2020; Medeiros and Maçada 2022), which especially increases productivity, performance and corporate returns (Halper and Stodder 2017). Additionally, shopfloor efficiency profits from supply-chain optimization (Agyei-Owusu et al. 2021).

B_2-P: *Revenue growth enabled through process efficiency:* Based on Visvizi et al. (2021) and Chaudhuri et al. (2021), DDC improves process management and business processes, enabling revenue growth (Halper and Stodder 2017).

B_3-I: *Dynamic adaption through early environmental change detection:* DDC fosters "environmental scanning" (Duan and Cao 2015) and an increased "sensing agility" (Hassna and Lowry), which both facilitate responses to dynamic changes within the markets (Chaudhuri et al. 2021).

B_4-I: *Product development catalyst:* Quick recognition of a transforming environment in combination with the ability to react to this, improves customer satisfaction and retention (Agyei-Owusu et al. 2021; Halper and Stodder 2017). DDC increases corporate innovation potential as an important initiator for innovation (Almazmomi et al. 2022; Chaudhuri et al. 2021; Duan and Cao 2015; Visvizi et al. 2021).

B_5-PM: *Corporate information consistency:* In line with Duan and Cao (2015), companies with a strong DDC have a clear focus on information quality and „strategic decision comprehensiveness".

B_6-PM: *Transparent decision-making process:* Organizations with a high information-based alignment make decisions more transparent and integrative (Duan and Cao 2015). This fosters efficient operation and a faster response rate (Halper and Stodder 2017).

Conclusions

Summary and Contribution to Knowledge

Our research provides timely and important contributions to knowledge in the field of DDC. DDC is of high importance to many organizations within the area of digital transformation and might be regarded as a necessary prerequisite of such a fundamental transformation, especially in contexts in which data play a crucial role for competitive advantage. To the best of our knowledge, we have conducted the first SLR on DDC. DDC is an emergent and heterogeneous research field and knowledge is dispersed in the literature. A comprehensive review and synthesis of the literature allows taking stock of knowledge, developing a holistic understanding of a field and hence provides an important contribution by itself. Based on this and refined with primary data from expert interviews, a novel conceptual framework covering essential success factors, embedding mechanisms, organizational change failure causes and benefits of implementing a DDC has been systematically and iteratively developed. The developed framework identifies, structures and relates the various factors of the different categories and consequently develops a holistic understanding of the transformative process to implement a DDC. Moreover, we also provide explanations of the various elements of the conceptual framework, especially regarding the success factors of a DDC given their specific relevance for the implementation of a sustainable DDC.

Implications for Theory and Research

From a theoretical perspective, the implications of our research are manifold. As indicated earlier, according to our observations the research field on DDC is heterogenous and the scholarly debate is fragmented in the literature, so until now a coherent theoretical foundation is missing. Given this, our aim was to develop a theoretical conceptual framework that covers major elements of the scholarly debate on DDC and structures the major developments and phenomena. Based on a SLR, we were able to integrate and combine a substantial stock of knowledge in the DDC field and evaluate the initial conceptual framework with primary data from expert interviews. This overall and holistic understanding allowed us to develop the above suggested transformative framework, which provides a novel theoretical contribution to DDC research and may have important implications for further research projects. The inductively developed categories leadership & people, technology, and organization offer a useful systematization of the identified success factors. Moreover, we have integrated a prominent organizational theory, Schein's (2004) theory of organizational culture into our theoretical conceptual framework. This induced a theoretically informed discussion how the success factors can be translated into concrete actions. Moreover, researchers can use our framework as a blueprint for further adaptations to industry-specific contexts or to elaborate concepts how the factors can be further detailed and turned into business benefits.

Implications for Practice

The identified mechanisms provide important managerial implications and practical advice to support the implementation of a DDC in the context of various organizations. The developed framework can serve as a guide for organizations seeking to adopt a DDC, providing a comprehensive set of factors and mechanisms to embed a DDC within their organizations. The mere existence and awareness of these factors may not necessarily lead to a DDC within a specific organization; consequently they need active management. To provide managerial advice and to support achieving an organizational DDC, we have connected Schein's (2004) theory of organizational culture to DDC and particularly his six primary embedding mechanisms were used to illustrate how a leader can actively influence organizational change resulting in a DDC. Practitioners can use the framework to critically analyze the current status of an implementation of a DDC, in a sense to identify factors that hinder or prevent such an implementation and identify areas for improvement. Our framework complements the above mechanisms with major organizational change failure causes, which should raise the awareness of leaders to developments that may lead to a failure of the transformation to develop a DDC or at least hinder such a transformation. These change failure causes require constant critical reflection and consideration by leaders. Our research highlights the importance of creating a supportive organizational culture, promoting data literacy, and providing adequate resources to ensure a successful adoption of a DDC. Finally, our findings suggest that the implementation of a DDC can drive profitability, innovation and performance management and hence support a competitive advantage. At the same time, organizations should carefully consider the possible drawbacks of actively implementing a DDC, such as costs and risks, in order to make a conscious decision.

Limitations and Future Work

As with every research activity, also our research faces limitations. In our DSR approach, the artifact has been evaluated using an 'artificial' strategy. In order to increase the rigor of the evaluation, an approach in a 'naturalistic' context (Venable et al. 2012), i.e. applying the framework in its real environment within organizations may be useful to further corroborate the findings. In-depth case study approaches or action research could be research approaches useful to apply and test the conceptual framework in real world settings and provide further important implications. Moreover, while the sample of five expert interviewees has a comprehensive knowledge of the phenomena under research and can be considered as an adequate sample for an evaluation of the artifact, results are not generalizable in a statistical sense. While we have perceived data saturation with our experts, further research could evaluate the framework with a different sample of experts. Furthermore, we have conducted a SLR and the systematic protocols may result in the fact that some articles on DDC have not been considered in our analysis. As our research objective is to develop a comprehensive framework, we have not applied a focus on a specific industry. Thus, it could be the case that our framework misses specific industry-related aspects. This could be tested, when applying our framework to specific industry contexts.

Appendix

	Guiding question 1	Guiding question 2	Guiding question 3
Abdul-Majied et al. 2018			•
Agyei-Owusu et al. 2021	•		
Almazmomi et al. 2022	•	•	
Almeida and Low-Choy 2021			•
Anderson 2015		•	
Berndtsson et al. 2018		•	
Berndtsson et al. 2020			•
Cao and Duan 2015	•		
Carillo et al. 2019		•	
Chatfield et al. 2015		•	•
Chatterjee et al. 2021	•		•
Chaudhuri et al. 2021	•	•	•
Dremel 2017		•	
Duan und Cao 2015	•		•
Esteller-Cucala et al. 2020			•
Gökalp et al. 2021		•	
Halper and Stodder 2017	•		•
Hannila et al. 2022			•
Hassanin and Hamada 2022			•
Hassna and Lowry	•		
Henke et al. 2016		•	•
Johnson et al. 2019	•	•	
Kline and Dolamore 2020		•	
Korherr and Kanbach 2021		•	
Lepri et al. 2017	•		
Liakh 2021		•	
Lorente-Martínez et al. 2022			•
McCarthy et al. 2017			•
Medeiros et al. 2020		•	
Medeiros and Maçada 2022		•	•
Omar et al. 2019		•	•
Pugna et al. 2019			•
Ronka et al. 2015		•	
Shaji et al. 2021		•	
Shao et al. 2022			•
Storm and Borgman 2020		•	•
Svensson and Taghavianfar 2020		•	•

Vanhoof and Mahieu 2013			•
Visvizi et al. 2021	•		
Wang et al. 2020	•		
Windt et al. 2019		•	•
Wisdom et al. 2006		•	•

Table 2. List of Papers from Systematic Literature Review.

References

Abdul-Majied, S., Figaro-Henry, S., and Suepaul, N. 2018. "A multiple case study of data use practice in eight early childhood centres in the Republic of Trinidad and Tobago," *Early Child Development and Care* (188:9), pp. 1287-1301.

Agyei-Owusu, B., Amedofu, M. K., Asamoah, D., and Kumi, C. A. 2021. "The Effect of Data Driven Culture on Customer Development and Firm Performance: The Role of Supply Chain Information Sharing and Supply Chain Information Quality," in *Responsible AI and Analytics for an Ethical and Inclusive Digitized Society*, D. Dennehy, A. Griva, N. Pouloudi, Y. K. Dwivedi, I. Pappas and M. Mäntymäki (eds.), Galway, Ireland. September 1–3, 2021, Springer, Cham, pp. 481-492.

Allaire, Y., and Firsirotu, M. E. 1984. "Theories of Organizational Culture," *Organization Studies* (5:3), pp. 193-226.

Almazmomi, N., Ilmudeen, A., and Qaffas, A. A. 2022. "The impact of business analytics capability on data-driven culture and exploration: achieving a competitive advantage," *Benchmarking: An International Journal* (29:4), pp. 1264-1283.

Almeida, F., and Low-Choy, S. 2021. "Exploring the relationship between big data and firm performance," *Management Research and Practice* (13:3), pp. 43-57.

Anderson, C. 2015. *Creating a data-driven organization*: *Practical advice from the trenches*, Beijing: O'Reilly Media.

Audet, J., Couteret, P., Matlay, H., and Rae, D. 2012. "Coaching the entrepreneur: features and success factors," *Journal of Small Business and Enterprise Development* (19:3), pp. 515-531.

Bag, S., Luthra, S., Mangla, S. K., and Kazancoglu, Y. 2021. "Leveraging big data analytics capabilities in making reverse logistics decisions and improving remanufacturing performance," *The International Journal of Logistics Management* (32:3), pp. 742-765.

Bange, C., and Lorenz, N. 2022. "BARC Data Culture Survey 22: How to Shape the Culture of a Data-Driven Organization," available at https://www.tableau.com/sites/default/files/2021-11/Data%20Culture%20Survey_new.pdf, accessed on May 1 2022.

Barends, E., and Rousseau, D. M. 2018. "Evidence-Based Management - How to Use Evidence to Make Better Organizational Decisions," available at https://cebma.org/faq/evidence-based-management/, accessed on Aug 7 2023.

Berndtsson, M., Forsberg, D., Stein, D., and Svahn, T. 2018. "Becoming a Data-Driven Organisation," *ECIS 2018 Proceedings*.

Berndtsson, M., Lennerholt, C., Svahn, T., and Larsson, P. 2020. "13 Organizations' Attempts to Become Data-Driven," *International Journal of Business Intelligence Research* (11:1), pp. 1-21.

Braun, V., and Clarke, V. 2006. "Using thematic analysis in psychology," *Qualitative Research in Psychology* (3:2), pp. 77-101.

Brown, B., Chui, M., and Manyika, J. 2011. "Are you ready for the era of 'big data'?" *McKinsey & Company*.

Brynjolfsson, E., and McElheran, K. 2016. "The Rapid Adoption of Data-Driven Decision-Making," *American Economic Review* (106:5), pp. 133-139.

Caldwell, D. F., and O'reilly, C. A. 2003. "The determinants of team-based innovation in organizations: The role of social influence," *Small Group Research* (34:4), pp. 497-517.

Campbell, C., Cola, P., and Lyytinen, K. 2021. "Factors Impacting the Influence of Analytic Capabilities on Organizational Performance in Higher Education," *Proceedings of the 54th Hawaii International Conference on System Sciences*.

Cao, G., and Duan, Y. 2015. "The Affordances of Business Analytics for Strategic Decision-Making and Their Impact on Organisational Performance," *PACIS 2015 Proceedings*.
Carillo, K. D. A., Galy, N., Guthrie, C., and Vanhems, A. 2019. "How to turn managers into data-driven decision makers," *Business Process Management Journal* (25:3), pp. 553-578.
Chatfield, A., Reddick, C., and Al-Zubaidi, W. 2015. "Capability Challenges in Transforming Government through Open and Big Data: Tales of Two Cities," *ICIS 2015 Proceedings*.
Chatterjee, S., Chaudhuri, R., and Vrontis, D. 2021. "Does data-driven culture impact innovation and performance of a firm? An empirical examination," *Annals of Operations Research*, pp. 1-26.
Chaudhuri, R., Chatterjee, S., Vrontis, D., and Thrassou, A. 2021. "Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture," *Annals of Operations Research*.
Connor, D. 2020. "DATA-INFORMED, DATA-DRIVEN, AND DATA-CENTRIC: WHAT'S THE DIFFERENCE?" available at https://www.ascendstl.com/press/2020/4/28/data-driven-and-data-centric-whats-the-difference, accessed on Aug 7 2023.
Corbin, J. M., and Strauss, A. L. 2008. *Basics of qualitative research*: *Techniques and procedures for developing grounded theory*, Los Angeles, Calif.: Sage Publ.
Dar, I. B., Khan, M. B., Khan, A. Z., and Mujtaba, B. G. 2021. "A qualitative analysis of the marketing analytics literature: where would ethical issues and legality rank?" *Journal of Marketing Analytics* (9:3), pp. 242-261.
Denison, D. R., and Mishra, A. K. 1995. "Toward a Theory of Organizational Culture and Effectiveness," *Organization Science* (6:2), pp. 204-223.
Doyle, C., Sammon, D., and Neville, K. 2016. "A design science research (DSR) case study: building an evaluation framework for social media enabled collaborative learning environments (SMECLEs)," *Journal of Decision Systems* (25:sup1), pp. 125-144.
Dremel, C. 2017. "Barriers to the Adoption of Big Data Analytics in the Automotive Sector," *AMCIS 2017 Proceedings*.
Duan, Y., and Cao, G. 2015. "Understanding the Impact of Business Analytics on Innovation," *ECIS 2015 Proceedings*.
Esteller-Cucala, M., Fernandez, V., and Villuendas, D. 2020. "Towards data-driven culture in a Spanish automobile manufacturer: A case study," *Journal of Industrial Engineering and Management* (13:2), pp. 228-245.
Gargeya, V. B., and Brady, C. 2005. "Success and failure factors of adopting SAP in ERP system implementation," *Business Process Management Journal* (11:5), pp. 501-516.
Garousi, V., Felderer, M., and Mäntylä, M. V. 2019. "Guidelines for including grey literature and conducting multivocal literature reviews in software engineering," *Information and Software Technology* (106), pp. 101-121.
Gökalp, M. O., Kayabay, K., Gökalp, E., Koçyiğit, A., and Eren, P. E. 2021. "Assessment of process capabilities in transition to a data-driven organisation: A multidisciplinary approach," *IET Software* (15:6), pp. 376-390.
Gupta, M., and George, J. F. 2016. "Toward the development of a big data analytics capability," *Information & Management* (53:8), pp. 1049-1064.
Halaweh, M., and Massry, A. 2015. "Conceptual Model for Successful Implementation of Big Data in Organizations," *Journal of International Technology and Information Management* (24:2), pp. 21-34.
Halper, F., and Stodder, D. 2017. "What It Takes to be Data-Driven: Technologies and Best Practices for Becoming a Smarter Organization," available at https://media.bitpipe.com/io_14x/io_141315/item_1674359/TDWI_BPReport_Q417.pdf, accessed on Aug 7 2023.
Hannila, H., Silvola, R., Harkonen, J., and Haapasalo, H. 2022. "Data-driven Begins with DATA; Potential of Data Assets," *Journal of Computer Information Systems* (62:1), pp. 29-38.
Hassanin, M. E., and Hamada, M. A. 2022. "A Big Data strategy to reinforce self-sustainability for pharmaceutical companies in the digital transformation era: A case study of Egyptian pharmaceutical companies," *African Journal of Science, Technology, Innovation and Development* (14:7), pp. 1-13.
Hassna, G., and Lowry, P. B. "Big Data Capability, Customer Agility, and Organization Performance: A Dynamic Capability Perspective," in *AMCIS 2018 Proceedings*.
Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., and Sethupathy, G. 2016. "The age of analytics: Competing in a data-driven world," *McKinsey & Company*.

Hevner, A. 2007. “A Three Cycle View of Design Science Research,” *Scandinavian Journal of Information Systems* (19:2), pp. 1-6.
Hevner, A. R., March, S. T., Park, J., and Ram, S. 2004. “Design science in information systems research,” *MIS Quarterly* (28:1), pp. 75-105.
Hogan, S. J., and Coote, L. V. 2014. “Organizational culture, innovation, and performance: A test of Schein's model,” *Journal of Business Research* (67:8), pp. 1609-1621.
Hupperz, M., Gür, I., Möller, F., and Otto, B. 2021. “What is a Data-Driven Organization?” *AMCIS 2021 Proceedings*.
Johnson, D. S., Muzellec, L., Sihi, D., and Zahay, D. 2019. “The marketing organization’s journey to become data-driven,” *Journal of Research in Interactive Marketing* (13:2), pp. 162-178.
Karaboga, H. A., Zehir, C., and Karaboga, T. 2019. “Big Data Analytics And Firm Innovativeness: The Moderating Effect Of Data-Driven Culture,” *European Proceedings of Social and Behavioural Sciences* (54), pp. 526-535.
Kiron, D., Shockley, R., Kruschwitz, N., Finch, G., and Haydock, M. 2012. “Analytics: The widening divide,” *MIT Sloan Management Review* (53:2), pp. 1-22.
Kitchenham, B. 2004. “Procedures for Performing Systematic Reviews,” *Keele University Joint Technical Report*.
Kline, A., and Dolamore, S. 2020. “Understanding Data-Driven Organizational Culture: A Case Study of Family League of Baltimore,” *Journal of Technology in Human Services* (38:3), pp. 247-270.
Korherr, P., and Kanbach, D. 2021. “Human-related capabilities in big data analytics: a taxonomy of human factors with impact on firm performance,” *Review of Managerial Science* (17), pp. 1-28.
Lepri, B., Staiano, J., Sangokoya, D., Letouzé, E., and Oliver, N. 2017. “The Tyranny of Data? The Bright and Dark Sides of Data-Driven Decision-Making for Social Good,” in *Transparent Data Mining for Big and Small Data*, Springer, Cham, pp. 3-24.
Liakh, O. 2021. “Accountability through Sustainability Data Governance: Reconfiguring Reporting to Better Account for the Digital Acceleration,” *Sustainability* (13:24), pp. 1-18.
Lorente-Martínez, J., Navío-Marco, J., and Rodrigo-Moya, B. 2022. “Are retailers leveraging in-store analytics? An exploratory study,” *International Journal of Retail & Distribution Management* (50:5), pp. 599-618.
McCarthy, J., Sammon, D., and Cirian, M. 2017. “Leadership Styles in a Data Driven Culture,” *European Conference on Management, Leadership & Governance* (2017).
Medeiros, M. M. de, Hoppen, N., and Maçada, A. C. G. 2020. “Data science for business: benefits, challenges and opportunities,” *The Bottom Line* (33:2), pp. 149-163.
Medeiros, M. M. de, and Maçada, A. C. G. 2022. “Competitive advantage of data-driven analytical capabilities: the role of big data visualization and of organizational agility,” *Management Decision* (60:4), pp. 953-975.
New Vantage Partners LLC. 2021. “Big Data and AI Executive Survey 2021: Executive Summary of Findings,” available at https://c6abb8db-514c-4f5b-b5a1-fc710f1e464e.filesusr.com/ugd/e5361a_76709448ddc6490981f0cbea42d51508.pdf, accessed on Aug 7 2023.
Oates, B. J. 2006. *Researching information systems and computing*, Los Angeles, London New Delhi, Singapore, Washington, DC: Sage.
Omar, Y. M., Minoufekr, M., and Plapper, P. 2019. “Business analytics in manufacturing: Current trends, challenges and pathway to market leadership,” *Operations Research Perspectives* (6), p. 100127.
Patton, M. Q. 2015. *Qualitative research & evaluation methods*: *Integrating theory and practice*, Thousand Oaks California: SAGE Publications Inc.
Peffers, K., Rothenberger, M., Tuunanen, T., and Vaezi, R. 2012. “Design Science Research Evaluation,” in *Design Science Research in Information Systems. Advances in Theory and Practice*, K. Peffers, M. Rothenberger and B. Kuechler (eds.), Berlin, Heidelberg. 2012, Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 398-410.
Porter, M. E., and Heppelmann, J. E. 2014. “How smart, connected products are transforming competition,” *Harvard business review* (92:11), pp. 64-88.
Pranjić, G. 2018. “DECISION MAKING PROCESS IN THE BUSINESS INTELLIGENCE 3.0 CONTEXT,” *Ekonomska misao i praksa* (2), pp. 603-619.
Pugna, I., Duțescu, A., and Stănilă, O. 2019. “Corporate Attitudes towards Big Data and Its Impact on Performance Management: A Qualitative Study,” *Sustainability* (11:3), pp. 1-26.

Recker, J. 2013. *Scientific Research in Information Systems*: *A Beginner's Guide*, Berlin, Heidelberg: Springer Berlin Heidelberg.
Ronka, D., Geier, R., and Marciniak, M. 2015. "A Practical Framework For Building A Data-Driven District Or School," available at https://www.publicconsultinggroup.com/media/1573/edu_data-driven-district_practical-ideas_white_paper.pdf, accessed on Aug 7 2023.
Saldaña, J. 2009. *The coding manual for qualitative researchers*, Los Angeles: Sage.
Saunders, M., Lewis, P., and Thornhill, A. 2007. *Research methods for business students*, Harlow: Financial Times Prentice Hall.
Schein, E. H. 1990. "Organizational Culture," *American Physologist* (45:2), pp. 109-119.
Schein, E. H. 1996. "Culture: The Missing Concept in Organization Studies," *Administrative Science Quarterly* (41:2), p. 229.
Schein, E. H. 2004. *Organizational Culture and Leadership Third Edition*.
Shaji, I. A., Doctor, G., and Dore, P. 2021. "Data-driven decision-making in Indian Smart Cities: Promoting data culture, use cases and visualization," in *Loukis (Hg.) 2021 – 14th International Conference on Theory and Practice of Electronice Governance*, pp. 346-351.
Shao, Z., Benitez, J., Zhang, J., Zheng, H., and Ajamieh, A. 2022. "Antecedents and performance outcomes of employees' data analytics skills: an adaptation structuration theory-based empirical investigation," *European Journal of Information Systems*, pp. 1-20.
Sheng, H., Feng, T., Chen, L., and Chu, D. 2021. "Responding to market turbulence by big data analytics and mass customization capability," *Industrial Management & Data Systems* (121:12), pp. 2614-2636.
Stobierski, T. 2019. "THE ADVANTAGES OF DATA-DRIVEN DECISION-MAKING," available at https://online.hbs.edu/blog/post/data-driven-decision-making, accessed on Aug 7 2023.
Storm, M., and Borgman, H. 2020. "Understanding challenges and success factors in creating a data-driven culture," *Proceedings of the 53rd Hawaii International Conference on System Sciences*.
Svensson, R. B., and Taghavianfar, M. 2020. "Toward Becoming a Data-Driven Organization: Challenges and Benefits," in *Research Challenges in Information Science*, Dalpiaz (ed.), Cham: Springer International Publishing, pp. 3-19.
Treder, M. 2019. *Becoming a data-driven Organisation*: *Unlock the value of data*, Berlin, Heidelberg: Springer Berlin Heidelberg; Imprint Springer Vieweg.
Vanhoof, J., and Mahieu, P. 2013. "Local Knowledge Brokerage for Data-Driven Policy and Practice in Education," *Policy Futures in Education* (11:2), pp. 185-199.
Venable, J., Pries-Heje, J., and Baskerville, R. 2012. "A Comprehensive Framework for Evaluation in Design Science Research," in *Design Science Research in Information Systems. Advances in Theory and Practice*, D. Hutchison, T. Kanade, J. Kittler, J. M. Kleinberg, F. Mattern, J. C. Mitchell, M. Naor, O. Nierstrasz, C. Pandu Rangan, B. Steffen, M. Sudan, D. Terzopoulos, D. Tygar, M. Y. Vardi, G. Weikum, K. Peffers, M. Rothenberger and B. Kuechler (eds.), Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 423-438.
Venable, J., Pries-Heje, J., and Baskerville, R. 2016. "FEDS: a Framework for Evaluation in Design Science Research," *European Journal of Information Systems* (25:1), pp. 77-89.
Visvizi, A., Troisi, O., Grimaldi, M., and Loia, F. 2021. "Think human, act digital: activating data-driven orientation in innovative start-ups," *European Journal of Innovation Management* (25:6), pp. 452-478.
Wang, Z., Wang, N., Su, X., and Ge, S. 2020. "An empirical study on business analytics affordances enhancing the management of cloud computing data security," *International Journal of Information Management* (50), pp. 387-394.
Webster, J., and Watson, R. 2002. "Analyzing the Past to Prepare for the Future: Writing a Literature Review," *MIS Quarterly* (26:2), pp. 13-23.
Windt, B., Borgman, H., and Amrit, C. 2019. "Understanding Leadership Challenges and Responses in Data-driven Transformations," *Proceedings of the 52nd Hawaii International Conference on System Sciences*.
Wisdom, J. P., Ford II, J. H., Hayes, R. A., Edmundson, E., Hoffman, K., and McCarty, D. 2006. "Addiction treatment agencies' use of data: a qualitative assessment," *The Journal of Behavioral Health Services & Research* (33:4), pp. 394-407.
Zareravasan, A. 2021. "Boosting innovation performance through big data analytics: An empirical investigation on the role of firm agility," *Journal of Information Science* (OnlineFirst), 1-16.