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Toward the role of organizational culture in data-driven digital transformation

Abstract

Data-driven digital transformation is increasingly recognized as a crucial element of unlocking new business value, leveraging data-driven approaches in organizational business strategies and operations. Concurrently, organizational culture emerges as a critical factor in the organizational transformation process and success. However, current literature offers sparse insights into how organizational culture affects data-driven digital transformation. To gain deeper insights, this study leverages two complementary organizational culture frameworks to examine their relationship with data-driven digital transformation. Moreover, we investigate the link between data-driven digital transformation and operational performance in a manufacturing context. Utilizing data from 317 surveys, our findings show that organizational culture significantly affects data-driven digital transformation, which consequently impacts operational performance. This study advances understanding of the critical role of organizational culture in facilitating data-driven digital transformation, addressing a previously underexplored area in Operations and Supply Chain Management literature. By employing a dual-framework approach, it provides a more nuanced comprehension of organizational culture's impact on data-driven digital transformation while clarifying the complex relationship between digital transformation and operational performance within the manufacturing sector. Our study also delivers significant practical contributions, guiding organizations in effectively implementing and benefiting from data-driven digital transformation initiatives.

Keywords: data-driven digital transformation, organizational culture, operational performance, Hofstede, Competing value model, manufacturing.

Introduction

Data-driven digital transformation (DDDT) refers to utilizing emerging technologies that leverage data to develop new organization's value propositions (Papanagnou et al., 2022). This notion is gaining significant attention within the business field and the Operations and Supply Chain Management (OSCM) domain (Verhoef et al., 2021). The increased focus on DDDT is reflected in the number of academic publications (Bag et al., 2023; Belhadi et al., 2024; Dubey et al., 2024; Gosavi & Gosavi, 2024; Hamann-Lohmer et al., 2023; Saihi et al., 2023; Wamba et al., 2024; Yang et al., 2023), practice articles (Bonnet & Westerman, 2020; Chamorro-Premuzic, 2021), and business reports (World Economic Forum, 2023). The significance of data in digital transformation initiatives cannot be overstated, as leveraging external and internal data available to the organization is essential for offering new value propositions (Bharadwaj et al., 2013; Chamorro-Premuzic, 2021; Davenport & Spanyi, 2019; Pettey, 2019). The critical role of data in organizational contexts is well-documented in the scholarly literature (Dubey et al., 2022; Wamba et al., 2023). Zeng and Glaister (2018) underscore the critical importance of data in developing novel value propositions, emphasizing the necessity of a data-driven approach in the creation of these new propositions. DDDT's primary distinction from other technological innovations lies in the scope of changes it introduces, influencing every aspect of the organization (Amit & Zott, 2001). It transcends beyond simple changes in basic organizational tasks and processes as it fundamentally reshapes processes, thus transforming the business logic of an organization (Verhoef et al., 2021). In the realm of OSCM, there are numerous benefits and implications associated with DDDT. For instance, higher supply chain productivity, greater agility, and lower costs are some of the benefits that can be achieved through DDDT (Dwivedi et al., 2017; Shi et al., 2023; Stank et al., 2019). This is enabled by the application of emerging technologies, such as big data analytics (Bag et al., 2022), blockchain (Kouhizadeh et al., 2021), and artificial intelligence (Sharma et al., 2022). One of the key sectors where an increasing number of businesses are undergoing data-driven digital initiatives is the manufacturing industry (Tian et al., 2023). According to Gartner (2023), around 80% of manufacturing companies are considering investing in digital transformation to survive the current economic challenges.

Despite offering numerous advantages, digital transformation initiatives present their own set of challenges. A recent report indicates that while 89% of large organizations worldwide are undergoing digital transformation, they have only achieved 31% of the predicted revenue growth and 25% of the anticipated cost savings (Lamarre et al., 2023). One factor highlighted in both academic and practice publications as an essential factor in the success of digital transformation is organizational culture (OC) (Gökalp & Martinez, 2022; Pedersen, 2022). In OSCM literature, OC has been identified as an essential factor influencing various organizational aspects, such as big data analytics capability (Dubey et al., 2019; Gupta & George, 2016; Lin & Kunnathur, 2019; Upadhyay & Kumar, 2020), lean production and management methods (Bortolotti et al., 2015; Hardcopf et al., 2021; Pakdil & Leonard, 2015), and supply chain performance (Chaudhuri et al., 2021; Osei et al., 2023; Škerlavaj et al., 2007; Valmohammadi & Roshanzamir, 2015; Zanon et al., 2021). Furthermore, OC's critical influence on technology adoption and innovation is also widely acknowledged in the business literature (Boynton & Zmud, 1987; Dasgupta & Gupta, 2019; Jackson, 2011)

Tiwari and Koehler (2022) note that real digital transformation initiatives rely more on changing the culture than just picking the right technology. Gökalp and Martinez (2022) mention culture as a pivotal element driving the success of digital transformation initiatives. Pedersen (2022) asserts that considering the cultural values in the organization might safeguard your transformation initiatives from failure, thereby increasing their chances of success. While earlier research has mainly viewed OC as a contributor to the success of DDDT, Alharthi et al. (2017) discuss cultural barriers in the context of big data, asserting that challenges arising during big data initiatives may more likely originate from organizational culture rather than in the data or technology itself. While the literature acknowledges the vital role of OC in DDDT, there remains a need to elucidate precisely how various aspects of OC influence DDDT. Hence, this study aims to fill the gap in the literature by exploring the impact of organizational culture on data-driven digital transformation. Additionally, to enrich the nomological network surrounding DDDT, its effect on operational performance is investigated. Therefore, we examine the ensuing research questions:

RQ1: What is the effect of organizational culture on data-driven digital transformation?

RQ2: What is the impact of data-driven digital transformation on operational performance?

To answer the research questions, we employ the competing values model (Quinn & Rohrbaugh, 1983) and organizational culture framework (Hofstede et al., 1990) to assess OC within the organization. In the past, complementary results have been obtained when two frameworks have been used to capture OC within a study (Gupta et al., 2022). Specifically, utilizing both the CVM and HOCF frameworks in our study confers two significant benefits. Firstly, it allows for a comprehensive analysis where the results obtained from each framework complement one another. Secondly, this dual-framework approach serves to effectively cross-validate the findings, enhancing the robustness and reliability of our results. Thus, using two frameworks allows us to gain a comprehensive view of cultural nuances and their potential implications for DDDT. As the U.S. ranks among the technological leaders in the world, we chose to collect data from 317 U.S.-based survey participants to capture the DDDT concept with greater accuracy. The contribution of this study to the existing literature is significant in several ways. First, we contribute to the digital transformation literature by bridging the gap between data-driven digital transformation and organizational culture. Our research provides a deeper comprehension of the vital role that OC plays in shaping DDDT, providing a solid foundation for future research. Second, by utilizing two different OC frameworks, we capture a more thorough view of OC in the organization. To the best of our knowledge, no prior research has used two complementary OC frameworks in the context of DDDT. Third, this study provides actionable insights for decision-makers within organizations. Drawing from the results of this study, decision-makers can align their organizational culture more closely with data-driven digital transformation, facilitating smoother transitions.

The remainder of this paper is organized as follows: the next section provides an overview of the existing body of literature surrounding data-driven digital transformation, organizational culture, and operational performance. Section 3 focuses on developing the hypotheses. The results and analysis are presented in Section 4. In section 5, we discuss the results, theoretical contribution, and practical implications. Furthermore, limitations and potential avenues for future research are discussed. Section 6 concludes the paper.

Literature Review

Data-Driven Digital Transformation

Digital transformation has been defined as "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (Vial, 2019, p. 121). On a macro level, the term *digital transformation* refers to the major shifts brought about by digital technologies in society and industries, but on an organizational level, it refers to strategies that utilize digital initiatives to enhance innovation in order to boost efficiency (Agarwal et al., 2010; Hess et al., 2016). It is essential to distinguish digital transformation initiatives from IT-enabled organizational changes. The former is characterized by the re-definition of an organization's value proposition, while the latter emphasizes improving an existing value proposition. In addition, digital transformation leads to the advent of a novel organizational identity, contrary to IT-enabled organizational changes, which strengthens the current one (Wessel et al., 2021). Digital transformation transcends typical technological innovations, instigating profound institutional change by fundamentally redefining organizational structures, practices, and values. This shift is not a mere adjustment but a significant leap towards new and legitimized organizational and institutional frameworks, drastically altering established norms and systems (Hinings et al., 2018). Numerous organizations struggle to achieve digital transformation benefits due to the complex nature of the process and the wide range of issues involved. However, a study by Li (2020) presents three approaches to lead a successful digital transformation that emerged from global digital champions (such as Google, Amazon, and Uber). These approaches include innovating by experimenting, achieving radical transformation through gradual changes, and maintaining sustainable advantages by continually adapting a collection of temporary advantages.

Taking a data-centric approach to digital transformation, Papanagnou et al. (2022) defined data-driven digital transformation (DDDT) as “a process that aims to improve a firm by triggering significant changes to its capabilities and design through the use of various technologies and data. Digital transformation implies a redesign of core processes with the reallocation of resources and competencies of the firm” (p. 3). The role of DDDT has been shown in numerous contexts, such as data-driven operation management (Gölzer & Fritzsche, 2017), manufacturing (Apilioğulları, 2022; Battistoni et al., 2023), and maintenance (Saihi et al., 2023).

In the realm of OSCM, DDDT has increasingly been acknowledged as a pivotal element, exerting a profound influence on various organizational dimensions. Enrique et al. (2022) examined the influence of digitally transformed supply chains on enhancing supply chain flexibility within environments with high uncertainty. Their findings revealed that the smart supply chain is linked to operational performance, mediated by supply chain flexibility. Papanagnou et al. (2022) explored the effect of DDDT on supply chain resilience in emergencies, with a particular emphasis on the moderating role of predictive analytics and processes. They argue that DDDT strategies correspond positively with supply chain resilience. This association is further strengthened when organizations incorporate predictive analytics into their operational processes. Fang et al. (2023) investigated the antecedents of DDDT by examining their impact on strategic agility and financial performance. Their findings show that data analytic capability, supply chain connectivity, and organizational learning significantly influence DDDT initiatives. Additionally, they found that not only the adoption but also the routinization of data-driven initiatives have meaningful impacts on both strategic agility and financial performance. Finally, in a study concerning Industry 4.0, Tortorella et al. (2023) note that for transformation initiatives to achieve success, careful consideration of an organization's socio-cultural facets is essential. This emphasizes that culture contributes to the effective deployment of transformational initiatives. In conclusion, the existing body of literature demonstrates the complex and imperative role of data-driven digital transformation in the OSCM. Moving forward, our examination shifts to the organizational culture.

Organizational Culture

In the context of OSCM, organizational culture has been defined "as a system of shared values and beliefs" (Marshall et al., 2016, p. 1508). Even though the extant body of literature shows that OSCM scholars are interested in organizational culture (Altay et al., 2018; Bortolotti et al., 2015; Liu et al., 2010; Naor et al., 2010; Prajogo & McDermott, 2011; Stock et al., 2007; Zhu et al., 2016), a review by Metters et al. (2019) showed that only 31 articles that focus on organizational culture have been published in the top-tier OSCM journals, which is less than 1% of articles published from 1990 to 2017. This gap indicates a critical need for a more in-depth exploration of organizational culture in the context of OSCM.

Numerous organizational culture frameworks have been used within business literature (Gupta et al., 2022). For example, the competing values model (CVM) by Quinn and Rohrbaugh (1983) is one of the well-established and most cited frameworks in the academic literature (Metters et al., 2019). In addition, the Hofstede organizational culture framework (HOCF) by Hofstede et al. (1990) has recently gained significant recognition in OSCM literature (Cadden et al., 2020; Zanon et al., 2021). In the following section, each framework and its key components are discussed.

Competing Values Model

The CVM has been widely employed in the OSCM literature (Dubey et al., 2017; Dubey et al., 2019; Hardcopf et al., 2021; Metters et al., 2019; Škerlavaj et al., 2007; Zu et al., 2010). This framework is structured around two opposing values, each representing varying orientations: (1) flexibility in contrast to stability and (2) internal in contrast to external focus (Quinn & Rohrbaugh, 1983). The first dimension indicates how much emphasis the organization places on the change or stability in its structure. The second dimension distinguishes the values associated with the well-being of its employees and operations taking place within the organization (i.e., internal focus) from the welfare of the organization and activities that take place outside the organization (i.e., external focus). These two dimensions are intersected to form four quadrants representing distinct dimensions of organizational culture: group culture, developmental culture, hierarchical culture, and rational culture.

Group culture is found where internal focus and flexibility converge. Revealed by differences between U.S. and Japanese organizations in the 1970s (Cameron & Quinn, 2011), group culture emphasizes the welfare of its employees, teamwork, and human resource improvement (Quinn & Rohrbaugh, 1983). *Developmental culture* corresponds to external focus and flexibility. Emerging from intensified unpredictability in the modern era (Cameron & Quinn, 2011), developmental culture focuses on risk-taking, readiness, and customer feedback. It also values growth opportunities, a future-oriented perspective, and innovation. It places a strong emphasis on learning from mistakes, viewing them as invaluable lessons that facilitate the establishment of conditions conducive to sustainable growth and more efficient resource acquisition (Cameron & Quinn, 2011; Quinn & Rohrbaugh, 1983). *Hierarchical culture* is characterized by its emphasis on internal focus and stability. Its roots can be traced to Weber (1947) study on bureaucracy and the early 1900s challenges of product and service development in a stable market. Hierarchical culture focuses on standardization, routinization, and uniformity. Strict adherence to established rules and policies not only ensures a consistent and predictable environment but also reinforces stability and control inside the company. *Rational culture* corresponds to external focus and stability. Originating from the emergence of competitive markets in the late 1960s and particularly influenced by the contributions of Ouchi and Johnson (1978) and Williamson (1981), rational culture focuses on well-defined goals and external competition to achieve enhanced productivity (Quinn & Rohrbaugh, 1983).

Hofstede's Organizational Culture Framework

An alternative framework that has been referenced by business scholars originates from the seminal work of Hofstede et al. (1990), in which they delve into the core values and practices of organizations. They point out that organizational culture is most effectively assessed by practices in the organization, whereas national culture is best determined by the core values. Consequently, in scholarly research, organizational culture is primarily measured at the practice level (Cadden et al., 2013; Verbeke, 2000; Zanon et al., 2021). Hofstede et al. (1990) initially developed a set of organizational practice dimensions for assessing organizational culture. Noting validity and replication challenges with this initial scale, Verbeke (2000) refined and extended the scale to enhance its reliability and validity. Ultimately, to better align with the OSCM context, Cadden et al. (2013) further modified it to ensure its reliability, validity, and applicability within the domain. The final set of organizational practices identified by Cadden et al. (2013) consists of results versus process, employee versus job, open versus closed, loose versus tight, normative versus pragmatic, and market versus internal.

The results-process dimension pertains to the manner in which management expects employees to participate in the business workflow. The primary objective of result-oriented organizations is to achieve their goals, even if it means navigating around established rules or overlooking certain conventions. However, in organizations that are focused on processes, employees strictly adhere to the rules and rigidly stick to their designated roles within their specific departments. The employee-job dichotomy reflects the way management supports the employees within an organization. Employee-oriented organizations value their employees by encouraging personal growth and enrichment. In a job-oriented culture, the main focus of organizations is on task completion over employee development. The open-closed dimension captures how both employees and managers respond to criticism upon making errors and how they handle such situations in public. In an open culture organization, constructive criticism is actively promoted. Conversely, an organization with a closed culture exhibits a defensive orientation. The loose-tight dimension pertains to how management controls the members of the organization. In a loose-oriented culture, employees have flexibility and autonomy in performing their jobs, while in a tight-oriented culture, managers often oversee and guide the employees. The normative-pragmatic dimension delineates an organization's inclination toward following established norms and procedures versus being more pragmatic based on situational demands. In a normative-oriented culture, traditional ways of doing things are strongly emphasized, while in a pragmatic culture, when necessary, deviations from traditional procedures are made to achieve outcomes and results. The market-internal dimension outlines how the organization collectively engages with customers and competitors. In a market-oriented organization, the primary focus is on external market dynamics, such as customers and suppliers. On the other hand, an organization with an internal focus emphasizes internal organizational efficiencies, often overlooking consumer needs (Cadden et al., 2013; Hofstede et al., 1990; Verbeke, 2000).

Operational Performance

Operational performance (OP) is often influenced by the competitive choices companies make in the marketplace. It is a constantly changing, multifaceted concept that underscores a company's operational efficiency and emphasizes its profitability and market competitiveness. (Hong et al., 2019; Lee et al., 2023). OP has been broadly utilized in the business literature as a significant concept, indicating improvements and advancements in organizational effectiveness and efficiency (Bhamra et al., 2022; Buer et al., 2021; Chae et al., 2014; Devaraj et al., 2007; Dubey et al., 2020; Gupta & George, 2016; Khanchanapong et al., 2014; Munir et al., 2020;

Pagell & Gobeli, 2009; Wong et al., 2011). In the OSCM literature, various studies have investigated the effect of diverse factors on OP, such as supply chain quality management practices (Hong et al., 2019), supply chain risk management (Munir et al., 2020), lean production methods (Hardcopf et al., 2021), and data-driven decision-making and digitalization (Colombari et al., 2023). Given the inherent challenges in capturing business performance through a single measure, a range of metrics has been adopted in research (Bayraktar et al., 2009; Lee et al., 2023). In this study, our operational performance assessment encompasses several key metrics, including the unit cost associated with manufacturing, lead time durations, the number of recorded customer complaints, and instances of scrap, rework, and product defects (Cadden et al., 2020; Gambi et al., 2015).

Hypothesis Development

Organizational Culture and DDDT

For any new process in the organization to be successful, recognizing the culture within the organization is of utmost importance (Desouza & Evaristo, 2006). Culture has been referred to as a fundamental element impacting every facet of organizational activities and decisions in the transformation process (Rowles & Brown, 2017). Specifically, OC is a pivotal factor that can either promote or obstruct the success of DDDT (Fitzgerald et al., 2014; Philip & McKeown, 2004). Vial (2019) pointed out that culture is a key factor in creating value propositions, which are the primary goal of DDDT initiatives. Research shows that to create novel value propositions using digital technologies, it is central for organizations to create and maintain the necessary culture to support the essential capabilities (Karimi & Walter, 2015).

Gupta and George (2016) highlight the importance of a data-driven organizational culture in establishing hard-to-imitate big data capabilities. They contend that to fully utilize the transformational power of big data analytics capability, developing a data-driven culture is critically important. Upadhyay and Kumar (2020) employed a mediation model to capture the impact of internal analytical knowledge on company performance by considering OC and big data analytics capability as mediators. They found that OC plays an important role in scenarios where firm performance is improved by big data analytics capability and internal analytical knowledge. Saihi et al. (2023) explored the determinants of successful digital initiatives in maintenance function in businesses and found OC as one of the critical factors, emphasizing developing a digital culture, promoting a continuous improvement attitude, nurturing an innovative culture, and establishing a culture of data-driven decision-making. A different approach was taken by Yu et al. (2021) in their study of supply chain finance initiatives, where they considered OC as a moderator. They concluded that a data-driven culture strengthens the link that exists between big data analytics capability and supply chain finance integration. A recurring theme throughout these studies is the vital role that OC plays in enabling the various aspects of DDDT. Therefore, it is reasonable to expect that:

H1: Organizational culture impacts data-driven digital transformations.

As previously noted, business literature has used various organizational culture frameworks. In the present study, we employ Quinn and Rohrbaugh (1983) competing values model (CVM) and Hofstede et al. (1990) organizational culture framework (HOCF). The choice to adopt two frameworks rather than one stems from the desire to capture the multifaceted nature of organizational culture comprehensively, as prior research indicates that no single framework can capture all its nuances (Gupta et al., 2022). This allows us to capture valuable insights and ensures a more holistic understanding of both frameworks, accounting for diverse dimensions and nuances that a single framework might overlook. Therefore, this dual-framework approach enhances the depth and breadth of our analysis, ensuring that the complexities inherent in organizational culture are adequately addressed.

Competing Values Model and DDDT

Group Culture and DDDT

In an organization where group-oriented culture prevails, the emphasis is on cooperation and collaboration. Employees in the group culture are typically devoted to their community, emphasizing common values and communication. Leaders are viewed as guiding figures, promoting a cohesive, supportive, and inclusive environment. There is an open flow of communication and information across the organization, and active participation from employees is highly encouraged. In the process of DDDT, organizations redefine their value propositions (Wessel et al., 2021), necessitating the engagement of the entire organization in this pivotal endeavor. This requires different teams and departments to work together in a friendly and supportive work environment, which can help to reduce the stress and anxiety associated with significant changes induced by data-driven transformations. Collaboration is viewed as one of the important factors in DDDT (Vial, 2019). A group-oriented culture emphasizes the free flow of information across the organization. This ensures that employees have access to essential data and insights, thereby facilitating easier collaboration and communication. Therefore, we propose:

H1a: Group culture positively impacts DDDT.

Developmental Culture and DDDT

Similar to group culture, unrestricted communication and employee involvement are encouraged by developmental culture. It fosters an environment that inspires active engagement in conversations that could encourage creativity and innovation. Additionally, developmental culture acknowledges the volatility of the external environment, actively identifying and assessing future trends in order to formulate strategies that not only mitigate potential risks but also capitalize on emergent opportunities. Moreover, the developmental mindset adopts a forward-focused approach by placing a strong emphasis on the generation of new ideas to navigate and prosper in unpredictable environments. Li (2020) identified innovation and experimentation as an approach for leading successful digital initiatives. This approach aligns with the developmental culture's emphasis on innovation and experimentation, which can help overcome resistance—a barrier to DDDT—to the introduction of new technologies in the organization (Vial, 2019). Accordingly, we hypothesize:

H1b: Developmental culture positively impacts DDDT.

Rational Culture and DDDT

A rational culture emphasizes the importance of competition, achievement, and quick results. Managers define clear purposes for employees to increase short-term profits. Additionally, rational cultures underscore control and stability, often resulting in a leadership style that limits open discussions and dissenting opinions. Since rational culture has an external focus, there is a greater emphasis on the market. Rational culture views markets as hostile, encouraging a focus on competitor activities in order to outperform them, as success is seen as defeating the opposition. While emphasizing control and stability might complicate the DDDT process, the primary focus of rational culture is to outperform competitors in the market (Cameron & Quinn, 2011). An organization that emphasizes competition and achievement will likely innovate and adopt new technologies faster to stay ahead of its competitors. In turn, DDDT can be accelerated to win the competition in the market. Therefore, we propose:

H1c: Rational culture positively impacts DDDT.

Hierarchical Culture and DDDT

Hierarchical culture is characterized by predictable and reliable business performance. Employees focus on daily operations, resisting anything that might cause failure or uncertainty. Leaders concentrate on optimizing processes, creating policies and rules, and controlling employees with a pre-defined roadmap. Information flow is restricted, and unproductive projects are regularly discarded. Internal affairs receive primary attention, often at the expense of adapting to external changes. While this culture can lead to smooth and efficient operations, in extreme cases, it can result in organizational stagnation. DDDT, however, entails significant changes to an organization's capabilities and structure (Papanagnou et al., 2022). Hierarchical cultures, on the other hand, emphasize stability over change. In such environments, information flow, collaboration and communication can become challenging, elements that are crucial for the success of DDDT. Matarazzo et al. (2021) note that it is essential for digital initiatives to have dynamic capabilities. This demonstrates an incongruity with hierarchical culture. Hence, we posit:

H1d: Hierarchical culture negatively impacts DDDT.

Hofstede's Organizational Culture Framework and DDDT

Results-Oriented Culture and DDDT

In result-oriented organizations, the main aim is to reach their objectives. When faced with challenges, employees frequently receive aid from other departments. They step in to handle tasks for absent colleagues. Employees address requests without always following formal procedures. They cooperate extensively on special projects, using flexible strategies often guided by managerial suggestions. DDDT aligns well with a result-oriented culture since both of them prioritize achieving specific targets. As DDDT is defined by the re-definition of an organization's value proposition and boosting efficiency and performance (Enrique et al., 2022), a resultsdriven mindset will naturally focus on the tangible outcomes that digital tools can provide. This alignment is particularly evident in the literature, where result-oriented culture has been linked to improvement in performance (Thi Tran et al., 2022; Verbeeten & Speklé, 2015). Moreover, a result-driven culture fosters an environment conducive to DDDT due to its emphasis on collaborative and cross-functional teamwork, which is crucial for effective implementation. Therefore, we propose:

H1e: Results-oriented culture positively impacts DDDT.

Employee-Oriented Culture and DDDT

In organizations that have an employee-oriented culture, managers encourage their employees to pursue personal growth. They consistently show genuine interest in employees' well-being and involve them in pertinent decisions. Leaders frequently offer praise and commendation for exemplary performance. They also ensure that work pressures remain within manageable limits for their team members. When employees feel cared for and valued, they are more likely to embrace change and adapt to new technologies and processes. Hence, when employees have support and trust from management, employees are more inclined to embrace DDDT tools and strategies. Resistance and inertia have both been identified as obstacles to the DDDT process (Vial, 2019); however, an employee-oriented culture can help the organization overcome these barriers. Therefore, we hypothesize:

H1f: Employee-oriented culture positively impacts DDDT.

Loose-Oriented Culture and DDDT

In an organization with a loose culture, there is a prevailing emphasis on flexibility and autonomy in achieving business objectives. Managers seldom monitor employees' working hours, breaks, or the details of their expenses. They tolerate occasional lateness or when employees require leave during work hours. Additionally, if employees do not begin their work on time, they can extend their work hours to ensure tasks are completed promptly. For DDDT, a loose-oriented culture can pose challenges. In a relaxed environment, it could be difficult to track progress across departments, as employees rarely report to their managers (Verbeke, 2000). Similarly, the high level of flexibility might lead to inconsistencies among different departments, as previous literature has shown that a loose-oriented culture will lead to less accountability in the organization (Tang et al., 2016). Since DDDT impacts all levels of an organization, it is imperative to maintain a certain degree of control to ensure that the process of digitalization progresses as planned. As a result, a loose-oriented culture might hinder the effective implementation of DDDT. Hence, we posit:

H1g: Loose-oriented culture negatively impacts DDDT.

Market-Oriented Culture and DDDT

In market-oriented organizations, data from consumers, distributors, and suppliers is utilized to develop operational strategies. Customer satisfaction measurements and comprehensive investigations of customers' preferences are conducted regularly. Detailed reporting of services from partner agencies is also maintained. Market analysis is frequently conducted to customize business services to fulfill the various needs of the target groups. Current and future customer needs are discussed extensively across departments. Market-oriented organizations can align their DDDT strategies more effectively by gathering and analyzing customer and supplier information. By doing so, their digital initiatives reflect the evolving demands of the market, resulting in enhanced customer satisfaction. Regular measurements of customer satisfaction can serve as valuable feedback loops for digital initiatives. Since one of the goals of DDDT is to improve performance (Kristoffersen et al., 2021), having actionable insights into customer preferences and supplier dynamics ensures that these tools are optimized for market conditions. Hence, we propose:

H1h: Market-oriented culture positively impacts DDDT.

Open-Oriented Culture and DDDT

In an organization with an open culture, constructive criticism is actively promoted. Managers discuss their critiques openly with employees. Employees are encouraged to voice their criticisms of management's decisions and performance directly. Moreover, colleagues' mistakes are addressed directly with the individual involved. The company's DDDT will benefit from the transparency and receptiveness inherent in an open culture as it promotes iterative improvements in the organization. Employees' criticisms lead to early identification of potential challenges in the DDDT process. Specifically, the iterative feedback mechanism that is part of an open culture system accelerates the optimization of digital tools, which in turn helps the DDDT process. This open culture, as Bortolotti et al. (2015) note, not only aligns employees with the firm's strategy but also actively involves them in shaping and executing it, further strengthening the DDDT process. Thus, we suggest the subsequent hypothesis:

H1i: An open culture environment positively impacts DDDT.

Pragmatic-Oriented Culture and DDDT

In a pragmatic culture, deviations from established procedures are occasionally made to ensure desired outcomes and results. In organizations with a pragmatic approach, a strong focus is placed on business achievements. This is evident in the prioritization of customer needs and results over procedures. Employees may rarely discuss the organization's history, and when necessary, normative procedures are avoided. The adaptability intrinsic to this culture becomes pivotal during the DDDT process. As organizations modify their existing value propositions

(Huang et al., 2017), some established procedures may become obsolete. Yet, organizations rooted in pragmatism often manage these shifts with greater ease. On the other hand, an over-emphasis on organizational history can lead to stagnation, presenting a formidable barrier to the DDDT process. Tian et al. (2023) find that DDDT bolsters productivity in organizations. Such productivity gains are congruent with a pragmatic-oriented culture, where outcomes and tangible results are prioritized. Based on these insights, we hypothesize:

H1j: Pragmatic culture positively impacts DDDT.

DDDT and Operational Performance

In the context of manufacturing firms, the literature suggests that the relationship between DDDT and OP remains ambiguous. One perspective indicates that there is a positive association between DDDT and OP. More specifically, DDDT has been linked to business operations improvement (Björkdahl, 2020). For example, significant impacts on operational performance have been observed due to big data analytics (Dubey et al., 2020; Wamba et al., 2020a), AI capability (Mikalef & Gupta, 2021; Mikalef et al., 2023), and digital supply chain (Saryatmo & Sukhotu, 2021). Grounded in the practice-based view of the organization, a recent study focusing on Chinese manufacturing firms delves into this contentious issue by arguing that companies' operational efficiency, namely workforce productivity, physical asset efficiency, and working capital efficiency, is significantly improved by DDDT practices (Tian et al., 2023). Conversely, some argue that the relationship between DDDT and OP is not always evident, pointing to the digitalization paradox where investments often yield minimal returns (Gebauer et al., 2020; Yang et al., 2021). A recent study by Colombari et al. (2023) explored the effect of data-driven decision-making on operational performance while considering the extent of digitalization in the organization. They found that while a higher level of data integration may strengthen the relationship between data-driven decision-making and operational performance, utilizing novel technologies in the organization may lead to lower operational performance.

Despite concerns such as the digitalization paradox, we refer to the practice-based perspective of organizational theory to propose that DDDT could substantially improve operational performance. The prioritization of data-driven approaches within DDDT processes significantly impacts the resulting enhancements in operational performance. Literature, including studies by Jin et al. (2020) and Tian et al. (2023), has substantiated the significant role played by data-driven approaches in transformational initiatives. Hence, based on the compelling evidence put forth, we argue that DDDT has significant potential to enhance OP in the manufacturing sector. Therefore, we propose the following hypothesis:

H2: DDDT leads to superior operational performance in manufacturing companies.

Table 1

Proposed Hypotheses

Hypotheses	
H1: Organizational culture impacts data-driven digital transformation.	
CVM	**HOCF**
H1a: Group culture positively impacts DDDT.	H1e: Results-oriented culture positively impacts DDDT.
H1b: Developmental culture positively impacts DDDT.	H1f: Employee-oriented culture positively impacts DDDT.
H1c: Rational culture positively impacts DDDT.	H1g: Loose-oriented culture negatively impacts DDDT.
H1d: Hierarchical culture negatively impacts DDDT.	H1h: Market-oriented culture positively impacts DDDT.
	H1i: An open culture environment positively impacts DDDT.
	H1j: Pragmatic culture positively impacts DDDT.
H2: DDDT leads to superior operational performance in manufacturing companies.	

Research Methodology

To test the hypotheses presented in Table 1, we obtained data from Amazon Mechanical Turk (MTurk), an internet-based crowdsourcing platform where participants engage in studies for monetary compensation (Gupta et al., 2023; Parra et al., 2022). MTurk has been utilized for data collecting by academics from a variety of fields since it is regarded as a reliable source, especially when attention checks are applied (Li et al., 2023; Salcedo & Gupta, 2021).

Survey Participants

We collected data in three phases. We conducted a pretest before collecting data for the pilot test to improve the face and content validity of the measures. Four business school faculty members with the knowledge of operations management and data analytics, in addition to all the authors, participated in the pretest. We incorporated their feedback to enhance the survey for readability and clarity. Then, we collected data from 65 respondents to conduct a pilot to investigate the reliability of the instrument. These responses were not used in the primary analysis.

Then, we collected data for the main study. All participants reside in the U.S., and we offered them $1.50 for their participation. Although our survey was answered by individual representatives, our study's primary focus is on the organization as the unit of analysis. Each question was meticulously crafted to draw out insights reflecting the organization's collective perspectives and practices, a methodology consistent with precedents set in existing literature (Bag et al., 2022; Kirchoff & Falasca, 2022; Wamba et al., 2020a). We inserted several attention-check questions to make sure the participants were answering the questions correctly and thus the data collected was accurate.

We collected a total of 317 completed and usable surveys from 166 males and 151 females. About half of the participants are between 30 and 39 years old and the majority of them have a bachelor's degree. The participants work in 13 different industries, in different company sizes, and in various supply chain tiers (see Table 2).

Table 2 Participants' Demographic Information

Demography	Frequency	% in Sample
Gender		
Male	166	52.37
Female	151	47.63
Age		
20-29	129	40.69
30-39	140	44.16
40-49	18	5.68
50-59	16	5.05
60-70	14	4.42
Education Level		
High School Diploma	38	11.98
Bachelor's Degree	206	64.98
Master's or Ph.D. Degree	73	23.02
Income		
< $50,000	34	10.73
$50,000—$75,000	127	40.06
$75,000—$100,000	127	40.06
> $100,000	29	9.15
Work Experience		
1-5 years	149	47
6-10 years	129	40.69
More than 10 years	39	12.30
Industry		
Building Materials	43	13.56
Chemicals and Petrochemicals	10	3.15
Electronics and Electrical	37	11.67
Equipment	28	8.83
Food, beverage, and Alcohol	26	8.20
Metal, Mechanical, and Engineering	73	23.03
Pharmaceutical and Medical	25	7.89
Publishing and Printing	31	9.78
Rubber and Plastics	9	2.84
Textiles and Apparel	3	0.95
Toys	5	1.58
Wood and Furniture	18	5.68
Building Materials	7	2.21
Firm Size (# of employees)		
< 100	25	7.89
101-500	162	51.10
501-1000	102	33.12
>1000	25	7.89
Supply Chain Tier		
B2C	153	48.26

B2B	144	45.43
B2B of raw material and basic components	20	6.31

Organizational Culture Measures

We adopted the measures from previous published studies to ensure high validity and reliability. Participants were asked to rate how much they agreed (or disagreed) with each statement using a 7-point Likert scale, where "1=Strongly Disagree" and "7=Strongly Agree." Measures of organizational culture constructs pertaining to the competing-values model (CVM) were adopted from Cameron and Quinn (2011). Table 3.a includes the measures of these constructs.

Table 3.a Survey Items (CVM)

Construct/ Item	Mean	Std. Deviation	Measures
Group Culture (GC)			
GC1	5.49	1.32	The leadership in our organization is generally considered to exemplify mentoring, facilitating, or nurturing.
GC2	5.48	1.14	The management style in our organization is characterized by teamwork, consensus, and participation.
GC3	5.48	1.124	Our organization emphasizes human development, high trust, openness, and participation persist.
Developmental Culture (DC)			
DC1	5.38	1.18	Our organization is a very dynamic and entrepreneurial place. People are willing to stick their necks out and take risks.
DC2	5.41	1.11	The glue that holds our organization together is a commitment to innovation and development. There is an emphasis on being on the cutting edge.
DC3	5.48	1.21	Our organization emphasizes acquiring new resources and creating new challenges. Trying new things and prospecting for opportunities are valued.
Rational Culture (RC)			
RC1	5.47	1.19	The leadership in our organization is generally considered to exemplify an aggressive, results-oriented, no-nonsense focus.
RC2	5.44	1.13	The management style in our organization is characterized by hard-driving competitiveness, high demands, and achievement.
RC3	5.39	1.17	Our organization emphasizes competitive actions and achievement. Hitting stretch targets and winning in the marketplace are dominant.
Hierarchical Culture (HC)			
HC1	5.32	10.9	Our organization is a very controlled and structured place. Formal procedures generally govern what people do.
HC2	5.44	1.09	The management style in our organization is characterized by the security of employment, conformity, predictability, and stability in relationships.

HC3	5.50	1.09	The glue that holds our organization together is formal rules and policies. Maintaining a smooth-running organization is important.

Measures of the organizational culture (HOCF) were adopted from Cadden et al. (2015) and Cadden et al. (2020). The measures of these constructs, along with the averages and standard deviations, are shown in table 3.b. Due to the significant cross-loading, the rational culture construct was dropped from subsequent analysis. This is not surprising, as this has been observed in earlier studies (Chen & Zahedi, 2016; Iivari & Huisman, 2007; Scheibe & Gupta, 2017). The cross-loading in this study is understandable since the result-oriented culture and pragmatic-oriented culture share similar characteristics (e.g., both emphasize results over procedures within organizations).

Table 3.b Survey Items (HOCF)

Construct/ Item	Mean	Std. Deviation	Measures
Employee Focused (EMP)			
EMP1	5.37	1.24	With respect to people who do not feel too happy about their job, but who still perform well, new possibilities are being investigated for them to work on.
EMP2	5.37	1.29	Employees are encouraged to take courses and to go to seminars and conferences to help their self-development.
EMP3	5.65	1.10	My manager compliments employees on work well done.
Loose Management Control (LOOSE)			
LOOSE1	4.88	1.43	Managers do not always check if the employees are working.
LOOSE2	5.39	1.39	If one is a little late for an appointment with the manager, he/she will not be rapped on his/her knuckles.
LOOSE3	5.26	1.27	If an employee goes to the dentist during working hours, there is no checking on how long he/she stays away.
Market-focused (MRK)			
MRK1	5.68	1.03	Customers' preferences are investigated thoroughly.
MRK2	5.59	0.98	The organization provides services that meet the needs of the various target groups.
MRK3	5.72	1.10	The future needs of customers are discussed extensively with the various departments.
MRK4	5.68	1.04	In talks with customers, people try to find out about the future needs of the customers.
Open Communication (OPN)			

OPN1	5.48	1.13	If a manager has criticism of an employee, he/she discusses it openly with them.
OPN2	5.42	1.34	Employees express any criticisms of the management directly to the management.
OPN3	5.38	1.24	The mistakes of colleagues are personally discussed with him/her.
Pragmatic (PRAG)			
PRAG1	5.60	1.22	Results are more important than procedures.
PRAG2	5.30	1.34	Employees never talk about the history of the organization.
PRAG3	5.45	1.38	I believe where I work contributes little to society.

Measures of DDDT were adopted from Papanagnou et al. (2022) and those of operational performance from Cadden et al. (2020). The measures of these constructs are shown in table 3.c.

Table 3.c Survey Items (DDDT and OP)

Construct /Item	Mean	Std. Deviation	Measures
Data-Driven Digital Transformation (DDDT)			
DDDT1	5.30	1.07	Our organization allocates through digitalization a variety of mechanisms to alert for rapid changes in supply and delivery.
DDDT2	5.45	1.06	Our organization redesigns the processes integrating digitalization for maintenance of real-time customer sales fulfillment levels.
DDDT3	5.61	1.23	Our organization reconfigures resources and processes in a dynamic environment with the use of digital technology.
Operation Performance (OP): Please assess the following performance measure based on your own organization: (from consistently decreasing to consistently increasing)			
OP1	5.61	1.11	Unit cost (of manufacture)
OP2	6.52	1.18	Lead time
OP3	6.16	1.48	Number of customer complaints
OP4	5.26	1.45	Scrap, rework and defects

Analysis and Results

In this section, the results of the reliability and validity tests are presented. Subsequently, the results of the hypotheses testing are shown.

Statistical Analysis

The present study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis, specifically utilizing Smart PLS 4 software, to assess the research hypotheses. Initially, we evaluated the measurement model by examining the convergent and discriminant validities. Tables 4.a and 4.b show the Cronbach's α and CR coefficients of all constructs are above 0.7, illustrating robust composite reliabilities (Hair Jr et al., 2021). Given that all AVE values are also above 0.50, all constructs in the study are convergent.

Table 4.a: Reliabilities and Correlations (CVM)

	A	CR	AVE	DC	GC	HC	RC	DDDT	OP
DC	0.85	0.85	0.77	**0.88**					
GC	0.86	0.87	0.79	0.71	**0.89**				
HC	0.70	0.72	0.62	0.58	0.58	**0.79**			
RC	0.78	0.78	0.70	0.57	0.53	0.62	**0.83**		
DDDT	0.76	0.78	0.67	0.66	0.68	0.62	0.61	**0.82**	
OP	0.80	0.81	0.62	0.53	0.54	0.47	0.59	0.50	**0.79**

Note: The square roots of average variance extracted (AVE) appear along the diagonal in bold.

Table 4.b: Reliabilities and Correlations (HOCF)

	α	CR	AVE	EMP	LOOSE	MRK	OPN	PRAG	DDDT	OP
EMP	0.82	0.89	0.73	**0.86**						
LOOSE	0.72	0.84	0.63	0.56	**0.80**					
MRK	0.84	0.90	0.68	0.68	0.47	**0.82**				
OPN	0.74	0.85	0.66	0.68	0.61	0.65	**0.81**			
PRAG	0.73	0.85	0.65	0.59	0.38	0.51	0.55	**0.80**		
DDDT	0.82	0.88	0.65	0.63	0.33	0.64	0.66	0.50	**0.80**	
OP	0.75	0.84	0.58	0.63	0.44	0.61	0.60	0.59	0.64	**0.76**

Note: The square roots of average variance extracted (AVE) appear along the diagonal in bold.

We evaluated the discriminant validity by comparing the square root of the AVEs of each construct to the correlation of a pair of constructs (see Tables 4.a and 4.b). The constructs demonstrate adequate discriminant validity, as all the values of the square root of the AVEs are greater than their correlation with any other constructs (Fornell & Larcker, 1981). Furthermore, in order to determine the discriminant validity of the constructs, the measures' cross-loadings are assessed (see Tables 5.a and 5.b). The results show that the measures load highly on the respective constructs and very low on other constructs.

Table 5.a: Cross-Loadings (CVM)

	DC	GC	HC	RC	DDDT	OP
DC1	**0.89**	0.64	0.55	0.52	0.54	0.47
DC2	**0.88**	0.62	0.48	0.54	0.60	0.52
DC3	**0.87**	0.61	0.49	0.44	0.59	0.41
GC1	0.67	**0.90**	0.53	0.50	0.65	0.56
GC2	0.58	**0.87**	0.54	0.44	0.60	0.46
GC3	0.64	**0.90**	0.47	0.46	0.55	0.42
HC1	0.30	0.21	**0.71**	0.39	0.39	0.24
HC2	0.52	0.63	**0.80**	0.47	0.51	0.37
HC3	0.52	0.48	**0.85**	0.58	0.55	0.47
RC1	0.45	0.46	0.47	**0.79**	0.48	0.45
RC2	0.45	0.47	0.53	**0.85**	0.51	0.53
RC3	0.52	0.38	0.55	**0.86**	0.53	0.48
DDDT1	0.51	0.44	0.51	0.42	**0.77**	0.28
DDDT2	0.55	0.60	0.47	0.49	**0.84**	0.42
DDDT3	0.57	0.62	0.40	0.58	**0.85**	0.49
OP1	0.41	0.48	0.41	0.42	0.37	**0.72**
OP2	0.47	0.43	0.46	0.53	0.45	**0.81**
OP3	0.36	0.34	0.24	0.40	0.33	**0.78**
OP4	0.41	0.45	0.34	0.47	0.40	**0.84**

Table 5.b: Cross-Loadings (HOCF)

	EMP	LOOSE	MRK	OPN	PRAG	DDDT	OP
EMP1	**0.86**	0.54	0.52	0.52	0.47	0.57	0.51
EMP2	**0.87**	0.46	0.55	0.61	0.57	0.54	0.54
EMP3	**0.84**	0.42	0.68	0.62	0.45	0.52	0.56
LOOSE 1	0.29	**0.70**	0.25	0.38	0.22	0.15	0.23
LOOSE 2	0.46	**0.81**	0.43	0.46	0.27	0.25	0.33
LOOSE 3	0.52	**0.87**	0.40	0.58	0.38	0.34	0.43
MRK1	0.64	0.34	**0.85**	0.51	0.48	0.54	0.52
MRK2	0.50	0.38	**0.82**	0.54	0.39	0.53	0.49
MRK3	0.56	0.41	**0.78**	0.54	0.44	0.49	0.48
MRK4	0.53	0.41	**0.83**	0.55	0.38	0.53	0.51
OPN1	0.55	0.50	0.50	**0.73**	0.37	0.45	0.40
OPN2	0.61	0.47	0.55	**0.87**	0.50	0.63	0.55
OPN3	0.48	0.53	0.54	**0.83**	0.45	0.48	0.49
PRAG1	0.48	0.35	0.40	0.46	**0.76**	0.40	0.44
PRAG2	0.44	0.36	0.40	0.46	**0.78**	0.35	0.47
PRAG3	0.49	0.22	0.43	0.41	**0.87**	0.45	0.51
DDDT1	0.44	0.21	0.41	0.47	0.33	**0.78**	0.52
DDDT2	0.56	0.29	0.46	0.52	0.40	**0.81**	0.49
DDDT3	0.50	0.25	0.60	0.53	0.39	**0.83**	0.50
OP1	0.37	0.25	0.36	0.38	0.33	0.50	**0.73**

OP2	0.56	0.40	0.52	0.57	0.48	0.55	**0.83**
OP3	0.48	0.35	0.46	0.45	0.49	0.39	**0.70**
OP4	0.49	0.33	0.51	0.41	0.50	0.47	**0.77**

We also examined the discriminant validity by checking the Heterotrait-Monotrait Ratio (HTMT) matrix (Henseler et al., 2015). In order for HTMT values to demonstrate discriminant validity, they should remain below 0.90. (Hair et al., 2019; Henseler et al., 2015). Results indicate that all HTMT matrix values are below the threshold of 0.90 and in accordance with research recommendations (Queiroz et al., 2022; Wamba et al., 2020b). To determine multicollinearity in our data, we calculated variance inflation factors (VIFs), which showed that all values were below 3.3, indicating there is no issue with multicollinearity.

Hypotheses Results

After examining the measurement model, a bootstrapping (500 re-samples) procedure was performed to test the hypotheses (Hair et al., 2019). PLS-SEM utilizes a nonparametric bootstrap method (Davison & Hinkley, 1997) for assessing the significance of estimated path coefficients within the PLS-SEM framework because it does not assume that the data are normally distributed (Streukens & Leroi-Werelds, 2016). Bootstrapping involves generating subsamples by randomly selecting observations from the original dataset with replacements. These subsamples are utilized to estimate the PLS path model (Streukens & Leroi-Werelds, 2016).

The CVM constructs accounted for 60% of the variance in DDDT. All hypotheses are supported by the data with the exception of a hierarchical culture (H1d) (see Table 6.a). The results indicate that group culture (H1.a: $\beta = .31$; $p < .01$), development culture (H1b: $\beta = .21$; $p < .05$), and rational culture (H1c: $\beta = .21$; $p < .05$) positively impact DDDT. Moreover, DDDT positively impacts OP (H2: $\beta = .50$; $p < .0001$).

Table 6.a: Results (CVM)

Hypotheses	Betas	P Values	Hypotheses
GC -> DDDT	0.314	**0.006**	***Supported***: Group culture positively impacts DDDT.
DC -> DDDT	0.208	**0.022**	***Supported***; Development culture positively impacts DDDT.
RC -> DDDT	0.208	**0.018**	***Supported***: Rational culture positively impacts DDDT.
HC -> DDDT	0.193	0.063	*Not Supported:* Hierarchical culture did not negatively impact (or in a statistically significant manner) DDDT.
DDDT -> OP	0.504	**0.000**	***Supported:*** Data-Driven Digital Transformation positively impacts OP.

R^2 of DDDT is 0.60

Similar results were found when testing the hypothesis of the HOCF (See Table 6.b). Of the five proposed hypotheses, four are statistically significant. The data show that employee-oriented (H1f: $\beta = .26$; $p < .01$), loose-oriented culture (H1g: $\beta = -0.21$; $p < .01$), market-focused culture (H1h: $\beta = .26$; $p < .01$), and open culture (H1i: $\beta = .40$; $p < .001$) significantly impact DDDT. Pragmatic culture (H1j) was not found to have a statistical impact on DDDT. However, DDDT positively impacts OP (H2: $\beta = 0.64$; $p < .0001$).

Table 6.b: Results (HOCF)

Hypotheses	Betas	P Values	Hypotheses
EMP -> DDDT	0.26	**0.004**	***Supported***: Employee-focused culture positively impacts DDDT.
LOOSE -> DDDT	-0.206	**0.002**	***Supported***; Loose management control positively impacts DDDT.
MRK -> DDDT	0.259	**0.007**	***Supported***: Market-focused culture positively impacts DDDT.
OPEN -> DDDT	0.399	**0.000**	***Supported:*** Open communication climate positively impacts DDDT.
PRAG -> DDDT	0.076	0.231	*Not Supported*: Pragmatic culture did not positively impact (or in a statistically significant manner) DDDT.
DDDT -> OP	0.641	**0.000**	***Supported:*** Data-Driven Digital Transformation positively impacts OP.

R^2 of DDDT is 0.56; R^2 of OP is 0.41

Robustness Check

We conducted several tests to check for the robustness of the model. We first assessed the potential nonlinearity in the structural model using the quadratic effect. The results indicate that all quadratic effects are insignificant. Second, we checked for potential endogeneity based on the Gaussian copula approach. We tested for all possible combinations of Gaussian copulas. These results indicate that none of the Gaussian copulas is significant. Therefore, we can conclude that endogeneity is not present in the structural model, which supports the robustness (Sarstedt et al., 2020). Finally, we assessed the unobserved heterogeneity in PLS path models. We used the FIMIX-PLS procedure. To determine the maximum number of segments to be used, we had to compute the minimum size required for each segment (Sarstedt et al., 2020). It is advised to have a minimum sample size requirement of 85 per segment for an effect size of 0.15 and a power level of 80%. Based on this, we used three segments and ran three different tests from one to three segments (Sarstedt et al., 2020). The results are displayed in Table 7 and point to an ambiguous picture.

Table 7. Fit Indices for the one-to-three-segment solutions

	Number of Segments		
Criteria	**1**	**2**	**3**
AIC	1427.816	1294.087	**1252.615**
AIC3	1434.816	1309.087	**1275.615**
AIC4	1441.816	**1298.615**	1324.087
BIC	1454.128	**1339.069**	1350.47
CAIC	1461.128	1362.47	1365.069
HQ	1438.326	1316.609	**1287.149**
MDL5	1696.004	**1615.377**	1868.888
EN	na	0.501	**0.397**

For instance, AIC3 indicates a three-segment solution, whereas CAIS points to a two-segment solution. Similarly, MDL5 (2) and HQ (3) point to different segment solutions. AIC3 and CAIC point to different segments than AIC4, BIC, and MDL5. Thus, jointly, the analyses do not unambiguously point to a specific segmentation (Sarstedt et al., 2020). Hence, unobserved heterogeneity is not at a critical level in the model.

In conclusion, our model is considered robust based on the robustness checks we performed.

Discussion

Data-driven digital transformation has become prevalent to the point that it permeates almost every industry, leading a vast majority of organizations to consider its integration. Its potential is evidently becoming more widely recognized, as spending on DDDT initiatives is expected to reach an astounding amount of 3.4 trillion U.S. dollars by 2026 (Statista, 2022). This massive investment demonstrates the collective belief in the transformative power of digital initiatives, indicating businesses' intention to remain relevant and competitive in a rapidly evolving marketplace. This study investigated the effect of organizational culture on data-driven digital transformation. The association between DDDT and operational performance has also been evaluated. Next, we will discuss our findings.

Summary of Results

The significant influence of OC on DDDT, as highlighted in our study, is consistent with the growing body of literature emphasizing the pivotal role of OC in the success of data-driven digital initiatives. Desouza and Evaristo (2006) highlight the need to recognize the existing culture in the organizations for the success of any new process, echoed by Rowles and Brown (2017), citing its fundamental impact on all activities and decisions of an organization during any transformations. This is further supported by Vial (2019) and Karimi and Walter (2015), who emphasize culture's role in creating effective value propositions. Moreover, the results of this study support the previous findings in the literature, indicating the importance of culture in the success of data-driven transformational initiatives (Dubey et al., 2019; Gupta & George, 2016; Saihi et al., 2023; Upadhyay & Kumar, 2020; Yu et al., 2021). Following the affirmation of our hypothesis regarding the impact of OC on DDDT, we next delve into a nuanced exploration of the complexities of OC's influence on DDDT, exploring two distinct yet complementary frameworks.

Employing the CVM framework in our study provided us with valuable findings, emphasizing the crucial significance of culture in DDDT. Due to the collective nature of DDDT initiatives in organizations, creating an environment that emphasizes collaboration, effective communication, and shared goals becomes essential. The group culture in the CVM inherently focuses on these principles, making it well-suited to support digital initiatives in businesses. This type of culture is appropriate for DDDT as it allows an open flow of information and the participation of different stakeholders within the organization. Therefore, it is comprehensible that DDDT will benefit from a group culture in a meaningful way (H1a). This mirrors findings from previous studies, as they highlight the role of collaboration and communication across the organization (Vial, 2019). Prior research also demonstrates the role of innovation and creativity in the success of DDDT initiatives within organizations (Li, 2020), which are fundamental characteristics of developmental culture in the CVM (Gupta et al., 2019). Along with group culture, developmental culture promotes communication and collaboration within companies. The forward-thinking and innovative nature of a developmental culture can help overcome resistance and facilitate more successful DDDT initiatives. This reinforces the importance of our hypothesis that a developmental culture with its focus, innovation, and future-oriented perspective has the potential to promote DDDT (H1b). This relationship has been validated by prior studies that highlight the capacity of digital technology to create innovation, which in turn changes value propositions within organizations (Huang et al., 2017).

Our study validates the salient role of rational culture in data-driven initiatives in the organization. The main emphasis of rational culture is on the external environment, where the objective is to lead over the competition. Several scholars note that sustainable competitive advantages allow organizations to outperform the competition. One of the ways in which companies can achieve sustainable competitive advantages is through the reconfiguration of their resources (Teece et al., 1997). In their seminal paper, Gupta and George (2016) show how big data analytics creates capabilities, which thereby benefit organizations by achieving higher performance, gaining competitive advantage, and ultimately outdoing their competitors. Therefore, it is not surprising that a company with a rational culture supports DDDT (H1c) since they recognize that by DDDT, they can improve their competitive performance. Due to the inherent characteristics of hierarchical culture, we were expecting it to affect the DDDT negatively. However, we did not find any significant result pertaining to the influence of hierarchical culture on DDDT. The lack of a significant relationship emphasizes the complex relationship between DDDT and hierarchical culture. It also highlights the potential for other mediating or moderating factors that might influence the direct effects of a hierarchical culture on DDDT.

Similar to CVM, HOCF has proven to be beneficial in shedding light on the significance of culture within the context of DDDT. Researchers have noted that inspiring and motivating employees are crucial to the successful execution of DDDT initiatives. This becomes more crucial as some employees show resistance to digital initiatives (Singh & Hess, 2020). In such scenarios, a culture that actively supports, guides, and encourages its employees becomes indispensable. Therefore, it is clear that a culture centered around employees helps achieve DDDT (H1f). This outcome is consistent with the research by Eden et al. (2019), who note that building a cultural foundation that supports employees in the turbulence of DDDT initiatives is crucial for success. The employee-oriented culture is comparable to the group culture in CVM in that both place an emphasis on employees. However, the employee-oriented culture stresses the well-being and growth of individual employees, while the group culture highlights the collective, prioritizing teamwork, shared values, and collaboration above all.

Considering the loose-oriented culture, our finding shows that loose management orientation will negatively influence the DDDT initiatives. This is consistent with Singh and Hess (2020), who assert that creating a Chief Digital Officer to help oversee employees during the transformation process can ensure the appropriate utilization of digital technologies. In an excessively relaxed environment, it could be challenging to track progress across departments. Furthermore, in the absence of adequate supervision, there is a potential for a lack of alignment between DDDT projects and the company's goals. When comparing loose-oriented culture with hierarchical culture from CVM, it becomes evident that these two cultures represent contrasting paradigms: the former emphasizes flexibility, autonomy, and adaptability, while the latter focuses on structure, control, and predictability. While no significant relationship was found between DDDT and hierarchical culture, based on the result of HOCF, we can argue that in digital initiatives, some level of structured guidance, oversight, and boundaries are important for achieving the desired outcomes.

Our study's finding confirms that a market-oriented culture promotes DDDT within organizations (H1h). The fundamental idea behind DDDT is to use data and digital tools to create novel value propositions. Hence, it is logical to expect that a company with a market-oriented culture, emphasizing market data collection and analysis, would be in a position to incorporate and make the most of DDDT. Moreover, measuring and analyzing customer satisfaction in a market-focused organization enables them to customize their offerings more effectively. This is underscored by Gupta and George (2016), who consider data-driven culture as an intangible resource in building big data capabilities in the organization. They define the data-driven culture as “the extent to which organizational members make decisions based on the insights extracted from data” (p. 1053). This is congruent with a market-oriented culture, where the focus is to collect customer data in order to make informed business decisions. Günther et al. (2017) note the importance of customer data, arguing that by using big data analytics, organizations will gain a competitive advantage by providing effective services for their customers. The market-oriented culture is comparable to rational and developmental culture in the CVM model as they emphasize the market (i.e., external focus). However, companies interpret and respond to this external focus in different ways. The market-oriented culture focuses on customer and market data to improve business strategies. On the other hand, rational culture considers the market as a competitive arena with the objective of surpassing rivals. Lastly, companies with a developmental culture focus on innovation and adaptation to anticipate unpredictable environments.

Our results provide further attest to the influence of an open-oriented culture on data-driven initiatives (H1i). The primary characteristics of an open culture environment are ongoing reflection, iterative feedback, and constructive criticism, all of which perfectly fit with DDDT. An organization’s open culture facilitates DDDT initiatives as the participants in the transformation process are encouraged to express their observations, criticisms, and suggestions. Additionally, mistakes are bound to happen in any endeavor that aims to bring about transformation. However, the iterative feedback and constructive criticism in an open culture ensure that any potential drawbacks in the DDDT process are identifiable at an early stage; thus, mistakes can be used as opportunities to learn rather than being viewed as problems. The significance of the feedback loop in digital initiatives is illustrated by Sjödin et al. (2021), who point out that the feedback loop in AI capabilities enables value creation in organizations. Vial (2019) highlights the role of iterative adjustments in DDDT, which resembles the open mindset within organizations.

The relationship between pragmatic-oriented culture and DDDT did not yield any significant results. Due to the intrinsic attributes of a pragmatic culture, this unexpected outcome illustrates the intricacies of both the pragmatic culture and the process of transformation. One possible explanation is that in a pragmatic culture, while the tendency to bypass traditional procedures can offer flexibility, it risks undermining the foundational insights drawn from organizational history essential for informed DDDT decisions. Another possible rationalization is that a pragmatic-oriented culture favors short-term gains over long-term ones. This can challenge DDDT, which requires a longer-term perspective, understanding that immediate returns might be sacrificed for future growth and competitiveness.

The focus of our final hypothesis centers on examining the impact of DDDT in improving the operational performance of manufacturing firms. Our findings indicate that data-driven digital initiatives contribute to operational performance significantly, hence suggesting the absence of a digitalization paradox in our research context. This finding has been validated by prior academic studies (Dubey et al., 2020), as well as practice research (Hess et al., 2016). Therefore, manufacturers looking to enhance their operational performance can confidently initialize DDDT, knowing that it aligns with both theoretical and practical findings. This illuminates the crucial role of integrating digital tools and data analytics into the manufacturing process not as a passing trend but as a transformative approach, towards achieving operational excellence.

Theoretical Contributions

In OSCM, culture is considered a necessary factor that affects various dimensions within organizations (Zanon et al., 2021). Data-driven digital transformation has garnered significant attention in OSCM literature (Hanelt et al., 2021). However, the research examining the relationship between OC and DDDT has been limited. Specifically, scant information is available on how each cultural dimension impacts DDDT. This study contributes significantly to the literature on data-driven digital transformation by providing empirical evidence on the intricate interplay between organizational culture and DDDT, a domain that has attracted increasing attention in contemporary business literature. Our study not only addresses this gap by contributing to the emerging literature on digital transformation but also responds to the recent call for theoretical research backed by strong empirical evidence on DDDT (Spanaki et al., 2023). This is important as DDDT is not a minor modification within organizations but a substantial change that transforms various aspects of the organization (Hinings et al., 2018). Although organizational culture has been studied in the OSCM literature in specific transformational technologies contexts, such as maintenance digital transformation (Saihi et al., 2023) and big data analytics (Upadhyay & Kumar, 2020; Yu et al., 2021), this study is among the first to empirically investigate the role of organizational culture, by employing OC frameworks that could capture cultural nuances. Building upon previous theoretical discussions in the literature (Fitzgerald et al., 2014; Philip & McKeown, 2004), our study is among the first to empirically investigate and confirm that not all types of organizational culture are conducive to successful DDDT. For instance, an employee-oriented culture can foster DDDT, while a loose culture might hinder its progress.

Second, many different approaches have been taken in exploring organizational culture in business literature over the years. Given its multifaceted nature and inherent complexities, we know from research that it is difficult to capture OC using one single universal framework (Gupta et al., 2022). As a result, relying on a single framework may lead to an incomplete or over-simplified comprehension of OC. Our research presents a substantial contribution to the literature on organizational culture by making use of a dual-framework approach—the Competing Values Model and Hofstede's Organizational Culture Framework—to understand the nuances that exist in OC. This is also reflected in our results. For example, from the CVM, we know that rational culture, developmental culture, and group culture can facilitate DDDT, while in HOCF, the finding indicates that employee-oriented culture, market-oriented culture, and open culture improve the success rate of DDDT. Indeed, had we opted for just one of these frameworks, our results would likely lack the depth and detail we have now achieved.

Third, the findings of this study clarify the indefinite association between DDDT and OP within the manufacturing sector. While one perspective posits a positive relationship between DDDT and OP, others counter this view by highlighting the digitalization paradox, suggesting that the relationship is not always clear-cut (Tian et al., 2023). Leveraging a synthesis of existing evidence, this study confirms that DDDT plays a crucial role in enhancing OP. By doing so, our research contributes to the literature by clarifying this relationship within the context of U.S. manufacturing firms and furthering our understanding beyond the confines of the prevailing digitalization paradox narrative.

Practical Implications

Our study presents valuable practical implications. First, the results of our study suggest that some culture profiles in the organization are more conducive to ensuring the success of DDDT initiatives. As previously noted, one of the major reasons that DDDT fails is culture (Fitzgerald et al., 2014). Hence, it is essential for managers to recognize the current cultural values in their organization and determine if these values align with the requirements for DDDT success. As a result of promoting a culture that supports DDDT, companies can not only improve their chances of success but also accelerate their ability to realize benefits. For instance, drawing on HOCF, we know that an employee-oriented culture provides an ideal environment for conducting DDDT within an organization. However, a process-oriented culture might pose some challenges in the transformation process. The aforementioned distinction highlights the crucial significance of organizational culture in successfully navigating the intricate path of data-driven digital initiatives. It is, therefore, imperative for organizational leaders to conduct periodic cultural assessments, ensuring alignment with their transformational goals.

Furthermore, in organizational studies, there is a common agreement that culture cannot be approached with a one-size-fits-all mentality (Gupta et al., 2022). Every company has its own unique set of core values, fundamental principles, and central rules, all of which have an effect on the overall dynamics of the organization. Hence, implementing a standardized data-driven digital transformation approach might result in several challenges, including resistance, misinterpretation, and, ultimately, unsuccessful outcomes. Similarly, to ensure the success of any novel process within an organization, it is necessary to possess a holistic view of the organizational culture (Desouza & Evaristo, 2006). This comprehension can assist managers in customizing transformative techniques to fit with employees, fostering a sense of inclusion in the change process rather than pushing it onto them. It will also facilitate smoother integration of new technologies, workflows, and practices, as they will be in sync with the existing cultural fabric. In essence, acknowledging and valuing the social context during the process of designing DDDT can significantly impact business outcomes, transforming obstacles into catalysts for progress.

Third, this study offers an important implication regarding the positive association between DDDT and operational performance in manufacturing companies. With manufacturers increasingly relying on data to optimize their business operations, understanding DDDT initiatives' specific dynamics, challenges, and potential outcomes becomes imperative. Incorporating DDDT can provide manufacturers with the capability to reduce costs and defects, save time, and reduce customer complaints. This provides an opportunity for managers and policymakers to support DDDT initiatives by promoting a data-driven culture, investing in the required technological infrastructure, and ensuring that the workforce is adequately trained to utilize these tools. Recognizing the tangible benefits of DDDT, managers can better articulate the business case for such initiatives, prioritize projects based on their potential impact, and ensure alignment with the company's strategic objectives.

Limitations and Future Research

As with most scholarly work, this study has intrinsic limitations that bring attention to prospective avenues for further research. First, we employ a cross-sectional design, which limits our ability to observe changes over time. This is especially important given that it is not possible to investigate the long-term effects of DDDT on OC. Future research should consider a longitudinal study design to investigate the possible effect of digital initiatives on organizational culture over prolonged periods. Second, we dropped the result-oriented culture dimension from HOCF because of the cross-loading issue. Future research could explore the HOCF dimensions, identifying the overlaps to refine them further. The marginal insignificance of HC in our outcomes suggests a need for further examination in different settings to reach more definitive conclusions. Third, our study only investigates U.S.-based firms. As Hofstede (1993) points out, there are considerable differences between U.S.-based and non-U.S.-based companies when it comes to culture. Numerous studies in the literature have demonstrated the significance of differences between U.S.-based and non-U.S.-based companies in the OSCM literature (Wamba et al., 2023). Hence, future studies may explore the dynamics in other regions, considering how local cultural nuances and technological transformation patterns might differ (Gupta & Gupta, 2019). Fourth, in this study, we did not specifically differentiate between public and private organizations; however, we know from prior research that implementation of data-driven technologies may differ across public and private enterprises (Mikalef et al., 2022). Fifth, while we adopted the two most popular frameworks to assess organizational culture, namely CVM and HOCF, it is not an exhaustive list. Future research could benefit from using or integrating other frameworks (e.g., organizational cultural profile (O'Reilly III et al., 1991)). Thus, scholars would be able to further decode the mechanisms of how various cultural values interact with DDDT, capturing subtleties and dynamics that would otherwise be missed. Sixth, this study uses Amazon Mechanical Turk to collect all the data. While Mturk is regarded as a credible resource (Gupta et al., 2021; Marett et al., 2017), other sources of data could be used in the future to replicate our findings.

Conclusion

In the modern business environment, characterized by swift changes, organizations are undergoing data-driven digital transformation to make substantial modifications in their structure and processes to augment their operational performance (Bag et al., 2023; Benitez et al., 2023). While most organizations aim to capitalize on the benefits offered by such transformation, only one-third succeed in drawing the full benefits out of this (Lamarre et al., 2023). This disparity highlights the necessity of understanding the key factors that contribute to the success of DDDT (Spanaki et al., 2023). Therefore, to further understand the critical factors behind the varying success rates in DDDT, this study specifically investigates the interplay between organizational culture, data-driven digital transformation, and operational performance in the manufacturing sector.

Utilizing the Competing Values Model and Hofstede's Organizational Culture Framework, our findings show that organizational culture significantly affects data-driven digital transformation, which consequently impacts operational performance. Our findings highlight that certain types of organizational cultures are more conducive to the success of DDDT than others. These findings indicate that, apart from technological innovations and strategic actions, the success of data-driven digital transformation is also significantly impacted by the underlying organizational culture. Aligning culture with the DDDT goals not only enables easier transitions but also enhances the overall operational performance, bridging the gap between transformation efforts and the actual realization of benefits.

References

Agarwal, R., Gao, G., DesRoches, C., & Jha, A. K. (2010). Research commentary—The digital transformation of healthcare: Current status and the road ahead. *Information systems research*, *21*(4), 796-809.

Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. *Business Horizons*, *60*(3), 285-292.

Altay, N., Gunasekaran, A., Dubey, R., & Childe, S. J. (2018). Agility and resilience as antecedents of supply chain performance under moderating effects of organizational culture within the humanitarian setting: a dynamic capability view. *Production Planning & Control*, *29*(14), 1158-1174.

Amit, R., & Zott, C. (2001). Value creation in e-business. *Strategic management journal*, *22*(6-7), 493-520.

Apilioğulları, L. (2022). Digital transformation in project-based manufacturing: Developing the ISA-95 model for vertical integration. *International Journal of Production Economics*, *245*, 108413.

Bag, S., Rahman, M. S., Srivastava, G., Chan, H.-L., & Bryde, D. J. (2022). The role of big data and predictive analytics in developing a resilient supply chain network in the South African mining industry against extreme weather events. *International Journal of Production Economics*, *251*, 108541.

Bag, S., Rahman, M. S., Srivastava, G., Giannakis, M., & Foropon, C. (2023). Data-driven digital transformation and the implications for antifragility in the humanitarian supply chain. *International Journal of Production Economics*, *266*, 109059.

Battistoni, E., Gitto, S., Murgia, G., & Campisi, D. (2023). Adoption paths of digital transformation in manufacturing SME. *International Journal of Production Economics*, *255*, 108675.

Bayraktar, E., Demirbag, M., Koh, S. L., Tatoglu, E., & Zaim, H. (2009). A causal analysis of the impact of information systems and supply chain management practices on operational performance: evidence from manufacturing SMEs in Turkey. *International Journal of Production Economics*, *122*(1), 133-149.

Belhadi, A., Venkatesh, M., Kamble, S., & Abedin, M. Z. (2024). Data-driven digital transformation for supply chain carbon neutrality: Insights from cross-sector supply chain. *International Journal of Production Economics*, 109178.

Benitez, G. B., Ghezzi, A., & Frank, A. G. (2023). When technologies become Industry 4.0 platforms: Defining the role of digital technologies through a boundary-spanning perspective. *International Journal of Production Economics*, *260*, 108858.

Bhamra, R., Hicks, C., Small, A., & García-Villarreal, E. (2022). Value, product delivery strategies and operational performance in the medical technology industry. *International Journal of Production Economics*, *245*, 108399.

Bharadwaj, A., El Sawy, O. A., Pavlou, P. A., & Venkatraman, N. v. (2013). Digital business strategy: toward a next generation of insights. *MIS Quarterly*, 471-482.

Björkdahl, J. (2020). Strategies for digitalization in manufacturing firms. *California Management Review*, *62*(4), 17-36.

Bonnet, D., & Westerman, G. (2020). The new elements of digital transformation. *MIT Sloan Management Review*, *62*(2).

Bortolotti, T., Boscari, S., & Danese, P. (2015). Successful lean implementation: Organizational culture and soft lean practices. *International Journal of Production Economics*, *160*, 182-201.

Boynton, A. C., & Zmud, R. W. (1987). Information technology planning in the 1990's: Directions for practice and research. *MIS Quarterly*, 59-71.

Buer, S.-V., Semini, M., Strandhagen, J. O., & Sgarbossa, F. (2021). The complementary effect of lean manufacturing and digitalisation on operational performance. *International journal of production research*, *59*(7), 1976-1992.

Cadden, T., Marshall, D., & Cao, G. (2013). Opposites attract: organisational culture and supply chain performance. *Supply Chain Management: an international journal*, *18*(1), 86-103.

Cadden, T., Marshall, D., Humphreys, P., & Yang, Y. (2015). Old habits die hard: exploring the effect of supply chain dependency and culture on performance outcomes and relationship satisfaction. *Production Planning & Control*, *26*(1), 53-77.

Cadden, T., Millar, K., Treacy, R., & Humphreys, P. (2020). The mediating influence of organisational cultural practices in successful lean management implementation. *International Journal of Production Economics*, *229*, 107744.

Cameron, K. S., & Quinn, R. E. (2011). *Diagnosing and Changing Organizational Culture: Based on the Competing Values Framework* (3rd edition ed.). Jossey-Bass.

Chae, B. K., Yang, C., Olson, D., & Sheu, C. (2014). The impact of advanced analytics and data accuracy on operational performance: A contingent resource based theory (RBT) perspective. *Decision support systems*, *59*, 119-126.

Chamorro-Premuzic, T. (2021, 2021-11-23). The Essential Components of Digital Transformation. https://hbr.org/2021/11/the-essential-components-of-digital-transformation

Chaudhuri, R., Chatterjee, S., Vrontis, D., & 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*, 1-35.

Chen, Y., & Zahedi, F. M. (2016). Individuals' internet security perceptions and behaviors. *MIS Quarterly*, *40*(1), 205-222.

Colombari, R., Geuna, A., Helper, S., Martins, R., Paolucci, E., Ricci, R., & Seamans, R. (2023). The interplay between data-driven decision-making and digitalization: A firm-level survey of the Italian and US automotive industries. *International Journal of Production Economics*, *255*, 108718.

Dasgupta, S., & Gupta, B. (2019). Espoused organizational culture values as antecedents of internet technology adoption in an emerging economy. *Information & Management*, *56*(6), 103142.

Davenport, T. H., & Spanyi, A. (2019). Digital transformation should start with customers. *MIT Sloan Management Review*, *8*.

Davison, A. C., & Hinkley, D. V. (1997). *Bootstrap methods and their application*. Cambridge university press.

Desouza, K. C., & Evaristo, J. R. (2006). Project management offices: A case of knowledge-based archetypes. *International Journal of Information Management*, *26*(5), 414-423.

Devaraj, S., Krajewski, L., & Wei, J. C. (2007). Impact of eBusiness technologies on operational performance: the role of production information integration in the supply chain. *Journal of Operations Management*, *25*(6), 1199-1216.

Dubey, R., Bryde, D. J., Blome, C., Dwivedi, Y. K., Childe, S. J., & Foropon, C. (2024). Alliances and digital transformation are crucial for benefiting from dynamic supply chain capabilities during times of crisis: A multi-method study. *International Journal of Production Economics*, *269*, 109166.

Dubey, R., Bryde, D. J., Dwivedi, Y. K., Graham, G., & Foropon, C. (2022). Impact of artificial intelligence-driven big data analytics culture on agility and resilience in humanitarian supply chain: A practice-based view. *International Journal of Production Economics*, *250*, 108618.

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., Roubaud, D., & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics*, *226*, 107599.

Dubey, R., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Hazen, B., Giannakis, M., & Roubaud, D. (2017). Examining the effect of external pressures and organizational culture on shaping performance measurement systems (PMS) for sustainability benchmarking: Some empirical findings. *International Journal of Production Economics*, *193*, 63-76.

Dubey, R., Gunasekaran, A., Childe, S. J., Roubaud, D., Wamba, S. F., Giannakis, M., & Foropon, C. (2019). Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *International Journal of Production Economics*, *210*, 120-136.

Dwivedi, G., Srivastava, S. K., & Srivastava, R. K. (2017). Analysis of barriers to implement additive manufacturing technology in the Indian automotive sector. *International Journal of Physical Distribution & Logistics Management*, *47*(10), 972-991.

Eden, R., Burton-Jones, A., Casey, V., & Draheim, M. (2019). Digital transformation requires workforce transformation. *MIS Quarterly Executive*, *18*(1), 1-17.

Enrique, D. V., Lerman, L. V., de Sousa, P. R., Benitez, G. B., Santos, F. M. B. C., & Frank, A. G. (2022). Being digital and flexible to navigate the storm: How digital transformation enhances supply chain flexibility in turbulent environments. *International Journal of Production Economics*, *250*, 108668.

Fang, M., Liu, F., Xiao, S., & Park, K. (2023). Hedging the bet on digital transformation in strategic supply chain management: A theoretical integration and an empirical test. *International Journal of Physical Distribution & Logistics Management*.

Fitzgerald, M., Kruschwitz, N., Bonnet, D., & Welch, M. (2014). Embracing digital technology: A new strategic imperative. *MIT Sloan Management Review*, *55*(2), 1.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50.

Gambi, L. D. N., Boer, H., Gerolamo, M. C., Jørgensen, F., & Carpinetti, L. C. R. (2015). The relationship between organizational culture and quality techniques, and its impact on operational performance. *International Journal of Operations & Production Management*, *35*(10), 1460-1484.

Gartner. (2023). *Digital Transformation in Manufacturing Industry*. Gartner. https://www.gartner.com/en/industries/manufacturing-digital-transformation

Gebauer, H., Fleisch, E., Lamprecht, C., & Wortmann, F. (2020). Growth paths for overcoming the digitalization paradox. *Business Horizons*, *63*(3), 313-323.

Gökalp, E., & Martinez, V. (2022). Digital transformation maturity assessment: development of the digital transformation capability maturity model. *International journal of production research*, *60*(20), 6282-6302.

Gölzer, P., & Fritzsche, A. (2017). Data-driven operations management: organisational implications of the digital transformation in industrial practice. *Production Planning & Control*, *28*(16), 1332-1343.

Gosavi, A., & Gosavi, A. A. (2024). CONWIP control in the digitized world: The case of the cyber-physical jobshop. *International Journal of Production Economics*, 109169.

Günther, W. A., Mehrizi, M. H. R., Huysman, M., & Feldberg, F. (2017). Debating big data: A literature review on realizing value from big data. *The Journal of Strategic Information Systems*, *26*(3), 191-209.

Gupta, M., Dennehy, D., Parra, C. M., Mäntymäki, M., & Dwivedi, Y. K. (2023). Fake news believability: The effects of political beliefs and espoused cultural values. *Information & Management*, *60*(2), 103745.

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049-1064.

Gupta, M., George, J. F., & Xia, W. (2019). Relationships between IT department culture and agile software development practices: An empirical investigation. *International Journal of Information Management*, *44*, 13-24.

Gupta, M., Gupta, A., & Cousins, K. (2022). Toward the understanding of the constituents of organizational culture: The embedded topic modeling analysis of publicly available employee-generated reviews of two major US-based retailers. *Production and Operations Management*, *31*(10), 3668-3686.

Gupta, M., & Gupta, S. (2019). Influence of national cultures on operations management and supply chain management practices—a research agenda. *Production and Operations Management*, *28*(11), 2681-2698.

Gupta, M., Parra, C. M., & Dennehy, D. (2021). Questioning racial and gender bias in AI-based recommendations: Do espoused national cultural values matter? *Information Systems Frontiers*, 1-17.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European business review*, *31*(1), 2-24.

Hair Jr, J., Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hamann-Lohmer, J., Bendig, M., & Lasch, R. (2023). Investigating the impact of digital transformation on relationship and collaboration dynamics in supply chains and manufacturing networks–A multi-case study. *International Journal of Production Economics*, 108932.

Hanelt, A., Bohnsack, R., Marz, D., & Antunes Marante, C. (2021). A Systematic Review of the Literature on Digital Transformation: Insights and Implications for Strategy and Organizational Change. *Journal of Management Studies*, *58*(5), 1159-1197. https://doi.org/https://doi.org/10.1111/joms.12639

Hardcopf, R., Liu, G. J., & Shah, R. (2021). Lean production and operational performance: The influence of organizational culture. *International Journal of Production Economics*, *235*, 108060.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*, 115-135.

Hess, T., Matt, C., Benlian, A., & Wiesböck, F. (2016). Options for formulating a digital transformation strategy. *MIS Quarterly Executive*, *15*(2).

Hinings, B., Gegenhuber, T., & Greenwood, R. (2018). Digital innovation and transformation: An institutional perspective. *Information and Organization*, *28*(1), 52-61.

Hofstede, G. (1993). Cultural constraints in management theories. *Academy of Management Perspectives*, *7*(1), 81-94.

Hofstede, G., Neuijen, B., Ohayv, D. D., & Sanders, G. (1990). Measuring organizational cultures: A qualitative and quantitative study across twenty cases. *Administrative science quarterly*, 286-316.

Hong, J., Liao, Y., Zhang, Y., & Yu, Z. (2019). The effect of supply chain quality management practices and capabilities on operational and innovation performance: Evidence from Chinese manufacturers. *International Journal of Production Economics*, *212*, 227-235.

Huang, J., Henfridsson, O., Liu, M. J., & Newell, S. (2017). Growing on steroids. *MIS Quarterly*, *41*(1), 301-314.

Iivari, J., & Huisman, M. (2007). The relationship between organizational culture and the deployment of systems development methodologies. *MIS Quarterly*, 35-58.

Jackson, S. (2011). Organizational culture and information systems adoption: A three-perspective approach. *Information and Organization*, *21*(2), 57-83.

Jin, J., Ma, L., & Ye, X. (2020). Digital transformation strategies for existed firms: from the perspectives of data ownership and key value propositions. *Asian Journal of Technology Innovation*, *28*(1), 77-93.
Karimi, J., & Walter, Z. (2015). The role of dynamic capabilities in responding to digital disruption: A factor-based study of the newspaper industry. *Journal of Management Information Systems*, *32*(1), 39-81.
Khanchanapong, T., Prajogo, D., Sohal, A. S., Cooper, B. K., Yeung, A. C., & Cheng, T. C. E. (2014). The unique and complementary effects of manufacturing technologies and lean practices on manufacturing operational performance. *International Journal of Production Economics*, *153*, 191-203.
Kirchoff, J. F., & Falasca, M. (2022). Environmental differentiation from a supply chain practice view perspective. *International Journal of Production Economics*, *244*, 108365.
Kouhizadeh, M., Saberi, S., & Sarkis, J. (2021). Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. *International Journal of Production Economics*, *231*, 107831.
Kristoffersen, E., Mikalef, P., Blomsma, F., & Li, J. (2021). The effects of business analytics capability on circular economy implementation, resource orchestration capability, and firm performance. *International Journal of Production Economics*, *239*, 108205.
Lamarre, E., Smaje, K., & Zemmel, R. (2023). *Rewired: The McKinsey Guide to Outcompeting in the Age of Digital and AI*. Wiley.
Lee, B. W., Nittala, L., Jacobs, M. A., & Yu, W. (2023). Impact of psychological safety on supply chain operational performance. *International journal of production research*, *61*(3), 754-773.
Li, F. (2020). Leading digital transformation: three emerging approaches for managing the transition. *International Journal of Operations & Production Management*, *40*(6), 809-817.
Li, X., Tse, Y. K., Zhang, M., & Phi, H. D. (2023). Impact of relocation strategy on brand trustworthiness and word-of-mouth: experimental vignette research on the US fashion industry. *International Journal of Production Economics*, *257*, 108775.
Lin, C., & Kunnathur, A. (2019). Strategic orientations, developmental culture, and big data capability. *Journal of Business Research*, *105*, 49-60.
Liu, H., Ke, W., Wei, K. K., Gu, J., & Chen, H. (2010). The role of institutional pressures and organizational culture in the firm's intention to adopt internet-enabled supply chain management systems. *Journal of Operations Management*, *28*(5), 372-384.
Marett, K., George, J. F., Lewis, C. C., Gupta, M., & Giordano, G. (2017). Beware the dark side: Cultural preferences for lying online. *Computers in Human Behavior*, *75*, 834-844. https://doi.org/https://doi.org/10.1016/j.chb.2017.06.021
Marshall, D., Metters, R., & Pagell, M. (2016). Changing a leopard's spots: A new research direction for organizational culture in the operations management field. *Production and Operations Management*, *25*(9), 1506-1512.
Matarazzo, M., Penco, L., Profumo, G., & Quaglia, R. (2021). Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective. *Journal of Business Research*, *123*, 642-656.
Metters, R., Marshall, D., & Pagell, M. (2019). Cultural research in the production and operations management field. *Foundations and Trends® in Technology, Information and Operations Management*, *13*(1-2), 1-150.
Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & Management*, *58*(3), 103434.

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2022). Enabling AI capabilities in government agencies: A study of determinants for European municipalities. *Government Information Quarterly*, *39*(4), 101596.

Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., Gupta, M., & Niehaves, B. (2023). Examining how AI capabilities can foster organizational performance in public organizations. *Government Information Quarterly*, *40*(2), 101797.

Munir, M., Jajja, M. S. S., Chatha, K. A., & Farooq, S. (2020). Supply chain risk management and operational performance: The enabling role of supply chain integration. *International Journal of Production Economics*, *227*, 107667.

Naor, M., Linderman, K., & Schroeder, R. (2010). The globalization of operations in Eastern and Western countries: Unpacking the relationship between national and organizational culture and its impact on manufacturing performance. *Journal of Operations Management*, *28*(3), 194-205.

O'Reilly III, C. A., Chatman, J., & Caldwell, D. F. (1991). People and organizational culture: A profile comparison approach to assessing person-organization fit. *Academy of management journal*, *34*(3), 487-516.

Osei, M. B., Papadopoulos, T., Acquaye, A., & Stamati, T. (2023). Improving sustainable supply chain performance through organisational culture: A competing values framework approach. *Journal of Purchasing and Supply Management*, *29*(2), 100821.

Ouchi, W. G., & Johnson, J. B. (1978). Types of organizational control and their relationship to emotional well being. *Administrative science quarterly*, 293-317.

Pagell, M., & Gobeli, D. (2009). How plant managers' experiences and attitudes toward sustainability relate to operational performance. *Production and Operations Management*, *18*(3), 278-299.

Pakdil, F., & Leonard, K. M. (2015). The effect of organizational culture on implementing and sustaining lean processes. *Journal of manufacturing technology management*, *26*(5), 725-743.

Papanagnou, C., Seiler, A., Spanaki, K., Papadopoulos, T., & Bourlakis, M. (2022). Data-driven digital transformation for emergency situations: The case of the UK retail sector. *International Journal of Production Economics*, *250*, 108628.

Parra, C. M., Gupta, M., & Cadden, T. (2022). Towards an understanding of remote work exhaustion: A study on the effects of individuals' big five personality traits. *Journal of Business Research*, *150*, 653-662.

Pedersen, C. L. (2022). Cracking the Culture Code for Successful Digital Transformation. *MIT Sloan Management Review*, *63*(3), 1-4.

Pettey, C. (2019). Why data and analytics are key to digital transformation. *Gartner. Retrieved July*, *10*, 2020.

Philip, G., & McKeown, I. (2004). Business transformation and organizational culture:: The role of competency, IS and TQM. *European management journal*, *22*(6), 624-636.

Prajogo, D. I., & McDermott, C. M. (2011). The relationship between multidimensional organizational culture and performance. *International Journal of Operations & Production Management*, *31*(7), 712-735.

Queiroz, M. M., Wamba, S. F., Jabbour, C. J. C., & Machado, M. C. (2022). Supply chain resilience in the UK during the coronavirus pandemic: a resource orchestration perspective. *International Journal of Production Economics*, *245*, 108405.

Quinn, R. E., & Rohrbaugh, J. (1983). A spatial model of effectiveness criteria: Towards a competing values approach to organizational analysis. *Management science*, *29*(3), 363-377.

Rowles, D., & Brown, T. (2017). *Building digital culture: A practical guide to successful digital transformation*. Kogan Page Publishers.

Saihi, A., Ben-Daya, M., & As' ad, R. (2023). Underpinning success factors of maintenance digital transformation: A hybrid reactive Delphi approach. *International Journal of Production Economics*, *255*, 108701.

Salcedo, E., & Gupta, M. (2021). The effects of individual-level espoused national cultural values on the willingness to use Bitcoin-like blockchain currencies. *International Journal of Information Management*, *60*, 102388.

Sarstedt, M., Ringle, C. M., Cheah, J.-H., Ting, H., Moisescu, O. I., & Radomir, L. (2020). Structural model robustness checks in PLS-SEM. *Tourism Economics*, *26*(4), 531-554.

Saryatmo, M. A., & Sukhotu, V. (2021). The Influence of the Digital Supply Chain on Operational Performance: A Study of the Food and Beverage Industry in Indonesia. *Sustainability*, *13*(9), 5109. https://www.mdpi.com/2071-1050/13/9/5109

Scheibe, K. P., & Gupta, M. (2017). The effect of socializing via computer-mediated communication on the relationship between organizational culture and organizational creativity. *Communications of the Association for Information Systems*, *40*(1), 13.

Sharma, R., Shishodia, A., Gunasekaran, A., Min, H., & Munim, Z. H. (2022). The role of artificial intelligence in supply chain management: mapping the territory. *International journal of production research*, *60*(24), 7527-7550.

Shi, Y., Venkatesh, V., Venkatesh, M., Fosso Wamba, S., & Wang, B. (2023). Guest editorial: Digital transformation in supply chains: challenges, strategies and implementations. *International Journal of Physical Distribution & Logistics Management*, *53*(4), 381-386.

Singh, A., & Hess, T. (2020). How chief digital officers promote the digital transformation of their companies. In *Strategic information management* (pp. 202-220). Routledge.

Sjödin, D., Parida, V., Palmié, M., & Wincent, J. (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, *134*, 574-587.

Škerlavaj, M., Štemberger, M. I., & Dimovski, V. (2007). Organizational learning culture—the missing link between business process change and organizational performance. *International Journal of Production Economics*, *106*(2), 346-367.

Spanaki, K., Dennehy, D., Papadopoulos, T., & Dubey, R. (2023). Data-driven Digital Transformation in Operations and Supply Chain Management. *International Journal of Production Economics*.

Stank, T., Esper, T., Goldsby, T. J., Zinn, W., & Autry, C. (2019). Toward a digitally dominant paradigm for twenty-first century supply chain scholarship. *International Journal of Physical Distribution & Logistics Management*, *49*(10), 956-971.

Statista. (2022). *Spending on digital transformation technologies and services worldwide from 2017 to 2026 (in trillion U.S. dollars)*. https://www.statista.com/statistics/870924/worldwide-digital-transformation-market-size/

Stock, G. N., McFadden, K. L., & Gowen III, C. R. (2007). Organizational culture, critical success factors, and the reduction of hospital errors. *International Journal of Production Economics*, *106*(2), 368-392.

Streukens, S., & Leroi-Werelds, S. (2016). Bootstrapping and PLS-SEM: A step-by-step guide to get more out of your bootstrap results. *European management journal*, *34*(6), 618-632.

Tang, M., Li, M. g., & Zhang, T. (2016). The impacts of organizational culture on information security culture: a case study. *Information Technology and Management*, *17*, 179-186.

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533.

Thi Tran, Y., Nguyen, N. P., & Nguyen, L. D. (2022). Results-oriented culture and organizational performance: the mediating role of financial accountability in public sector organizations in Vietnam. *International Journal of Public Administration*, *45*(3), 257-272.

Tian, M., Chen, Y., Tian, G., Huang, W., & Hu, C. (2023). The role of digital transformation practices in the operations improvement in manufacturing firms: A practice-based view. *International Journal of Production Economics*, *262*, 108929.

Tiwari, A., & Koehler, B. (2022). Culture: The Engine of Transformation. *2023*(9/8/2023). https://sloanreview.mit.edu/mitsmr-connections/culture-the-engine-of-transformation/

Tortorella, G. L., Saurin, T. A., Hines, P., Antony, J., & Samson, D. (2023). Myths and facts of industry 4.0. *International Journal of Production Economics*, *255*, 108660.

Upadhyay, P., & Kumar, A. (2020). The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *International Journal of Information Management*, *52*, 102100.

Valmohammadi, C., & Roshanzamir, S. (2015). The guidelines of improvement: Relations among organizational culture, TQM and performance. *International Journal of Production Economics*, *164*, 167-178.

Verbeeten, F. H., & Speklé, R. F. (2015). Management control, results-oriented culture and public sector performance: Empirical evidence on new public management. *Organization studies*, *36*(7), 953-978.

Verbeke, W. (2000). A revision of Hofstede et al.'s (1990) organizational practices scale. *Journal of Organizational Behavior*, *21*(5), 587-602.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Dong, J. Q., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. *Journal of Business Research*, *122*, 889-901.

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, *28*(2), 118-144.

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020a). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics*, *222*.

Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2020b). Dynamics between blockchain adoption determinants and supply chain performance: An empirical investigation. *International Journal of Production Economics*, *229*, 107791.

Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2023). The role of artificial intelligence-enabled dynamic capability on environmental performance: The mediation effect of a data-driven culture in France and the USA. *International Journal of Production Economics*, 109131.

Wamba, S. F., Queiroz, M. M., & Trinchera, L. (2024). The role of artificial intelligence-enabled dynamic capability on environmental performance: The mediation effect of a data-driven culture in France and the USA. *International Journal of Production Economics*, *268*, 109131.

Weber, M. (1947). The theory of economic and social organization. *Trans. AM Henderson and Talcott Parsons. New York: Oxford University Press*.

Wessel, L., Baiyere, A., Ologeanu-Taddei, R., Cha, J., & Blegind-Jensen, T. (2021). Unpacking the difference between digital transformation and IT-enabled organizational transformation. *Journal of the Association for Information Systems*, *22*(1), 102-129.

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American journal of sociology*, *87*(3), 548-577.

Wong, C. Y., Boon-Itt, S., & Wong, C. W. (2011). The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance. *Journal of Operations Management*, *29*(6), 604-615.

World Economic Forum. (2023). *Digital Transition Framework: An action plan for public-private collaboration*. https://www.weforum.org/whitepapers/digital-transition-framework-an-action-plan-for-public-private-collaboration/

Yang, G., Nie, Y., Li, H., & Wang, H. (2023). Digital transformation and low-carbon technology innovation in manufacturing firms: The mediating role of dynamic capabilities. *International Journal of Production Economics*, *263*, 108969.
Yang, M., Fu, M., & Zhang, Z. (2021). The adoption of digital technologies in supply chains: Drivers, process and impact. *Technological Forecasting and Social Change*, *169*, 120795.
Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics*, *236*, 108135.
Zanon, L. G., Marcelloni, F., Gerolamo, M. C., & Carpinetti, L. C. R. (2021). Exploring the relations between supply chain performance and organizational culture: A fuzzy grey group decision model. *International Journal of Production Economics*, *233*, 108023.
Zeng, J., & Glaister, K. W. (2018). Value creation from big data: Looking inside the black box. *Strategic Organization*, *16*(2), 105-140.
Zhu, A. Y., Von Zedtwitz, M., Assimakopoulos, D., & Fernandes, K. (2016). The impact of organizational culture on Concurrent Engineering, Design-for-Safety, and product safety performance. *International Journal of Production Economics*, *176*, 69-81.
Zu, X., Robbins, T. L., & Fredendall, L. D. (2010). Mapping the critical links between organizational culture and TQM/Six Sigma practices. *International Journal of Production Economics*, *123*(1), 86-106.

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