

Research Repository

Leveraging Digital Transformation Strategy and Data-Driven Decision Making to Improve Organisational Performance in a Hostile Environment

Accepted for publication in Industrial Management and Data Systems.

Research Repository link: <https://repository.essex.ac.uk/41196/>

Please note:

Changes made as a result of publishing processes such as copy-editing, formatting and page numbers may not be reflected in this version. For the definitive version of this publication, please refer to the published source. You are advised to consult the published version if you wish to cite this paper.

<https://doi.org/10.1108/IMDS-10-2024-1039>

Leveraging Digital Transformation Strategy and Data-Driven Decision Making to Improve Organisational Performance in a Hostile Environment

Abstract

Purpose: This study examines whether and how a digital transformation strategy (DTS) can improve organisational performance (OP) when confronted with environmental hostility (EH) disruptions. Based on the Resource Base View, Dynamic Capability theories, and literature straddling digital transformation and organisational development, this study developed and tested a conceptual model consisting key elements and relationships between digital transformation strategy (DTS), business analytic capabilities (BAC), organisational agility (OA), data-driven decision making (DDM), organisational performance (OP) and environmental hostility (EH).

Design/methodology: The study is based on a quantitative cross-sectional design, using a survey sample of 309 respondents, working in mainly IT and different industry sectors in North America. Structural equation modelling was used and five hypotheses have been tested.

Findings: The results suggest that environment hostility has a negative effect on organisational performance, while DTS via business analytics capability and organisational agility enable Data Driven Decision (DDM) to enhance the organisational performance. The specific paths are uncovered - both digital capability and organisational agility drive dynamic capability development. DDM, in the form of decision automation by non-human entities and collective sense-making, leads to superior performance and reduces the impact of environmental hostility.

Originality/Value: The study contributes to the theoretical development of the dynamic capability framework from digital capability and organisational agility perspectives. The practical implications will support IT managers in designing IT strategies and agile practices that embed business analytic capabilities for data-driven decision making that increases organisational performance.

Keywords: Digital transformation, dynamic capability, data-driven decision making, organisational agility, environment hostility

1 Introduction

For organisations and individuals to prosper in the contemporary digital environment, advanced analytical capabilities, agile processes, and effective digital transformation strategies (DTS) are now indispensable (Omol, 2023). Yet, many businesses struggle to identify the right competencies and align their digital ambition to achieve desired performance outcomes. In contrast, firms that purposely invest in business analytical capabilities (BAC) appear more successful, not only in meeting their performance targets with agility but also in extending their performance objectives through first loop learning (Tosey *et al.*, 2012), and ongoing digital reconfiguration (Teece *et al.*, 2016a). These successes underscore the pressing question of how organisations can systematically leverage DTS, analytics, and agility to secure long-term competitiveness in a constantly evolving marketplace.

Recent industry insights underscore the complexities associated with digital transformation. For instance, Mirjam Johannes (2019) explores how leading companies have redefined their performance objectives by integrating digital initiatives and data analytics, thereby reaffirming their commitment to strategic digital capabilities. The phenomenon of businesses undergoing digital transformation raises critical questions about our understanding of strategic management processes, particularly regarding how environmental uncertainty influences business strategies, organisational structures, and decision-making, ultimately affecting performance outcomes. This multifaceted process aligns with foundational theories in strategy and organisational decision-making such as Ansoff's strategic management theory, Simon's administrative behavior theory, and theories related to organizational information processing and decision-making under uncertainty (Ansoff, 1964; Daft and Macintosh, 1981; Daft and Weick, 1984a; Geldof, 1988; Joseph and Gaba, 2020a; Simon, 1997). These theoretical perspectives highlight the dynamic interrelationships among the business environment, strategic formulation, decision-making (information processing), and organisational performance. Within the information systems (IS) domain, researchers continue to explore how these established relationships evolve amid digital transformation, particularly given the accelerated integration of AI technologies. Although existing IS research acknowledges Digital Transformation Strategies (DTS) as pivotal for enhancing organisational performance (OP) (Gu *et al.*, 2023), substantial knowledge gaps remain. These gaps include understanding the core attributes of DTS, notably in embedding analytics and agility (Omol,

2023), and clarifying how DTS effectively promotes data-driven decision-making (DDM) to elevate organisational performance. Additionally, environmental hostility (EH) introduces further complexity. Organisations frequently presume that their current DDM capabilities inherently lead to improved performance. However, the precise role and impact of EH on these capabilities and performance outcomes remain unclear, underscoring the need for deeper empirical investigation.

This lack of clarity calls for further scholarly attention to the intricate relationships among DTS, business analytics, DDM, organisational agility (OA), and performance. Addressing these gaps is vital not only for advancing theoretical discussions in IS but also for offering practical guidance to organisations grappling with the challenges of digital transformation strategies. Specifically, DTS should not be viewed as a one-time event (Hirschi and Sabherwal, 2001) or a mere endpoint of business strategy but as a continuous cycle of adjustment and improvement (Yeow *et al.*, 2018a). By constantly adapting to emergent opportunities, DTS enables market responsiveness and supports the cultivation of analytics competencies (Li *et al.*, 2021; Mikalef, Krogstie, *et al.*, 2020; Wang *et al.*, 2020a). These BAC, in turn, facilitate the storage, processing, and interpretation of data, which generate actionable insights (Wamba *et al.*, 2015), and transform how businesses produce and utilise data to meet performance goals (Ramanathan *et al.*, 2017). Indeed, BAC usage has demonstrated significant operational and strategic benefits across sectors such as retail, manufacturing, and services (Dubey *et al.*, 2017; Wamba *et al.*, 2017a). As these analytic insights bolster DDM, an agile organisational structure further supports rapid, adaptive action (Ashrafi *et al.*, 2019; Tim *et al.*, 2020), allowing a company to swiftly reconfigure processes in response to external risks (Tallon, 2007a). Notably, such agility is often underpinned by information technology capabilities (Chen *et al.*, 2014a), aligning with IS perspectives that emphasise IT role in strengthening an organisation's capacity to respond to uncertainty (Chen *et al.*, 2014a; Tallon, 2007a). These connections suggest that DTS can shape OP through the mediating influence of OA (Yeow *et al.*, 2018a).

Although scholarly work on BAC, OA, DDM, and EH individually is extensive, the IS literature is less clear on how these elements converge within innovative digital transformation initiatives. Notably, few studies tackle the intertwined relationships among these constructs or illuminate the mechanisms through which DTS shapes DDM and ultimately influences OP. To address this shortcoming, our research introduces a comprehensive conceptual framework that synthesises current understandings and examines the mediating roles of OA and BAC, as well

as the moderating influence of EH. Through this integrative lens, we aim to offer deeper insights into how organisations can orchestrate effective digital transformations. We empirically evaluate our model and its associated relationships, enriching the discourse on DTS, OA, BAC, DDM, and EH in relation to OP as a primary outcome.

Underpinning our conceptual model components are two complementary theoretical perspectives: dynamic capability (Teece et al., 2016b) and the resource-based theories (Bharadwaj, 2000a). These theories elucidate how organizations strategically mobilize unique resources and continuously adapt capabilities in response to environmental disruptions. DC underscores organizations' abilities to dynamically reconfigure resources to sense, seize, and transform opportunities amid uncertainty, directly impacting strategic decision-making processes and organizational performance. Concurrently, RBV highlights the strategic importance of rare, valuable capabilities such as business analytics and organizational agility, which underpin effective data-driven decision making (DDM). Moreover, incorporating DDM into our analysis is pivotal, as it operationalizes the insights from analytics and agility, enabling organizations to better navigate complex and hostile business environments to achieve superior performance outcomes. Specifically, DC theory accentuates how organisations continuously reconfigure and adapt their resources to emerging challenges in rapidly shifting markets, while the resource-based view highlights the strategic value of cultivating unique and inimitable resources—including digital expertise, analytic know-how, and agile processes—that confer competitive advantage. By applying these theories, we illuminate the processes by which DTS, and its allied capabilities, can be harnessed to bolster DDM and OP, particularly in volatile or hostile environments. This approach not only augments the theoretical richness of IS research but also offers pragmatic insights for managers and practitioners seeking to navigate the complexities of digital transformation. In summary, this study seeks to answer the following research questions:

RQ1: *How does an organisational DTS lead to DDM, which subsequently influences the OP?*

RQ2: *How do OA and BAC influence the relationship between DTS and DDM? and*

RQ3: *What is the impact of EH on the pathways of DDM and OP?*

The paper is structured as follows. Section 2 presents the literature review on the relationships between DTS and OP, DT and EH, value of DDM, and the relevance of RBV, DC and OA. Section 3 highlights the development of the hypotheses and illustrates the conceptual framework in the study, while section 4 outlines the methodology. Section 5

presents the analysis and findings, and Section 6 showcases the theoretical and practical implications, limitations and directions for future research. Section 7 concludes the study.

2 Theoretical Background

2.1 Digital Transformation Strategy and Organisational Performance

In recent years, digital transformation (DT) has emerged as a critical factor influencing organisational performance in today's business environment (Vial, 2019; Kraus *et al.*, 2022). It is defined as changes that are led and built on the foundation of digital technology, introducing distinctive innovation in corporate operations, procedures, and value generation (Chanas *et al.*, 2019; Ferreira *et al.*, 2019). Ever since the DT has emerged, organisations are either on the verge of stipulating their new digital transformation strategy (DTS) or revamping the existing ones. As the formulation and implementation of DTS has become a prime concern for many pre-digital organisations, the transformative impacts it brings, undeniably, steers an organisation's internal and external environments towards new digitally transformed horizons (Li *et al.*, 2021). Recent research has enhanced our understanding of the specific aspects of DT that relate to competitive performance and firm differentiation. Studies demonstrate that technology is only one piece of the complex puzzle that organisations must solve in order to remain competitive in the digital world, as well as changes to an organisation, including its structure and processes (Vial, 2019).

As organisations integrate advanced digital technologies into their business operations, the role of a well-defined digital transformation strategy has become paramount (Hess *et al.*, 2020; Rubio-Andrés *et al.*, 2024). The relationship between DTS and organisational performance is multifaceted, involving change through strategic alignment, resource allocation and the integration of digital technologies into core business processes (Hess *et al.*, 2020; Kraus *et al.*, 2022; Zhang *et al.*, 2023). Bharadwaj *et al.* (2013) emphasise the scope, scale, speed and value generated from a digital transformation strategy enabling organisations to innovate, streamline processes and engage with customers in new ways. A digital transformation strategy allows firms to optimise their resource allocation, improve decision-making processes, and restructure business models for growth (Liu *et al.*, 2011; Bharadwaj, 2000). These efforts contribute to organisational performance by fostering higher levels of effectiveness, specifically in the economic, human resources and internationalisation dimensions (Rubio-Andrés *et al.*, 2024). Thus, scholars underline the need for a coherent DTS

to effectively leverage innovative technologies and manage the associated changes (Zhang *et al.*, 2023).

While scholars offer a resource-based framework that is imperative for an effective DTS (Liu *et al.*, 2011; Chen *et al.*, 2016), others underscore the need for organisations to define and implement clear digital transformation strategies that align with their business models to meet the challenges of the digital age (Korachi and Bounabat, 2020). This alignment is crucial to ensure that digital initiatives are not merely technological upgrades but are integrated into the strategic framework of the organisation. Some organisations struggle to align their DTS with broader business objectives and business models due to inadequate strategy implementation (Correani *et al.*, 2020). This highlights the importance of designing a robust DTS and ensuring its effective execution across the organisation. Halim *et al.* (2023) further echo that organisations with mature digital transformation strategies achieve better performance outcomes by focusing on specific technological goals. Thus, by identifying strategies through the utilisation of technologies such as data analytics, artificial intelligence, cloud computing, and the Internet of Things, research suggests that organisations with defined and comprehensive digital transformation strategies tend to achieve better performance (Halim *et al.*, 2023). Moreover, studies highlight that digital transformation strategies must evolve in response to external pressures, including technological and environmental contexts, (Ivanova *et al.*, 2023). The iterative nature of a DTS allows organisations to remain agile and responsive to market changes, thereby enhancing their overall performance (Ivanova *et al.*, 2023). Other studies display that digital transformation of firms involves changes in organisational structure, but also strategic shifts that enhance organisation performance (Tsou and Chen, 2023). This transformation is driven by internal capabilities and external market demands, underlining the need for a strategic approach to digital initiatives. Furthermore, Teng *et al.* (2022) assert that investing in novel digital technologies and formulating digital transformation strategies are vital for improving performance and sustainable growth.

Hence, the relationship between digital transformation strategy and organisational performance is characterised by change, or the necessity of strategic alignment, resource allocation, capabilities, and effective implementation of business models. Organisations that prioritise the development of a comprehensive DTS are better positioned to enhance their organisational performance in an increasingly digital marketplace.

2.2 Digital Transformation and Environmental Hostility

In recent years, EH has subjected organisations to resketch their strategies, including DTS, and re-consider their capabilities, particularly, agility to cope with unprecedented environments. According to Chen et al., (2014a), EH may include a range of unprecedented outcomes, but not confined to societal and political instability, natural disasters, unpredictable and unfavourable market conditions, technological innovations, and the diverse scope of an industry or an organisation's activities. Recent unprecedented disruptions have exacerbated pressure in numerous industries causing businesses to grapple with a variety of concerns, most notably regarding supply and demand (Zhang et al., 2015). As a result, this subject has never previously garnered such widespread interest and relevance for strategic management and decision-makers. It is noted that the disruption has both direct and indirect consequences on upstream and downstream transactions, depending on the industry and the function of the firm in the value chain (Dwivedi *et al.*, 2020).

Many businesses have attempted to respond to these unexpected conditions by leveraging a digital transformation plan or strategy for change, either by redesigning organisational processes with a digital focus, or by redefining traditional roles to be more digitally oriented (Ivanova et al., 2023). However, the impact of unprecedented disruptions on firms varies; depending on the degree of digitisation and the role of digital technology in value generation (Constantiou and Kallinikos, 2015). For some firms, EH may expedite strategic management to deploy a DTS that comprises of business analytic tools coupled with OA for managers to make decisions based on data to enhance organisational performance. On the contrary, firms that lack OA and other capabilities including BAC, may not swiftly respond to the effects of their hostile environment due to decisions based on intuition rather than data to boost performance in firms (Duan *et al.*, 2019a).

Without any doubt, one of the most crucial problems confronting businesses as they respond to EH is making the correct decision at the right time for the correct reasons. The ability of emerging technologies has enormous potential to execute routine tasks and DDM (Duan et al., 2019; Xu et al., 2022). It is evidenced that firms which embed digital capability tools showcase higher resilience, as digital technologies are flexible and adaptable strategic tools (Constantiou and Kallinikos, 2015). Especially, BAC as a strategic resource, may enable decision-makers to make the most effective and efficient choice under hostile conditions. Thus,

the relationship between DDM and performance can become more significant under hostile conditions. In addition, research indicates that even though firm-wide IT capability presents the characteristics of rarity, appropriability, non-reproducibility, and non-substitutability, its impact on organisational performance is fully mediated by business process agility (Chen et al., 2014; Chen et al., 2016). So, although research has established the overall benefits of IT competence on OP (Chen et al., 2014; Chen et al., 2016), the knowledge on the procedures by which these advantages are realised within a disruptive business environment are limited (Duan *et al.*, 2019a). Therefore, EH can have a moderating impact of DDM on OP, as organisations with advanced business analytics and OH may withstand adverse disrupting forces, and potentially exploit the opportunities for enhanced performance. Thus, the study focuses on environmental hostility (EH) as a particular external factor or moderator that can impact organisational performance.

2.3 The Value of Data-Driven Decision Making (DDM)

Data-driven decision making (DDM) is defined as the practice of basing decisions on the analysis of data rather than purely on intuition (Delen and Zolbanin, 2018). While data science involves principles, processes, and techniques for examining phenomena via data analytics, this improves decision making and is of paramount interest to organisations (Provost and Fawcett, 2013). For example, a marketer could select advertisement based on their vast experience and purely on their intuition of what will work, or they could base their decision on the analysis of data relating to how consumers react to different marketing campaigns. However, studies exhibit that decisions based on individual's knowledge are prone to error (Korherr et al., 2022). Building on these insights, business analytical models have emerged as a distinct factor in competitive business environments to drive data-driven decision making (Duan et al., 2019; Shamim et al., 2020; Yalcin et al., 2022). Other research highlights the fundamental capabilities required to apply analytics in the decision-making process. For example, scholars investigated the operational capabilities (Mikalef *et al.*, 2019a), organisational capabilities (Mishra *et al.*, 2019), data-related capabilities (Côte-Real *et al.*, 2017) and data analytics capabilities (Elgendy and Elragal, 2016; Gupta and George, 2016a) to pave way for future research to determine how business analytic capabilities effect on DDM for increased organisational performance.

The literature predominantly establishes that firms translate the potential of big data analytics into business value and improved performance (Gupta and George, 2016; Perdana et

al., 2022; Wamba et al., 2017). This implies that firms must invest in and develop strong business analytic capabilities to realise performance gains which involves the configurations of resources and contextual factors (Mikalef *et al.*, 2019a). Similarly, Gupta and George (2016) validate the relationship between business analytic capabilities and organisational performance drawing on the resource-based view. They highlight the importance of human skills for leaders. However, such studies have not taken organisational traits into consideration such as OA, or how DDM acts as a mediator between DTS and organisational performance. Although scholars apply a knowledge-based and dynamic capabilities view to study how and to what extent big data analytics disrupts the process of board level DDM, the findings do not establish the relationship between DDM and organisational performance (Merendino *et al.*, 2018). Hence, it is vital to study how DTS that features OA and BAC, leads to DDM for increased OP. Other scholars argue that business analytic capabilities affect a firm's ambidexterity and agility, which then affect its performance. Hence, these findings highlight that ambidexterity and agility mediate a positive relationship between business analytic capabilities and a firm's performance (Rialti *et al.*, 2019). However, it is not reported how organisational agility and BAC both account for performance gains through DDM. In addition, studies report that BAC provides business value to several stages of the value chain by creating organisational agility through knowledge management. Agility is seen to partially mediate the effect between knowledge resources and performance (Côte-Real *et al.*, 2017). Moreover, studies examine how data can add value to organisational decision-making within different industries and contexts (Mikalef, Boura, *et al.*, 2020). Furthermore, the use of data analytics in business decision-making processes mandates a paradigm shift within organisations at the strategic level (McAfee and Brynjolfsson, 2012). Studies examine managerial roles and success factors that demonstrate actionable guidance on how to manage the shift to DDM. This validates our claim that a digital transformation strategy toward business analytics may help in the execution of DDM processes (Korherr et al., 2022).

So far, studies offer generalised concepts pertaining to the general implementation of big data analytics (Ciampi *et al.*, 2021). In order to address these gaps, we require empirical evidence to illustrate how BAC and OA facilitate data-driven decision-making. While the use of data analytics for data-driven decision-making is increasing in organisations, the role of OA is crucial to drive DDM under a clear and comprehensive DTS. Hence, the novelty in this study lies in examining how organisational traits, such as BAC and OA, feed into DDM for enhanced organisational performance under the moderating effect of environmental hostility.

2.4 Resource-based View and Dynamic Capability Theory

In the literature, we observe that DT straddles two theoretical fields - IT strategy and organisational capabilities. The former concerns with the ability to mobilise and deploy IT based resources as a source of competitive advantage (Chen et al., 2014; Chen et al., 2016). However, the latter relates to dynamic capabilities and changes leading to sustained survivability and prolonged performance. Researchers have sought to hypothesise a relationship between the capabilities of big data and predictive analytics (BDPA) and corporate competitiveness (Mikalef *et al.*, 2019b). Akter et al., (2016) examined the effect of resources and BDPA capability on OP, but their study did not take EH into account. Despite the growing body of research on the analytic potential of big data, the IS literature does not provide any clear explications on how IT capability translates into BAC that influence OP. Empirical studies leading to this conceptualisation remain scarce (Akter et al., 2016; Gupta and George, 2016; Mikalef et al., 2019a; Wamba et al., 2017; Yeow et al., 2018).

This study draws on two theoretical perspectives when developing the conceptual model, specifically, the resource-based view (RBV) and the dynamic capabilities (DC) theory. These two theories form the basis of our conceptual model for examining the relationship between digital transformation strategy and organisational performance due to their emphasis on internal resources and the adaptive capabilities of firms in competitive and rapidly changing environments.

2.4.1 The Resource-based View (RBV)

The RBV theory suggests that resources that are valuable, scarce, imperfectly imitable, and non-substitutable are sources of prolonged competitive advantage. These resources enable a more intimate integration of a diverse range of organisational, social, information technology, and personalised phenomena within enterprises. Extant research has essentially discounted company's resource heterogeneity and immobility as potential sources of competitive advantage. Thus, the resource-based view of the firm presents two different views about analysing the sources of competitive advantage (Barney, 2001). This view assumes that strategic resources are heterogeneously distributed across firms and these differences are stable over time, and hence heterogeneity can be long-lasting (Barney and Hesterly, 2012). The RBV assumes that higher business performance is due to company specific resources and skills that are scarce and difficult to copy (Chen et al., 2016). With the reference to technology in leading

and supporting business strategies, researchers have consistently emphasised the importance of IT as a key organisational resource for driving digital innovation (Nwankpa and Roumani, 2016). Scholars predict that outcome variations in OP can be explained by how IT capability leverages the value of other resources and capabilities within the organisation (Radhakrishnan *et al.*, 2008). Moreover, studies highlight that the ability to mobilise and deploy IT-based resources, via digital transformation, can lead to competitive advantage (Nwankpa and Roumani, 2016) and improved company performance. However, researchers have recently argued that the RBV alone cannot explain for competitive advantage and that 'decision-maker's attention' should be included in the standard model (Bhandari *et al.*, 2022).

One of the emerging digital technologies, business analytics, has been regarded as a new generation of tools and architectures designed to economically extract value from very large volumes of diverse data through analytics (Mikalef *et al.*, 2019b). A data-driven culture and organisational learning become critical resource components for effective analytical capabilities deployment (Mikalef *et al.*, 2019b). RBV underlines managers' limitations in manipulating all business qualities (Barney, 2001) in making some firm's resources imperfectly imitable, and hence, potential sources of competitive advantage. It is reported that other organisational resources and a continuous learning approach also make business analytics a success (Mikalef *et al.*, 2019b; Mikalef and Pateli, 2017) given the innovative technology landscape. In this study, business analytics is considered as a valuable IT resource that can indirectly influence DDM within a firm. We use the term 'business analytic capabilities' (BAC) in the conceptual model in the same way as IT resource of the RBV, but focus on BAC that leads to DDM which improves OP, especially in hostile environments. The rationale for using the RBV assumes that BAC, is a valuable IT resource, embedded within the DTS to influence DDM that steers organisational performance. By fostering valuable resources within the organisation, firms are more likely to execute successful DT that result in enhanced performance.

2.4.2 The Dynamic Capability (DC) Theory

The dynamic capabilities (DC) theory provides a powerful lens for studying strategic change in turbulent environments (Schilke and Helfat, 2018). The early work on dynamic capability by (Teece *et al.*, 1997) attribute to 'the ability to integrate, build, and reconfigure internal and external competencies for addressing rapidly changing environments' (Teece *et al.*, 2016). DC requires the processes and routines to be continually reviewed and adapted in

order to ensure their suitability to the level of environmental dynamism in the organisation's economic ecosystem (Teece, 2014, 2019). The three clusters of DC processes; sensing (scanning), seizing, and, reconfiguration is directly relevant to the design of this study.

The sensing capabilities - the ability to learn and to make contextual sense of new knowledge, to both the managers and the organisation, may be enhanced by data analytics capability, hence leading to data-driven decision making. Akter et al. (2016) claim that big data analytics provide a competitive advantage to an organisation in highly dynamic settings. The seizing process is to make the necessary decisions at the appropriate time to realise the full potential of the opportunity. The reconfiguration process comprises of transformation and change management through continuous alignment and realignment of the organisation's resources- both tangible and intangible (Sharma *et al.*, 2014). Managers regularly decide how to update existing operational capabilities into new ones that better match the changing environment (Mikalef *et al.*, 2019b; Mikalef and Pateli, 2017). There is a general consensus that capabilities function in various ways and influence diverse levels of competitive advantage and organisational performance based on a plethora of internal and external circumstances (Drnevich and Kriauciunas, 2011). This suggests that organisations must be stable enough to continue to deliver value in their own distinctive way, while staying agile enough to adapt and restructure their value propositions when circumstances demand changes.

Uncertainty and volatility in the market place may degrade operational capabilities and cease to give competitive advantages (Drnevich and Kriauciunas, 2011). Thus, for firms to be operating in a turbulent environment, emphasis should be on increasing the dynamic capacity and continuously readjusting operating capabilities by (a) detecting and shaping opportunities and threats, (b) taking opportunities and (c) preserving competitiveness by merging, protecting, and reconfiguring its intangible and tangible assets (Teece *et al.*, 1997). This requires a shift towards data analytics and DDM to be successful. Despite critique on dynamic capabilities theory being characterised as an elusive black box (Pavlou and El Sawy, 2011) which makes it difficult for managers to make solid judgments in unstable situations, Warner and Wäger (2019) evidenced how digital technologies drive organisations to establish dynamic capabilities that help them update the business model, collaborative approach, and culture. Other scholars argue that aligning a firm's digital strategy involves sensing, seizing, and reconfiguration of capacities, and their associated activities (Yeow *et al.*, 2018b).

Business Analytic Capabilities (BAC) and Organisational Agility (OA)

In this study, BAC is perceived as a dynamic capability from a digital transformation perspective, i.e. a firm's powerful capacity to effectively deploy technology and expertise to acquire, store and analyse data, including the processes that drive changes in sensing and seizing that lead to data-driven decision making. The literature shows that digital transformation capabilities may potentially steer organisational performance objectives through agility (Ashrafi *et al.*, 2019). Digital transformation, as part of developing a firm's dynamic capabilities, requires organisational agility (OA) (Chen *et al.*, 2014b). OA is almost synonymous with flexibility (Teece *et al.*, 2016), and defined by Winby and Worley (2014) as 'a cultivated capability that allows the organisation to make timely, effective and sustained change when changing circumstances require it'. Scholars recognise OA as a capability of leadership to dispense with established decision-making rules and procedures (Helfat and Martin, 2015; Helfat and Peteraf, 2015). Chen *et al.* (2014) also refer agility as the ability to sense and respond to changes rapidly to enhance organisational performance in rapidly changing environments. However, it should be noted that being agile is not a one-size-fits-all approach, and agility is context-dependent. It can be achieved only in accordance with the business environment and firms can mitigate risk by other means (Teece *et al.*, 2016).

Hence, drawing on the definition above, OA is perceived as a dynamic capability and characterises the ability to sense opportunities and threats, making decisions to change the organisations resource base and solve problems. Agile organisations must support creativity and efficiency, and must possess all four routines; strategizing, perceiving, testing and implementing that confers agility and sustains performance. A few studies examined the mediating effect of agility on organisational performance. Van Oosterhout *et al.* (2017) report that OA is seen to partially mediate the effect between knowledge resources and performance. Rialti *et al.* (2019) suggest that a firm's ambidexterity and agility have a positive mediating effect on performance.

Viewing agility from business process point of view, research reveals - how rapidly organisations can retool their business processes to respond to changing market conditions (Tallon, 2007; Wang *et al.*, 2020). Business process agility is a key factor for explaining inter-firm performance variance across time (Van Oosterhout *et al.*, 2017; Raschke, 2010). Agility in business processes allows organisations to quickly modify existing processes and build new processes to take advantage of variable markets (Raschke, 2010). In this study, the DC

perspective extends RBV by focusing on the organisation's ability to adapt, integrate and reconfigure its resources – that is BAC and OA – as key dynamic resources in response to changes in the environment. DC is critical because digital technologies evolve rapidly, requiring organisations to respond and continuously reshape their resources and capabilities to stay competitive in times of environmental hostility. Hence, when applied together RBV and DC offer a comprehensive framework for examining how DTS can enhance OP. While RBV identifies the internal resources (BAC) that can be utilised for digital initiatives, DC highlights the processes that allow firms to adapt these resources (BAC and OA) to the changing digital landscape. Together, they provide a roadmap for organisations seeking to align their resources with DTS, ensuring they are agile in the face of environmental disruption.

Informed by the DC theory and the research on OA linking to OP, we consider OA as a key feature that affects DDM for sustained OP. Hence, our conceptual model includes both BAC and OA, belonging to the organisation's DTS for effective DDM, to enhance organisational performance, which is depicted in Figure 1.

3 Conceptual Model Development and Hypotheses

Drawing from the literature reviewed, a conceptual model has been developed as shown in Figure 1. The strategic management process i.e. strategy-structure (concerning decision making specifically in this study) - performance informs the overall relationship, and the five variables and their possible effects are identified from the literature and the two related theories - resource-based theory (RBT) and dynamic capabilities (DC). These variables include business EH, DTS, BAC, OA, DDM and OP. Their relationships and the underpinnings need further elaboration. The ensuing sub-section elucidates the academic and factual reasoning of the possible relationships, based on which five hypotheses have been formulated.

3.1 Digital transformation strategy and data-driven decision making

Rapid advances in digital technologies and data analytics have profoundly transformed numerous industries (Hsiao, 2024; Vial, 2019; Wamba *et al.*, 2017c). In response, many organisations have radically revised their digital transformation strategies (DTS) by integrating these emerging technologies into core strategic processes (Correani *et al.*, 2020). Digital transformation, is not only about technology and disruption, according to Rogers (2016), DT comprises of five domains - customer, value, data (asset), innovation and competition, which are transformed in incremental and disruptive ways. A DTS concerning the five domains

requires changes in the organisational process and structure for effective implementation. For instance, a change from traditional intuitional decision making to data driven decision making. Studies indicate that data-driven strategies lead to more informed and adaptive decision-making, as managers have access to higher-quality, real-time information (Lismont *et al.*, 2017a; Rouhani *et al.*, 2016; Wamba *et al.*, 2017a). Joseph and Gaba (2020b) suggest that recent advances such as big data, machine learning, and natural language processing methodologies offer substantial opportunities to more directly capture the decision-making implications of common maps. The DTS will set the strategic direction and new protocol of information processing and decision making.

Drawing on the Resource-Based View (RBV) (Bharadwaj, 2000b), such digital and analytic capabilities constitute valuable, rare, and inimitable resources that can confer a competitive edge. By harnessing data analytics to gather timely and relevant information, firms enhance their strategic decision-making processes, thus strengthening their long-term advantage. From a Dynamic Capability perspective (Teece *et al.*, 2016a), DTS represents the capacity to continually reconfigure digital resources and analytic competences to respond to evolving market conditions. Dynamic capabilities undergird firms' ability to deploy and reconfigure key resources—such as IT infrastructure and data management systems—so they can better sense, seize, and transform emerging opportunities (Correani *et al.*, 2020). Taken together, these insights suggest that organisations with well-developed DTS, grounded in robust analytics, can elevate their decision-making processes to achieve superior performance. Combining the RBV rationale—emphasising the strategic value of unique digital resources—and the dynamic capability lens—highlighting the continuous reconfiguration and renewal of those resources—provides a solid theoretical foundation for arguing that DTS positively influences data-driven decision-making (DDM). Hence, we propose the following hypothesis:

Hypothesis 1: Organisational DTS positively influences its DDM.

3.2 Data-driven decision making and organisational performance

Scholars have long proposed that data-driven decision-making (DDM) exerts a positive influence on organisational performance (McAfee and Brynjolfsson, 2012b; O'Reilly and Tushman, 2008; Seddon *et al.*, 2017; Wamba *et al.*, 2017a). From a Resource-Based View (RBV) perspective (Bharadwaj, 2000b), DDM can be seen as a valuable and difficult-to-imitate resource, integrating specialised analytics tools and expertise that bolster an organisation's competitiveness. Meanwhile, Dynamic Capability theory (Teece *et al.*, 2016b) suggests that

the ability to continually sense, seize, and transform resources—including data and advanced technologies—enables firms to adapt more effectively to environmental changes. In this light, advanced systems like artificial intelligence (AI) and machine learning (ML) not only automate routine decisions but also enhance managerial decision-making by providing robust insights that reduce uncertainties and complexities (Xu, Duan, Cao, *et al.*, 2022; Xu, Duan, Ong, *et al.*, 2022).

Recent disruptions across sectors such as education, health, and retail confirm the strategic role of DDM in reshaping business models for greater agility, particularly in supply chains (Dwivedi *et al.*, 2020). As organisations harness big data analytics, algorithms, and machine heuristics to inform strategic choices, they become better positioned to achieve improved sales growth, profitability, return on investment, return on equity, market share, and market value. Hence, by bringing together the RBV focus on strategic resources and the dynamic capabilities emphasis on continuous resource reconfiguration, it becomes evident that DDM can serve as a key driver of sustained performance gains. Hence, based on the above, the following hypothesis is posed:

Hypothesis 2: Organisational DDM positively influences OP

3.3 Business analytics capabilities and organisational agility

The strategic digital transformation (DT) paradigms (Vial, 2019; Wang *et al.*, 2020c) consistently emphasize that data analytics, organisational capabilities, and agile systems contribute significantly to organisational performance (Ashrafi *et al.*, 2019; Chen *et al.*, 2014a; Wamba *et al.*, 2017c). The two variables BAC and OA here are considered as necessary conditions to enable data driven decision making, hence, posited as two important mediators in the conceptual model. Drawing on the Resource-Based View (RBV) (Bharadwaj, 2000), business analytic capabilities (BAC) can be viewed as unique, valuable, and inimitable organisational resources that facilitate day-to-day data-driven decision-making (DDM). Such capabilities include forecasting, value proposition generation, and the redefinition of value networks, all of which can reshape interactions with suppliers and customers while improving organisational agility (OA) (Vial, 2019). Extant literature further indicates that BAC can help firms gain competitive advantage by enabling richer analytical insights (Delen and Zolbanin, 2018; Nam *et al.*, 2019). In practice, BAC is shown to hold a strong mediatory power between an organisation's digital transformation strategy (DTS) and its performance when decisions are data-driven (Torres *et al.*, 2018). Hence, BAC stands as a key intervening resource,

underscoring the RBV logic that strategic resources underpin enhanced organisational outcomes.

Parallely, from a Dynamic Capability perspective (Teece *et al.*, 2016b), agility serves as an essential mechanism for sensing and responding to continual market shifts. It is essentially adaptation (Joseph and Gaba, 2020b) capability - how organisations adapt by adding, redeploying, recombining, or divesting knowledge and resources to achieve efficiency, to explore new opportunities, and to innovate. The literature shows that agility supports organisational performance objectives (Ashrafi *et al.*, 2019; Chen *et al.*, 2014a; Sharma *et al.*, 2014) and is strengthened when digital transformation capabilities are effectively leveraged (Chen *et al.*, 2014a; Tallon, 2007a). Indeed, an organisation's DTS can influence its decision-making efficacy and overall performance through the mediating role of OA (Tallon, 2007a; Yeow *et al.*, 2018a). Firms adopting a DTS that integrates agile systems and processes can rapidly adapt to environmental changes, enabling managers to make timely, fact-based decisions (Li *et al.*, 2019; Wang *et al.*, 2020c). For instance, Dubey *et al.*, (2014) reveal that organisations addressing customer demands in supply chain management rely on agility to quickly align their operations with shifting requirements, while Kitchens *et al.*, (2018) highlight agility's extended role in strategy formulation and digital innovation. Although existing agility literature has mostly focused on infrastructure and cultural enablers for rapid response, agile systems can also bolster decision-making processes, allowing for prompt reconfiguration of resources and distributed, evidence-based decisions.

By synthesising RBV—which spotlights the strategic significance of analytics as core organisational resources—and dynamic capability theory—which emphasises the continuous reconfiguration of these resources to address dynamic market conditions—we suggest that both BAC and OA serve as essential mediators between DTS and decision-making effectiveness. Therefore, integrating these theoretical lenses offers a robust framework to understand why the successful adoption of DTS ultimately hinges on the intervening roles of analytic and agile capabilities. Based on this reasoning, we propose the following hypotheses:

Hypothesis 3: BAC mediate the relationship between organisational DTS and its DDM.

Hypothesis 4: OA mediates the relationship between DTS and its DDM.

3.4 The moderating role of environmental hostility

In general, the business environment comprises two key dimensions—dynamics and complexities—that shape organisations' strategic and operational choices. The degree of

uncertainty, along with the specific responses to environmental fluctuations, influences organisational performance (OP). Although classic strategic management literature concentrates on how organisations respond to environment uncertainties (Daft and Weick, 1984b), this study focuses on environmental hostility (EH) as a particular external factor that can negatively impact performance. As Chen et al., (2014a) note, EH can take many forms, including societal and political instability, natural disasters, unpredictable market conditions, novel technological advancements, and the diverse scope of an industry or an organisation's activities. In principle, higher EH can erode firm performance (Zhou *et al.*, 2019) by imposing greater costs and difficulties in responding effectively.

From the perspective of the Resource-Based View (RBV) (Bharadwaj, 2000b), firms with robust analytics, agility, and data-driven decision-making (DDM) possess valuable, rare, and inimitable resources that could mitigate the adverse effects of a hostile environment. Simultaneously, Dynamic Capability theory (Teece *et al.*, 2016b) highlights that these capabilities allow organisations to sense emerging threats and reconfigure assets quickly, enabling a more resilient and adaptive response to external turbulence. Despite limited direct empirical evidence, there are real-world examples—such as Amazon leveraging consumer data insights during the COVID-19 crisis—suggesting that when EH intensifies, it may prompt an even stronger reliance on DDM (Dwivedi *et al.*, 2020). As a result, the relationship between DDM and performance can become more pronounced, rather than diminished, under hostile conditions. Therefore, we posit that EH positively moderates the impact of DDM on OP, such that organisations equipped with advanced analytics and agility can not only withstand adverse external forces but also potentially convert them into opportunities for improved performance. Hence, we pose the following hypothesis:

Hypothesis 5: *EH moderates the relationship between DDM and OP; such that, higher the EH the stronger the relationship and vice versa.*

The key variables generated from the literature and theories, help us build our conceptual model and hypothesise the possible relationships, as depicted in Figure 1.

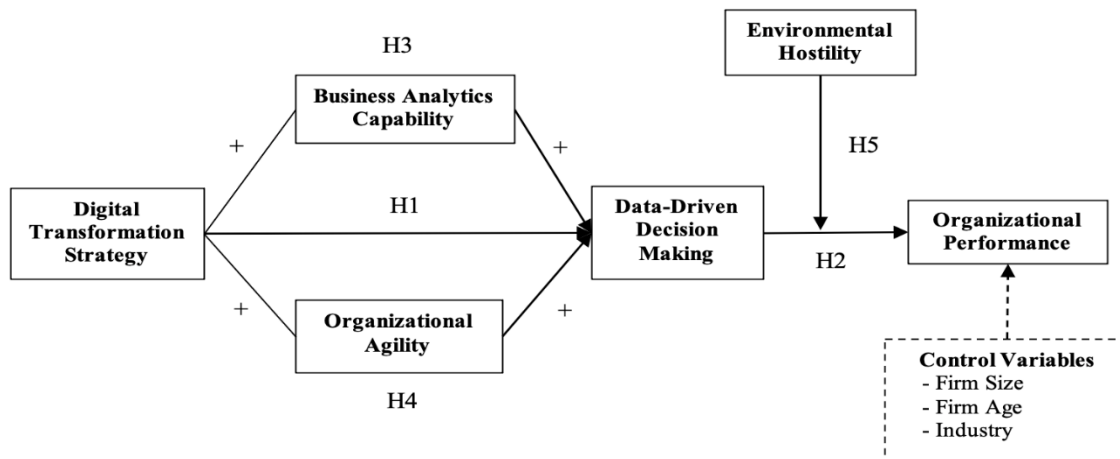


Figure 1: Conceptual model

4 Methodology

To test the conceptual model (Figure 1), data was collected online from the North American region, a well-known hub for digital transformation due to the presence of globally recognized industries and technology clusters. The selection of this region aligns with the study's objectives, as organisations in this area have undergone significant digital transformation over the years, providing a suitable environment for examining the proposed model. Collecting data from respondents within this region enhances the study's focus on digitally mature organisations, which are likely to have more advanced business analytics capabilities and data-driven decision-making practices. However, we acknowledge that this geographic focus may limit the generalizability of the findings to regions with different technological infrastructures or market conditions. Future research is encouraged to extend this model to diverse geographical settings to validate its broader applicability.

Additionally, consistent with the literature (AlNuaimi *et al.*, 2022; Colli *et al.*, 2018; Van Veldhoven and Vanthienen, 2022), organisational size, age, and type are important predictors of digital transformation adoption and maturity stages. Therefore, this information was collected to facilitate subgroup analyses and provide a comprehensive understanding of the varying impacts of digital transformation strategy across different organisational contexts. Furthermore, as ICT-based firms are often at the forefront of digital transformation in pursuit of higher organisational performance goals, the inclusion of this industry type adds variability to the dataset and supports the robustness of the analysis.

4.1 Survey Instruments and Pre-Testing

The scales to measure the six underlying latent constructs (i.e. DTS, BAC, OA, DDM, OP, and EH) have been adopted from the established literature. DTS has been measured using six items based on the scales adapted from (Aral & Weill, 2007; Liu et al., 2013; Nwankpa & Roumani, 2016). Five items to measure BAC have been adapted from Ashrafi et al. (2019). DDM has been measured using six items adapted from (Cao *et al.*, 2015). OA, OP, and EH have been measured by eight, four and five items each based on the scales adapted from Chen et al., 2014. The initial selection of items to measure latent constructs were reviewed by a team of six academics and non-academic experts to assess the content validity of the scale (Anderson and Gerbing, 1988; Gerbing and Anderson, 1988). For providing adequate context of the respondents and possible sub-group analysis, the survey instrument also included questions related to respondents' demographics, such as gender, education, position, industry type, firm age, firm size, experience etc. The final instrument was prepared incorporating the feedback from the expert review team which helped in improving the structure and readability of the questionnaire. The items used to measure latent constructs are presented in the web appendix.

4.2 Sample characteristics/ industry or respondent?

The sample comprised of respondents working in different industry sectors that included a large portion (42%) of ICT companies from the north America continent. Mainly, there were small medium enterprises (SME) (52.8%) and large companies (35.6%) according to the size (this does not make up 100%). Ethical approval was undertaken and granted by the institution to ensure the confidentiality and privacy of respondents and security of data. All data was stored in password protected files on personal laptops. Respondents were asked to provide their consent and were provided a participant information sheet outlining the research study.

The sample profile is presented in Table 1 below:

Table 1 Sample characteristics

Measures	Items	Frequency	Percent
Gender	Male	215	69.6
	Female	94	30.4
Age (Years)	21 – 30	141	45.6
	31 – 40	112	36.2

	41 – 50	37	12
	More than 50	19	6.1
Education	Undergraduate or below	128	41.4
	Postgraduate or above	181	58.6
Role	Senior management	88	28.5
	Middle Management	221	71.5
Tenure (Years)	< 6	93	30.1
	6-10	132	42.7
	More than 10	84	27.2
Industry Type	ICT	130	42.1
	Hospitality	15	4.9
	Health and Safety	47	15.2
	Education	28	9.1
	Bank and Financial services	42	13.6
	Construction	22	7.1
	Others	25	8.1
Organisation Size	Below 50	36	11.7
	50 – 249	163	52.8
	250+	110	35.6
Organisation Age	Less than 5 years	33	10.7
	5-10 years	119	38.5
	More than 10 years	157	50.8

N=309

5 Data analysis and results

PLS-SEM is regarded as a more appropriate technique as compared to covariance-based Structural Equation Modelling (SEM) (Diallo *et al.*, 2018; Hair *et al.*, 2017). Using SmartPLS 4.0, the data has been analysed following a variance-based partial least squares (PLS) structural equation modelling (SEM) approach (Hair *et al.*, 2017). The data analysis was conducted in two phases: the psychometric features of the scale were validated through employing measurement model, and then, using a structural model, the hypothesized relationships were examined.

5.1 Scale reliability, validity, and common method variance

Cronbach's alpha and rho_A were used to measure internal consistency and composite reliability, and rho established the reliability and validity of the scales. The Cronbach's alpha values and the composite reliability values for each of the latent constructs were significant over the required level of 0.70 (Hair *et al.*, 2017). In addition, the average variance recovered for each construct was above the required threshold of 0.5, demonstrating the scale's convergent validity (Fornell & Larcker, 1981). Table 2 summarises the reliability and validity statistics.

Table 2 Reliability and validity statistics

Constructs	Cronbach's alpha	Composite reliability (rho_A)	Average variance extracted (AVE)
DTS	0.883	0.887	0.682
BAC	0.869	0.870	0.656
OA	0.887	0.890	0.689
DDM	0.830	0.841	0.596
EH	0.885	0.959	0.675
OP	0.860	0.861	0.705

Note: DTS: DTS; BAC: BAC; OA: Organisational Agility; DDM: Data-Driven Decision Making;

Next, the scale was tested for discriminant validity by using (Fornell & Larcker, 1981) and (Henseler *et al.*, 2015) methods, since it applies to both simultaneously. To establish discriminant validity, (Fornell & Larcker, 1981) argued that the average variance extracted for each construct be greater than the corresponding shared variances. Whereas, (Henseler *et al.*, 2015) suggested that the HTMT values for each construct should not exceed 0.85. The square root of the AVE values for each underlying construct is greater than the inter-construct correlations, as shown in Table 3. In addition, the HTMT for none of the constructs exceeds 0.85. Consequently, the discriminant validity of the scale is established by both of these criteria.

Table 3 Discriminant validity

	DTS	BAC	OA	DDM	EH	OP
DTS	0.826	0.533	0.421	0.575	0.061	0.536
BAC	0.469	0.810	0.505	0.645	0.151	0.569
OA	0.377	0.446	0.830	0.575	0.089	0.493
DDM	0.495	0.558	0.500	0.772	0.099	0.642
EH	0.038	0.136	0.070	0.074	0.821	0.186
OP	0.470	0.491	0.434	0.555	0.181	0.840

Note: DTS: DTS; BAC: BAC; OA: Organisational Agility; DDM: Data-Driven Decision Making; EH: EH; OP: Organisational Performance; the diagonal numbers reflect the square root of the AVE, whereas the values below the diagonal indicate inter-construct correlations and the ones above the diagonal represent HTMT correlation ratios.

After verifying the psychometric characteristics of the scale, a structural regression model was utilised to derive the estimates for the underlying connections in the conceptual model. While it is hard to completely rule out the influence of common method bias in single-source cross-sectional designs, adequate ex-ante and ex-post measures may considerably reduce the impact (Guide and Ketokivi, 2015; Podsakoff *et al.*, 2003). To minimise the impact of a possible common method bias, various *ex-ante* (e.g., using a well-established scale to measure each of the latent constructs; pretesting the measurement instruments; randomising the order of questions; assuring the respondent of the data's anonymity; etc.) and *ex-post* (e.g., conducting a post-hoc analysis by using statistical techniques such as factor analysis, single factor confirmatory factor analysis, etc.) measures were employed. Furthermore, the results of our post-hoc analysis do not indicate any significant concerns regarding CMV in our data, further reinforcing the reliability of our findings.

5.2 Hypotheses testing

The statistical significance of the individual impacts has been estimated using Bootstrap with 5000 sub-samples. The results are shown in Table 4. The regression coefficient β indicates the level of effect of each variable and the statistical significance is indicated by the p value. All the hypotheses were supported but vary in the level of effect.

Table 4 Hypotheses testing results

Effect type	Hypothesis	Relationship	Estimates	T-statistics	P-values	Results
Direct effects	H1	DTS -> BAC	0.469	7.114	0.000	Supported
		DTS -> OA	0.377	6.141	0.000	
		DTS -> DDM	0.242	3.198	0.001	
		BAC -> DDM	0.328	4.051	0.000	
	H2	OA -> DDM	0.263	4.266	0.000	Supported
		DDM -> OP	0.480	10.909	0.000	
		EH -> OP	0.211	3.884	0.000	
		Age -> OP	0.039	0.687	0.492	
		Edu -> OP	0.237	1.942	0.052	
		Gender -> OP	0.213	2.433	0.015	
		Industry Type -> OP	0.016	0.311	0.756	
		Organisation Age -> OP	-0.051	1.059	0.290	
		Organisation Size -> OP	0.003	0.055	0.957	
		Role -> OP	-0.088	0.694	0.487	
		Tenure -> OP	-0.072	1.223	0.221	
Indirect Effects	H3	DTS -> BAC -> DDM	0.154	3.126	0.002	Supported
	H4	DTS -> OA -> DDM	0.099	3.483	0.000	Supported
Moderating Effects	H5	EH x DDM -> OP	-0.234	4.155	0.000	Not Supported

Note: DTS: DTS; BAC: BAC; OA: Organisational Agility; DDM: Data-driven Decision-making; EH: EH; OP: OP

As shown in Table 4, most hypothesised relationships were supported by structural regression model results except the moderating effects of EH. The results indicated that DTS had a positive impact on both BAC ($\beta = 0.469$, $p < 0.001$), and OA ($\beta = 0.377$, $p < 0.001$), which in turn had positive effects (BAC: $\beta = 0.328$, $p < 0.001$; OA: $\beta = 0.263$, $p < 0.001$) on DDM. Moreover, DTS is positively associated with DDM ($\beta = 0.242$, $p < 0.001$). DDM positively leads to OP ($\beta = 0.480$, $p < 0.001$). (see Table 4).

Further tests have been conducted to assess the mediating effect of BAC and OA on the relationship between DTS and DDM. The results, as shown in Table 4, confirms that both BAC ($\beta = 0.154$, $p < 0.05$) and OA ($\beta = 0.099$, $p < 0.001$) exert strong positive mediating influence on the relationship between DTS and DDM. Through H5, we investigated the moderating effects

of EH to outline the boundary conditions under which theorised linkages between DDM and OP change positively at varied degrees of EH. The interaction effect of EH and DDM on OP is statistically significant but negative ($\beta = -0.234$; $p < 0.001$), indicating that the effect of DDM on OP is not as expected. The negative beta coefficient shows that when EH grows, the link between DDM and OP weakens, and vice versa. This is an interesting finding that deserves specific attention. Figure 2 confirms this.

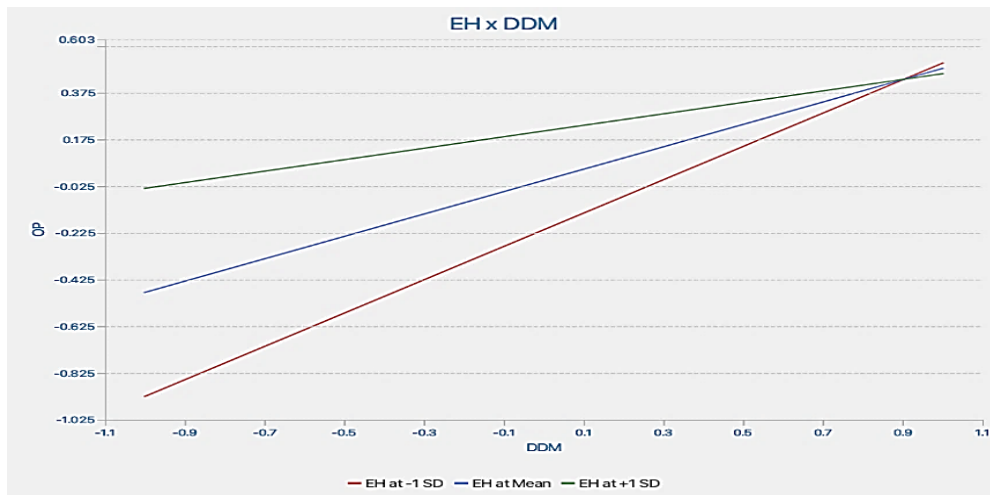


Figure 2: Moderating effect of EH on relationship between DDM and OP

6 Discussion

In light of the findings, it can be argued that DTS drives the development of dynamic capabilities like agility, BAC, and DDM that can improve OP. This can be significant in shaping the theoretical understanding on organisational studies regarding performance, decision making and the business environment. In the digital age, DTS becomes a driving force to reach organisational performance goals, exhibited by improved ability in collecting and analysing data, streamlining processes with resilience, and enhancing data-driven decision making. Our findings confirm that businesses that successfully implement DT initiatives and build DCs are more likely to have better financial performance, more satisfied customers, and more engaged employees (Vial, 2019; Wessel *et al.*, 2021). The impact of DTS on OP, however, can vary depending on the external environment in which it operates. The discussion of the hypotheses test results is as below

H1 – speculates that DTS has a positive effect on DDM. This hypothesis is supported ($\beta = 0.242$, $p < 0.001$) and the results reaffirms the assertions of previous studies (Correani et al., 2020; Lismont et al., 2017; Rouhani et al., 2016; Wamba et al., 2017). No doubt that digital technologies, such as advanced analytics and AI algorithms can process large amount of data to support both routine and complex decisions. Moreover, a DTS enables also demand transformation in processes, systems and even organisational culture to be agile, which alter the traditional ways of decision making for example, from individual sensing making (with risk of potential bias) to collective sensing making based on data and analytics, from centralised decision making to decentralised decision making based on network nodes, hence a change from initiation-based decision to rationale decision making. Our study examines two critical pillars in path for implementing DTS that leads to improved performance – the analytics capability and the organisational agility.

H2 – assumed that organisational DDM positively influences OP. The test result shows the highest standard regression coefficient ($\beta = 0.480$, $p < 0.000$) and the significance. Although OP can be measured by different variables and can be caused by many factors, this study shows a strong effect of DDM on an organisation's performance. There is plethora research on DDM and performance as reviewed in the literature. Broadly speaking, our test result confirms most reported studies in the literature (Mcafee & Brynjolfsson, 2012; O'Reilly & Tushman, 2008; Seddon et al., 2017; Wamba et al., 2017). This indicates a distinctive result of this study that data driving decision making is not only about using data and insight, but the art and protocol in making decision that supported by the organisational agility. The two cannot be decoupled for an effective DDM.

H3 – the results ($\beta = 0.154$, $p < 0.005$) confirms that BAC mediate the relationship between organisational DTS and its DDM. This result conforms previous studies that business analytics as an application of integrated technologies, systems, practices, methodologies, enable critical business data insight (Chen *et al.*, 2018; Ramanathan *et al.*, 2017) for evidence-based problem solving (Holsapple *et al.*, 2014). In light of the significant effects as shown from these results, we argue that business analytics should not only be seen as an essential function of digital technologies, it should be treated as a valuable, rare, inimitable and non-substitutable (VRIN) capability (Nevo and Wade, 2011) for organisations in digital age to sustain competitive advantages. Organisations need to develop this distinctive capability in order to differentiate itself from competitors. This supports the argument provided by Wamba et al.

(2017) that big data predictive analytics is a higher order organisational capability based on resource bundling.

H4 – was also supported ($\beta = 0.099$, $p < 0.005$), indicating that OA mediates the relationship between organisational DTS and its DDM. OA is referred to as the ease, and speed with which a firm can adjust their business processes to changes in the marketplace (Tallon, 2007; Dubey et al., 2014; Kitchens et al., 2018). It has also been recognised as an organisational ability by many researchers (Tallon, 2007; Yeow et al., 2018, Kwak et al., 2018; Ashrafi et al., 2019; Li et al., 2019). The close relationship between DTS and agility confirms the view that organisations stay mindful in pursuing a DTS which is coupled with agile abilities. The reason might be explained that **a)** DTS enables in developing an organisation's agility – for example, as aforementioned, decentralised - distributed decision making, **b)** Agility becomes a necessity or precondition for successful implementation of DTS. As DTS is centralised around continuous changes and readjustment of resources, agility must be an agent/catalyst of the transformation process. The result supports the view of Li et al. (2019) that agile systems and processes help managers to quickly adopt to environmental changes and make decisions based on factual data. Hence, the agility effects are on both the organisational systems and processes, also individual decision-making behaviour towards DDM.

H5 – states that EH moderates the relationship between organisational DDM and its performance; the effect is expected to be positive, i.e. the stronger the EH is, the stronger the relationship should be and vice versa. The remaining result shows a moderate interactive effect of EH and DDM on OP ($\beta = -0.234$, $p < 0.000$,) that is statistically significant but negative, indicating a weakening effect on the relationship between DDM and OP. This leads to the rejection of the hypothesis. The test shows that when EH grows, the link between data-driven decision making leading to OP weakens. This is not entirely surprising, because it is possible when DDM is incapable to deal with the negative force emitted from the complexity of the hostile environment. Considering the two mediating factors impacting DDM – BAC and OA, it could be that data are not available, unreliable or high uncertainty about the hostile environment, or the lack of agility in taking actions to respond appropriately to the hostile environment. The result does confirm the theoretical understanding that environment hostility has a wide negative impact on an organisation's strategy, operations and performance (Jahshan, 2020; Zhou et al., 2019). What we found interesting is that even organisations embarking on DTS, environment hostility continues emitting negative impact on organisational performance, this calls for a renewed mechanism to mitigate the effect from improved DTS and beyond.

6.1 Implications

The findings of this study, which include some novel perspectives on the development and implementation of DTS, provide academics and practitioners with profound insights and learning.

6.1.1 Theoretical implications

The foundational premises are in two folds. Firstly, the study examined the classic strategic management process (from strategy to performance) in the new context of digital transformation strategy and the path to organisational performance considering a specific environment condition (EH). The results confirm the relationship between strategy and performance, but reveals new resources (BAC) and new capability (AO and DDM) are the required conditions/enablers critical for implementing the strategy. These are not the tradition organisation resources and capabilities, but new resources and capabilities that can alter the status quo of organisational process and structure – e.g. data driving decision making as explored in this study. The significance of this finding is to stimulate more research to explore the new process and structure – both human and non-human entities, their roles and effects on driving performance. Secondly, prior research has inadequately contributed to comprehending the pathways that enhance organisational performance through DTS in hostile environments. This study addresses this gap identifying and examining the mediators i.e. BAC and OA on the path to implement the strategy. Both are the required resources and capabilities critical to the decision-making process, as well as organisations performance. The innovation is not only emphasising the crucial importance of DTS in improving performance in contemporary organisations, but the essential aspects of business analytics capacity and organisational agility in realising the digital transformation strategy. The mechanisms alter the decision-making process to encourage evidence-based and agile methods for quick and efficient replies. Hence, this extends the understanding of BAC that it gives an opportunity to access timely and relevant data by integrating structured and unstructured information which aids decision-making (Cao *et al.*, 2019). Moreover, a noteworthy contribution lies in enriching dynamic capability theory by aligning DTS – BAC-OA_DDM with organisational performance. It implies that the pathway from DTS to BAC and OA, leading to DDM, eventually influences performance. BAC is highlighted as playing a crucial role in digesting data and providing significant insights. This enhances the organisation's ability to detect opportunities and risks and enables learning from unexpected circumstances. Advanced BAC, such as artificial intelligence and intelligent

systems, improves the capacity to recognise the right timing and judgements to capitalise on opportunities. This alignment proposes a nuanced interplay among DTS, dynamic capability, and sustained competitive performance, thereby setting a course for future researchers to delve deeper into fortifying the concept of DTS.

In simple choice scenarios in less hostile environments, BAC enables decentralised decision-making, including automation and distributed decisions made by non-human entities. Conversely, in intricate, unorganised decision scenarios exacerbated by environmental antagonism, BAC is essential for improving collective understanding among managers. This change involves moving from isolated human cognition to communal sense-making and decision-making within organisations, although our current study does not have sufficient evidence to support this idea. Our findings support Schilke and Helfat, (2018) claim that BAC helps managers enhance, adjust, and adapt operational skills to better meet emerging environmental problems. Organisational Agility (OA) is a key element that allows for the reconfiguration and redeployment of resources after Dynamic Decision Making (DDM). Adapting to challenges and interruptions from the environment requires organisational agility to maintain flexibility and resilience. Implementing Data Technology Systems (DTS) requires continuously reorganising organisational resources to focus on digital technology. OA acts as a catalyst for reconfiguration capability and facilitates transformational changes, while also changing the decision-making process. Dynamic Decision Making (DDM) is unlikely to enhance performance without organisational agility.

Our research on environmental hostility does not contradict the established view that highlights the influence of the business environment on organisations, a concept extensively studied in strategic management. Data-driven decisions have a crucial role but cannot completely eradicate the adverse impacts of hostile surroundings. This introduces a new direction for future study, focusing on improving data and algorithms to increase the process of making sense of external environmental data. Furthermore, it is necessary to explore the creation of risk and resilience frameworks/models to manage disruptive forces. Can digital transformation efficiently turn adverse effects into beneficial prospects? This question is yet to be explored by future scholars.

6.1.2 Practical implications

The implications to practice are three-fold. Firstly, as advocated by Constantiou and Kallinikos (2015), firms should constantly evaluate their digitalisation approach in light of the unprecedented disruptions and other unforeseeable scenarios in the future. We suggest further

that firms should deploy resources in continuously monitoring and classifying the business environment and the decision situations in order to minimise the impact on operations and performance. For example, increase agility and response management through process, systems, decisions and being resilient could cope with adverse environment impact. It is critical to minimise the negative effects from EH by increasing OA and resilience through continuous re-adjustment of resources, processes, systems and culture.

Secondly, at the strategic level, organisations should strategically plan and implement a DTS considering the five domains for new opportunities, not way of doing business and developing a digital ecosystem to support the new value adding models. Thirdly, the study sheds light on how firms should develop a specific digital capability path for implementing the DTS in light of sensing-seizing-reconfiguration dynamic capabilities so that managerial and organisational decision-making is transformed into DDM. This implies management of non-human entities in performing tasks, making structured decisions, and re-skilling workforce and elevating leadership skills to manage using digital technologies

6.2 Limitations and future research directions

It is important to highlight some of the limitations of this study. The study is restricted to firms located in the north American continent, so to eliminate this bias, further research may investigate how a firm's DTS determines its OP under similar hostile environments in other continents/regions of the world for comparative studies. The objective would be to emphasise any contextual differences in these regions' countries that pertain to the uniqueness of cultural, social, and economic elements that influence the digital innovation and transformation processes of organisations. In addition, we need to acknowledge how the number of product or process innovations due to DDM might differ substantially from those of a manufacturing or service industry. Thus, future research may investigate more countries and sectors to enrich the existing theory and practice on implementing a DTS in times of environmental disruptions.

Moreover, this study is grounded on a deterministic view of an organisations' DTS that considers a structured approach to DDM mediated through BAC and OA. This top-down approach has limitations in discounting the notion of co-production of a firms' DTS by members operating from the strategic to tactical levels of the organisation. Thus, future research may utilise a more bottom-up approach that encompasses the role of all institutional actors, and not only confined to the views of IT executives. While this method is typical of IS research, it is by no means an ideal approach. Future research could employ methods involving multiple informants across multi-disciplinary teams, who are actively involved in the co-

creation and shaping of a dynamic and innovative DTS. This type of study will have to consider other methodological choices in the design of the study and should also allow us to probe deeper into the contextual features that are specific to an organisation's environmental, socio-cultural and economic factors. Hence, it would be interesting to employ different approaches to extend the current research on DTS and its effect on DDM in enhancing OP.

Furthermore, it is highly probable that the value of embarking on big data initiatives may be more beneficial and favourable to some firms over others, and be dependent on the time-frame since they have been deployed. Future research should also seek to address this concern, as it may be related to the costs of deploying big data analytics. Thus, it is important to understand in each industry sector how business data analytics capabilities are developed, and especially, through what processes they produce value, and how can that be measured. Hence, future studies may adopt a longitudinal design to include the notion of time that should account for the length it takes organisations to acquire and deploy BAC to achieve performance gains. However, the model derived from the study is novel and can be a stepping stone for future study to enrich and to validate.

7 Conclusion

The study contributes to the IS discipline and shed lights on the overall positive outcome for firms that deploy a DTS which improves OP when confronted with unprecedented disruptions or future hostile environments. This has been achieved by developing and testing five hypotheses concerning key model elements – DTS, BAC, OA, DDM, OP and EH. The results and the discussion lead to the conclusion that a DTS, via BAC and OA, enable DDM to take place at both the individual and organisational levels. The specific paths are uncovered - both BAC and OA drive dynamic capability development in sensing-seizing-reconfiguration of capabilities. DDM in the form of decision automation by non-human entities combined with collective sense-making and decision-making, leads to superior performance. EH has a negative effect on OP and DDM along does not reduce EH impact. It is particularly important to note the two distinctive entities and the interactive mechanism of BAC and OA forming the uncovered path of DTS that lead to DDM and improved performance This insight contributes to an advanced understanding of digital transformation literature. The theoretical contribution of the study extends the boundary of dynamic capability with the notion of digital capability for an organisation, which follows the path of DTS-BAC, OA and DDM. It is

envisaged that the theorised model will stimulate further investigation and validation of the path elements, and their relationships in new contextual settings.

References

- Akter, S., Wamba, S.F., Gunasekaran, A., Dubey, R. and Childe, S.J. (2016), "How to improve firm performance using big data analytics capability and business strategy alignment?", *International Journal of Production Economics*, Elsevier, Vol. 182, pp. 113–131, doi: 10.1016/J.IJPE.2016.08.018.
- AlNuaimi, B.K., Kumar Singh, S., Ren, S., Budhwar, P. and Vorobyev, D. (2022), "Mastering digital transformation: The nexus between leadership, agility, and digital strategy", *Journal of Business Research*, Elsevier, Vol. 145, pp. 636–648, doi: 10.1016/J.JBUSRES.2022.03.038.
- Anderson, J.C. and Gerbing, D.W. (1988), "Structural equation modeling in practice: A review and recommended two-step approach", *Psychological Bulletin*, Vol. 103 No. 3, pp. 411–423, doi: 10.1037/0033-2909.103.3.411.
- Ansoff, H.I. (1964), "A Quasi-Analytic Approach to the Business Strategy Problem", *Management Science*, Institute for Operations Research and the Management Sciences (INFORMS), Vol. MT-4 No. 1, pp. 67–77, doi: 10.1287/MANTECH.4.1.67.
- Aral, S. and Weill, P. (2007), "IT assets, organizational capabilities, and firm performance: How resource allocations and organizational differences explain performance variation", *Organization Science*, Vol. 18 No. 5, pp. 763–780, doi: 10.1287/orsc.1070.0306.
- Ashrafi, A., Zare Ravasan, A., Trkman, P. and Afshari, S. (2019), "The role of business analytics capabilities in bolstering firms' agility and performance", *International Journal of Information Management*, Elsevier, Vol. 47 No. December 2018, pp. 1–15, doi: 10.1016/j.ijinfomgt.2018.12.005.
- Barney, J.B. (2001), "Resource-based theories of competitive advantage: A ten-year retrospective on the resource-based view", *Journal of Management*, No longer published by Elsevier, Vol. 27 No. 6, pp. 643–650, doi: 10.1016/S0149-2063(01)00115-5.
- Barney, J.B. and Hesterly, W.S. (2012), *Strategic Management and Competitive Advantage : Concepts and Cases*, Pearson.
- Bhandari, K.R., Ranta, M. and Salo, J. (2022), "The resource-based view, stakeholder capitalism, ESG, and sustainable competitive advantage: The firm's embeddedness into ecology, society, and governance", *Business Strategy and the Environment*, John Wiley & Sons, Ltd, Vol. 31 No. 4, pp. 1525–1537, doi: 10.1002/BSE.2967.
- Bharadwaj, A.S. (2000a), "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation", *MIS Quarterly*, Management Information Systems Research Center, University of Minnesota, Vol. 24 No. 1, p. 169, doi: 10.2307/3250983.
- Bharadwaj, A.S. (2000b), "A Resource-Based Perspective on Information Technology Capability and Firm Performance: An Empirical Investigation", *MIS Quarterly*, Management Information Systems Research Center, University of Minnesota, Vol. 24 No. 1, p. 169, doi: 10.2307/3250983.
- Bharadwaj, A., El Sawy, O.A., Pavlou, P.A. and Venkatraman, N. (2013a), *DIGITAL BUSINESS STRATEGY: TOWARD A NEXT GENERATION OF INSIGHTS*, Vol. 37.
- Bharadwaj, A., El Sawy, O.A., Pavlou, P.A. and Venkatraman, N. (2013b), *DIGITAL BUSINESS STRATEGY: TOWARD A NEXT GENERATION OF INSIGHTS*, Vol. 37.

- Cao, G., Duan, Y. and El Banna, A. (2019), "A dynamic capability view of marketing analytics: Evidence from UK firms", *Industrial Marketing Management*, Vol. 76 No. May 2018, pp. 72–83, doi: 10.1016/j.indmarman.2018.08.002.
- Cao, G., Duan, Y. and Li, G. (2015), "Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis", *IEEE Transactions on Engineering Management*, Vol. 62 No. 3, pp. 384–395, doi: 10.1109/TEM.2015.2441875.
- Chanias, S., Myers, M.D. and Hess, T. (2019), "Digital transformation strategy making in pre-digital organizations: The case of a financial services provider", *The Journal of Strategic Information Systems*, North-Holland, Vol. 28 No. 1, pp. 17–33, doi: 10.1016/J.JSIS.2018.11.003.
- Chen, H., Chiang, R.H.L. and Storey, V.C. (2018), "Business intelligence and analytics: From big data to big impact", *MIS Quarterly*, Vol. 36 No. 4, pp. 1165–1188, doi: 10.5121/ijdps.2017.8101.
- Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L. and Chow, W.S. (2014a), "IT capability and organizational performance: The roles of business process agility and environmental factors", *European Journal of Information Systems*, Palgrave Macmillan Ltd., Vol. 23 No. 3, pp. 326–342, doi: 10.1057/ejis.2013.4.
- Chen, Y., Wang, Y., Nevo, S., Jin, J., Wang, L. and Chow, W.S. (2014b), "IT capability and organizational performance: the roles of business process agility and environmental factors", *European Journal of Information Systems*, Palgrave Macmillan UK, Vol. 23 No. 3, pp. 326–342, doi: 10.1057/ejis.2013.4.
- Chen, Y.-Y.K., Jaw, Y.-L. and Wu, B.-L. (2016), "Effect of digital transformation on organisational performance of SMEs Evidence from the Taiwanese textile industry's web portal", Vol. 26 No. 1, pp. 186–212, doi: 10.1108/IntR-12-2013-0265.
- Ciampi, F., Demi, S., Magrini, A., Marzi, G. and Papa, A. (2021), "Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation", *Journal of Business Research*, Elsevier Inc., Vol. 123, pp. 1–13, doi: 10.1016/j.jbusres.2020.09.023.
- Colli, M., Madsen, O., Berger, U., Møller, C., Wæhrens, B.V. and Bockholt, M. (2018), "Contextualizing the outcome of a maturity assessment for industry 4.0", *IFAC-PapersOnLine*, Elsevier B.V., Vol. 51 No. 11, pp. 1347–1352, doi: 10.1016/j.ifacol.2018.08.343.
- Constantiou, I.D. and Kallinikos, J. (2015), "New Games, New Rules: Big Data and the Changing Context of Strategy", <https://doi.org/10.1057/Jit.2014.17>, SAGE PublicationsSage UK: London, England, Vol. 30 No. 1, pp. 44–57, doi: 10.1057/JIT.2014.17.
- Correani, A., De Massis, A., Frattini, F., Petruzzelli, A.M. and Natalicchio, A. (2020), "Implementing a Digital Strategy: Learning from the Experience of Three Digital Transformation Projects", *California Management Review*, SAGE Publications Ltd, Vol. 62 No. 4, pp. 37–56, doi: 10.1177/0008125620934864.
- Côrte-Real, N., Oliveira, T. and Ruivo, P. (2017), "Assessing business value of Big Data Analytics in European firms", *Journal of Business Research*, Elsevier Inc., Vol. 70, pp. 379–390, doi: 10.1016/j.jbusres.2016.08.011.
- Daft, R.L. and Macintosh, N.B. (1981), "A Tentative Exploration into the Amount and Equivocality of Information Processing in Organizational Work Units", *Administrative Science Quarterly*, JSTOR, Vol. 26 No. 2, p. 207, doi: 10.2307/2392469.
- Daft, R.L. and Weick, K.E. (1984a), "Toward a Model of Organizations as Interpretation Systems1", <https://doi.org/10.5465/Amr.1984.4277657>, Academy of Management Briarcliff Manor, NY 10510, Vol. 9 No. 2, pp. 284–295, doi: 10.5465/AMR.1984.4277657.

- Daft, R.L. and Weick, K.E. (1984b), "Toward a Model of Organizations as Interpretation Systems¹", <https://doi.org/10.5465/Amr.1984.4277657>, Academy of Management Briarcliff Manor, NY 10510, Vol. 9 No. 2, pp. 284–295, doi: 10.5465/AMR.1984.4277657.
- Delen, D. and Zolbanin, H.M. (2018), "The analytics paradigm in business research", *Journal of Business Research*, Elsevier, Vol. 90 No. April, pp. 186–195, doi: 10.1016/j.jbusres.2018.05.013.
- Diallo, M.F., Diop-Sall, F., Djelassi, S. and Godefroit-Winkel, D. (2018), "How Shopping Mall Service Quality Affects Customer Loyalty Across Developing Countries: The Moderation of the Cultural Context", *Journal of International Marketing*, Vol. 26 No. 4, pp. 69–84, doi: 10.1177/1069031X18807473.
- Drnevich, P.L. and Kriauciunas, A.P. (2011), "Clarifying the conditions and limits of the contributions of ordinary and dynamic capabilities to relative firm performance", *Strategic Management Journal*, John Wiley & Sons, Ltd, Vol. 32 No. 3, pp. 254–279, doi: 10.1002/SMJ.882.
- Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019a), "Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda", *International Journal of Information Management*, Pergamon, Vol. 48, pp. 63–71, doi: 10.1016/J.IJINFOMGT.2019.01.021.
- Duan, Y., Edwards, J.S. and Dwivedi, Y.K. (2019b), "Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda", *International Journal of Information Management*, Elsevier Ltd, Vol. 48, pp. 63–71, doi: 10.1016/j.ijinfomgt.2019.01.021.
- Dubey, R., Ali, S.S., Aital, P. and Venkatesh, V.G. (2014), "Mechanics of humanitarian supply chain agility and resilience and its empirical validation", *International Journal of Services and Operations Management*, Inderscience Publishers, Vol. 17 No. 4, p. 367, doi: 10.1504/IJSOM.2014.059999.
- Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Luo, Z., Wamba, S.F. and Roubaud, D. (2017), "Can big data and predictive analytics improve social and environmental sustainability?", *Technological Forecasting and Social Change*, Elsevier, Vol. 144 No. July, pp. 534–545, doi: 10.1016/j.techfore.2017.06.020.
- Dwivedi, Y.K., Hughes, D.L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J.S., Gupta, B., et al. (2020), "Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life", *International Journal of Information Management*, Elsevier Ltd, p. 102211, doi: 10.1016/j.ijinfomgt.2020.102211.
- Egelhoff, W.G. (1988), "Strategy and structure in multinational corporations: A revision of the stopford and wells model", *Strategic Management Journal*, John Wiley & Sons, Ltd, Vol. 9 No. 1, pp. 1–14, doi: 10.1002/SMJ.4250090102.
- Elgendy, N. and Elragal, A. (2016), "Big Data Analytics in Support of the Decision Making Process", *Procedia Computer Science*, Vol. 100, Elsevier B.V., pp. 1071–1084, doi: 10.1016/j.procs.2016.09.251.
- Ferreira, J.J.M., Fernandes, C.I. and Ferreira, F.A.F. (2019), "To be or not to be digital, that is the question: Firm innovation and performance", *Journal of Business Research*, Elsevier, Vol. 101, pp. 583–590, doi: 10.1016/J.JBUSRES.2018.11.013.
- Fornell, C. and Larcker, D. (1981a), "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 50, 39.

- Fornell, C. and Larcker, D.F. (1981b), *Evaluating Structural Equation Models with Unobservable Variables and Measurement Error*, Source: *Journal of Marketing Research*, Vol. 18.
- Gerbing, D.W. and Anderson, J.C. (1988), "An Updated Paradigm for Scale Development Incorporating Unidimensionality and Its Assessment", *Journal of Marketing Research*, Vol. 25 No. 2, p. 186, doi: 10.2307/3172650.
- Guide, V.D.R. and Ketokivi, M. (2015), "Notes from the Editors: Redefining some methodological criteria for the journal", *Journal of Operations Management*, Vol. 37, pp. 5–8, doi: 10.1016/S0272-6963(15)00056-X.
- Gupta, M. and George, J.F. (2016a), "Toward the development of a big data analytics capability", *Information and Management*, Elsevier B.V., Vol. 53 No. 8, pp. 1049–1064, doi: 10.1016/j.im.2016.07.004.
- Gupta, M. and George, J.F. (2016b), "Toward the development of a big data analytics capability", *Information & Management*, North-Holland, Vol. 53 No. 8, pp. 1049–1064, doi: 10.1016/J.IM.2016.07.004.
- Gu, X., Chan, H.K., Thadani, D.R., Chan, F.K.S. and Peng, Y. (2023), "The role of digital techniques in organisational resilience and performance of logistics firms in response to disruptive events: Flooding as an example", *International Journal of Production Economics*, Elsevier, Vol. 266, p. 109033, doi: 10.1016/J.IJPE.2023.109033.
- Hair, J., Sarstedt, M., Ringle, C.M. and Gudergan, S.P. (2017), *Advanced Issues in Partial Least Squares Structural Equation Modeling*, 1 edition., SAGE Publications, Inc.
- Helfat, C.E. and Martin, J.A. (2015), "Dynamic Managerial Capabilities: Review and Assessment of Managerial Impact on Strategic Change", *Journal of Management*, SAGE Publications Inc., 4 July, doi: 10.1177/0149206314561301.
- Helfat, C.E. and Peteraf, M.A. (2015), "Managerial cognitive capabilities and the microfoundations of dynamic capabilities", *Strategic Management Journal*, John Wiley and Sons Ltd, Vol. 36 No. 6, pp. 831–850, doi: 10.1002/smj.2247.
- Hendra Halim, T. Meldi Kesuma and M. Ridha Siregar. (2023), "Digital Transformation Strategy to Optimize Company Performance", *Jurnal Manajemen Bisnis, Akuntansi Dan Keuangan*, PT Formosa Cendekia Global, Vol. 2 No. 2, pp. 189–200, doi: 10.55927/jambak.v2i2.7022.
- Henseler, J., Ringle, C.M. and Sarstedt, M. (2015), "A new criterion for assessing discriminant validity in variance-based structural equation modeling", *Journal of the Academy of Marketing Science*, Vol. 43 No. 1, pp. 115–135, doi: 10.1007/s11747-014-0403-8.
- Hess, T., Matt, C., Benlian, A. and Wiesböck, F. (2020), "Options for Formulating a Digital Transformation Strategy", *Strategic Information Management*, Routledge, pp. 151–173, doi: 10.4324/9780429286797-7.
- Hirschheim, R. and Sabherwal, R. (2001), "Detours in the Path toward Strategic Information Systems Alignment", *California Management Review*, Haas School of Business, Vol. 44 No. 1, pp. 87–108, doi: 10.2307/41166112.
- Holsapple, C., Lee-Post, A. and Pakath, R. (2014), "A unified foundation for business analytics", *Decision Support Systems*, Elsevier B.V., Vol. 64, pp. 130–141, doi: 10.1016/j.dss.2014.05.013.
- Hsiao, M.-H. (2024), "Resource integration and firm performance through organizational capabilities for digital transformation", *Digital Transformation and Society*, doi: 10.1108/dts-07-2023-0050.
- Ivanova, N., Nazarko, S., Denysenko, T., Kublitska, O. and Kononenko, S. (2023), "Business Strategy Transformation: The Impact of Global Digitalization and COVID-19 Pandemic

- Factors”, *Revista de La Universidad Del Zulia*, Vol. 14 No. 40, pp. 486–505, doi: 10.46925//rdluz.40.27.
- Jahshan Elias. (2020), “Primark looking for space to store £1.5bn surplus stock - Retail Gazette”, *Retail Gazette*, 3 May, available at: <https://www.retailgazette.co.uk/blog/2020/05/primark-looking-for-space-to-store-1-5bn-surplus-stock/> (accessed 7 September 2020).
- Joseph, J. and Gaba, V. (2020a), “Organizational Structure, Information Processing, and Decision-Making: A Retrospective and Road Map for Research”, *https://doi.org/10.5465/Annals.2017.0103*, Academy of Management Annals Briarcliff Manor, NY, Vol. 14 No. 1, pp. 267–302, doi: 10.5465/ANNALS.2017.0103.
- Joseph, J. and Gaba, V. (2020b), “Organizational Structure, Information Processing, and Decision-Making: A Retrospective and Road Map for Research”, *https://doi.org/10.5465/Annals.2017.0103*, Academy of Management Annals Briarcliff Manor, NY, Vol. 14 No. 1, pp. 267–302, doi: 10.5465/ANNALS.2017.0103.
- Kitchens, B., Dobolyi, D., Li, J. and Abbasi, A. (2018), “Advanced Customer Analytics: Strategic Value Through Integration of Relationship-Oriented Big Data”, *Journal of Management Information Systems*, Routledge, Vol. 35 No. 2, pp. 540–574, doi: 10.1080/07421222.2018.1451957.
- Korachi, Z. and Bounabat, B. (2020), “General approach for formulating a digital transformation strategy”, *Journal of Computer Science*, Science Publications, Vol. 16 No. 4, pp. 493–507, doi: 10.3844/JCSSP.2020.493.507.
- Korherr, P., Kanbach, D.K., Kraus, S. and Mikalef, P. (2022a), “From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes”, *Digital Business*, Elsevier B.V., Vol. 2 No. 2, doi: 10.1016/j.digbus.2022.100045.
- Korherr, P., Kanbach, D.K., Kraus, S. and Mikalef, P. (2022b), “From intuitive to data-driven decision-making in digital transformation: A framework of prevalent managerial archetypes”, *Digital Business*, Elsevier B.V., Vol. 2 No. 2, doi: 10.1016/j.digbus.2022.100045.
- Kraus, S., Durst, S., Ferreira, J.J., Veiga, P., Kailer, N. and Weinmann, A. (2022), “Digital transformation in business and management research: An overview of the current status quo”, *International Journal of Information Management*, Elsevier Ltd, Vol. 63, doi: 10.1016/j.ijinfomgt.2021.102466.
- Li, H., Wu, Y., Cao, D. and Wang, Y. (2019), “Organizational mindfulness towards digital transformation as a prerequisite of information processing capability to achieve market agility”, *Journal of Business Research*, Elsevier Inc., doi: 10.1016/j.jbusres.2019.10.036.
- Li, H., Wu, Y., Cao, D. and Wang, Y. (2021), “Organizational mindfulness towards digital transformation as a prerequisite of information processing capability to achieve market agility”, *Journal of Business Research*, Elsevier Inc., Vol. 122, pp. 700–712, doi: 10.1016/j.jbusres.2019.10.036.
- Lismont, J., Vanthienen, J., Baesens, B. and Lemahieu, W. (2017a), “Defining analytics maturity indicators: A survey approach”, *International Journal of Information Management*, Pergamon, Vol. 37 No. 3, pp. 114–124, doi: 10.1016/J.IJINFOMGT.2016.12.003.
- Lismont, J., Vanthienen, J., Baesens, B. and Lemahieu, W. (2017b), “Defining analytics maturity indicators: A survey approach”, *International Journal of Information Management*, Elsevier Ltd, Vol. 37 No. 3, pp. 114–124, doi: 10.1016/j.ijinfomgt.2016.12.003.

- Liu, D.Y., Chen, S.W. and Chou, T.C. (2011), "Resource fit in digital transformation: Lessons learned from the CBC Bank global e-banking project", *Management Decision*, Vol. 49 No. 10, pp. 1728–1742, doi: 10.1108/00251741111183852.
- Liu, H., Ke, W., Wei, K.K. and Hua, Z. (2013), "The impact of IT capabilities on firm performance: The mediating roles of absorptive capacity and supply chain agility", *Decision Support Systems*, Elsevier B.V., Vol. 54 No. 3, pp. 1452–1462, doi: 10.1016/j.dss.2012.12.016.
- Mcafee, A. and Brynjolfsson, E. (2012a), *HBR.ORG Spotlight on Big Data Big Data: The Management Revolution*.
- Mcafee, A. and Brynjolfsson, E. (2012b), *Spotlight on Big Data: The Management Revolution*.
- Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L. and Canhoto, A. (2018), "Big data, big decisions: The impact of big data on board level decision-making", *Journal of Business Research*, Elsevier Inc., Vol. 93, pp. 67–78, doi: 10.1016/j.jbusres.2018.08.029.
- Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019a), "Big data analytics and firm performance: Findings from a mixed-method approach", *Journal of Business Research*, Elsevier Inc., Vol. 98, pp. 261–276, doi: 10.1016/j.jbusres.2019.01.044.
- Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2019b), "Big Data Analytics Capabilities and Innovation: The Mediating Role of Dynamic Capabilities and Moderating Effect of the Environment", *British Journal of Management*, John Wiley & Sons, Ltd, Vol. 30 No. 2, pp. 272–298, doi: 10.1111/1467-8551.12343.
- Mikalef, P., Boura, M., Lekakos, G. and Krogstie, J. (2020), "The role of information governance in big data analytics driven innovation", *Information and Management*, Elsevier B.V., Vol. 57 No. 7, doi: 10.1016/j.im.2020.103361.
- Mikalef, P., Krogstie, J., Pappas, I.O. and Pavlou, P. (2020), "Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities", *Information and Management*, Elsevier B.V., Vol. 57 No. 2, p. 103169, doi: 10.1016/j.im.2019.05.004.
- Mikalef, P. and Pateli, A. (2017), "Information technology-enabled dynamic capabilities and their indirect effect on competitive performance: Findings from PLS-SEM and fsQCA", *Journal of Business Research*, Elsevier, Vol. 70, pp. 1–16, doi: 10.1016/J.JBUSRES.2016.09.004.
- Mirjam Johannes. (2019), "5 Companies With the Most Remarkable Digital Transformation Strategies", *ZIGURAT (Innovation and Technology Business School)*, available at: <https://www.e-zigurat.com/innovation-school/blog/companies-digital-transformation-strategies/> (accessed 21 April 2020).
- Mishra, D., Luo, Z., Hazen, B., Hassini, E. and Foropon, C. (2019), "Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: A resource-based perspective", *Management Decision*, Emerald Group Holdings Ltd., Vol. 57 No. 8, pp. 1734–1755, doi: 10.1108/MD-03-2018-0324.
- Nambisan, S., Wright, M. and Feldman, M. (2019), "The digital transformation of innovation and entrepreneurship: Progress, challenges and key themes", *Technological Forecasting and Social Change*, Vol. 147, pp. 1171–1191, doi: 10.1016/j.techfore.2019.117119.
- Nam, D., Lee, J. and Lee, H. (2019), "Business analytics use in CRM: A nomological net from IT competence to CRM performance", *International Journal of Information*

- Management*, Elsevier, Vol. 45 No. 96, pp. 233–245, doi: 10.1016/j.ijinfomgt.2018.01.005.
- Nevo, S. and Wade, M. (2011), “Firm-level benefits of IT-enabled resources: A conceptual extension and an empirical assessment”, *The Journal of Strategic Information Systems*, North-Holland, Vol. 20 No. 4, pp. 403–418, doi: 10.1016/J.JSIS.2011.08.001.
- Nwankpa, J.K. and Roumani, Y. (2016), “IT Capability and Digital Transformation: A Firm Performance Perspective”, p. 1.
- Omol, E.J. (2023), “Organizational digital transformation: from evolution to future trends”, *Digital Transformation and Society*, Emerald Publishing Limited, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/DTS-08-2023-0061.
- Van Oosterhout, M., Waarts, E. and Van Hillegersberg, J. (2017), “Change factors requiring agility and implications for IT”, <https://doi.org/10.1057/Palgrave.Ejis.3000601>, Taylor & Francis, Vol. 15 No. 2, pp. 132–145, doi: 10.1057/PALGRAVE.EJIS.3000601.
- O'Reilly, C.A. and Tushman, M.L. (2008), “Ambidexterity as a dynamic capability: Resolving the innovator's dilemma”, *Research in Organizational Behavior*, Elsevier, 1 January, doi: 10.1016/j.riob.2008.06.002.
- Pavlou, P.A. and El Sawy, O.A. (2011), “Understanding the Elusive Black Box of Dynamic Capabilities”, *Decision Sciences*, John Wiley & Sons, Ltd, Vol. 42 No. 1, pp. 239–273, doi: 10.1111/J.1540-5915.2010.00287.X.
- Perdana, A., Lee, H.H., Koh, S.K. and Arisandi, D. (2022), “Data analytics in small and mid-size enterprises: Enablers and inhibitors for business value and firm performance”, *International Journal of Accounting Information Systems*, Elsevier Inc., Vol. 44, doi: 10.1016/j.accinf.2021.100547.
- Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), “Common method biases in behavioral research: a critical review of the literature and recommended remedies”, *The Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879–903, doi: 10.1037/0021-9010.88.5.879.
- Provost, F. and Fawcett, T. (2013), “Data Science and its Relationship to Big Data and Data-Driven Decision Making”, *Big Data*, Mary Ann Liebert Inc., Vol. 1 No. 1, pp. 51–59, doi: 10.1089/big.2013.1508.
- Radhakrishnan, A., Zu, X. and Grover, V. (2008), “A process-oriented perspective on differential business value creation by information technology: An empirical investigation”, *Omega*, Pergamon, Vol. 36 No. 6, pp. 1105–1125, doi: 10.1016/J.OMEGA.2006.06.003.
- Ramanathan, R., Philpott, E., Duan, Y. and Cao, G. (2017), “Adoption of business analytics and impact on performance: a qualitative study in retail”, *Production Planning and Control*, Taylor & Francis, Vol. 28 No. 11–12, pp. 985–998, doi: 10.1080/09537287.2017.1336800.
- Raschke, R.L. (2010), “Process-based view of agility: The value contribution of IT and the effects on process outcomes”, *International Journal of Accounting Information Systems*, Pergamon, Vol. 11 No. 4, pp. 297–313, doi: 10.1016/J.ACCINF.2010.09.005.
- Rialti, R., Zollo, L., Ferraris, A. and Alon, I. (2019), “Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model”, *Technological Forecasting and Social Change*, Elsevier Inc., Vol. 149, doi: 10.1016/j.techfore.2019.119781.
- Rogers, D.L. (2016), “The Digital Transformation Playbook, Rethinking your Organisation for the Digital Age”, *Columbia University Press*, pp. 149–151.
- Rouhani, S., Ashrafi, A., Zare Ravasan, A. and Afshari, S. (2016), “The impact model of business intelligence on decision support and organizational benefits”, *Journal of*

- Enterprise Information Management*, Emerald Group Publishing Ltd., Vol. 29 No. 1, pp. 19–50, doi: 10.1108/JEIM-12-2014-0126.
- Rubio-Andrés, M., Linuesa-Langreo, J., Gutiérrez-Broncano, S. and Sastre-Castillo, M.Á. (2024), “Tackling digital transformation strategy: how it affects firm innovation and organizational effectiveness”, *Journal of Technology Transfer*, Springer, doi: 10.1007/s10961-024-10164-9.
- Schilke, O. and Helfat, C.E. (2018), “QUO VADIS, DYNAMIC CAPABILITIES? A CONTENT-ANALYTIC REVIEW OF THE CURRENT STATE OF KNOWLEDGE AND RECOMMENDATIONS FOR FUTURE RESEARCH”, *Academy of Management Annals*, Vol. 12 No. 1, pp. 390–439, doi: 10.5465/annals.2016.0014.
- Seddon, P.B., Constantinidis, D., Tamm, T. and Dod, H. (2017), “How does business analytics contribute to business value?”, *Information Systems Journal*, Vol. 27 No. 3, pp. 237–269, doi: 10.1111/isj.12101.
- Shamim, S., Zeng, J., Khan, Z. and Zia, N.U. (2020), “Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms”, *Technological Forecasting and Social Change*, Elsevier Inc., Vol. 161, doi: 10.1016/j.techfore.2020.120315.
- Sharma, R., Mithas, S. and Kankanhalli, A. (2014), “Transforming decision-making processes: a research agenda for understanding the impact of business analytics on organisations”, *European Journal of Information Systems*, Vol. 23 No. 4, pp. 433–441, doi: 10.1057/ejis.2014.17.
- Simon, N. (1997), *Models of Bounded Rationality: Empirically Grounded Economic Reason* NA Simon; H-Index: NA1 Simon; H-Index: NA: NA FNEGE: NA CoNRS: NA HCERE: NA CCF: NA BFI: 1 +.
- Tallon, P.P. (2007a), “A process-oriented perspective on the alignment of information technology and business strategy”, *Journal of Management Information Systems*, Vol. 24 No. 3, pp. 227–268, doi: 10.2753/MIS0742-1222240308.
- Tallon, P.P. (2007b), “A process-oriented perspective on the alignment of information technology and business strategy”, *Journal of Management Information Systems*, Vol. 24 No. 3, pp. 227–268, doi: 10.2753/MIS0742-1222240308.
- Tallon, P.P. (n.d.), “Inside the adaptive enterprise: an information technology capabilities perspective on business process agility”, doi: 10.1007/s10799-007-0024-8.
- Teece, D.J. (2014), “The foundations of enterprise performance: Dynamic and ordinary capabilities in an (economic) theory of firms”, *Academy of Management Perspectives*, Vol. 28, Academy of Management, pp. 328–352, doi: 10.5465/amp.2013.0116.
- Teece, D.J. (2019), “A capability theory of the firm: an economics and (Strategic) management perspective”, *New Zealand Economic Papers*, Routledge, Vol. 53 No. 1, pp. 1–43, doi: 10.1080/00779954.2017.1371208.
- Teece, D.J., Pisano, G. and Shuen, A. (1997), “DYNAMIC CAPABILITIES AND STRATEGIC MANAGEMENT”, *Strategic Management Journal*, Vol. 18, pp. 509–533, doi: 10.1002/(SICI)1097-0266(199708)18:7.
- Teece, D., Peteraf, M. and Leih, S. (2016a), “Dynamic capabilities and organizational agility: Risk, uncertainty, and strategy in the innovation economy”, *California Management Review*, University of California Press, Vol. 58 No. 4, pp. 13–35, doi: 10.1525/CMR.2016.58.4.13.
- Teece, D., Peteraf, M. and Leih, S. (2016b), “Dynamic Capabilities and Organizational Agility: Risk, Uncertainty, and Strategy in the Innovation Economy”, *California Management Review*, University of California Press, Vol. 58 No. 4, pp. 13–35, doi: 10.1525/cmr.2016.58.4.13.

- Teece, D., Peteraf, M. and Leih, S. (n.d.). *Dynamic Capabilities and Organizational Agility: RISK, UNCERTAINTY, AND STRATEGY IN THE INNOVATION ECONOMY*.
- Teng, X., Wu, Z. and Yang, F. (2022), "Research on the Relationship between Digital Transformation and Performance of SMEs", *Sustainability (Switzerland)*, MDPI, Vol. 14 No. 10, doi: 10.3390/su14106012.
- Tim, Y., Hallikainen, P., Pan, S.L. and Tamm, T. (2020), "Actualizing business analytics for organizational transformation: A case study of Rovio Entertainment", *European Journal of Operational Research*, Elsevier B.V., Vol. 281 No. 3, pp. 642–655, doi: 10.1016/j.ejor.2018.11.074.
- Torres, R., Sidorova, A. and Jones, M.C. (2018), "Enabling firm performance through business intelligence and analytics: A dynamic capabilities perspective", *Information and Management*, Elsevier B.V., Vol. 55 No. 7, pp. 822–839, doi: 10.1016/j.im.2018.03.010.
- Tosey, P., Visser, M. and Saunders, M.N.K. (2012), "The origins and conceptualizations of 'triple-loop' learning: A critical review", *Management Learning*, SAGE PublicationsSage UK: London, England, Vol. 43 No. 3, pp. 291–307, doi: 10.1177/1350507611426239/ASSET/IMAGES/LARGE/10.1177_1350507611426239-FIG1.JPEG.
- Tsou, H.-T. and Chen, J.-S. (2023), "How does digital technology usage benefit firm performance? Digital transformation strategy and organisational innovation as mediators", *Technology Analysis & Strategic Management*, Vol. 35 No. 9, pp. 1114–1127, doi: 10.1080/09537325.2021.1991575.
- Van Veldhoven, Z. and Vanthienen, J. (2022), "Digital transformation as an interaction-driven perspective between business, society, and technology", *Electronic Markets*, Springer Science and Business Media Deutschland GmbH, Vol. 32 No. 2, pp. 629–644, doi: 10.1007/S12525-021-00464-5/FIGURES/3.
- Vial, G. (2019), "Understanding digital transformation: A review and a research agenda", *Journal of Strategic Information Systems*, Elsevier B.V., 1 June, doi: 10.1016/j.jsis.2019.01.003.
- Wamba, S., Akter, S., Edwards, A., Chopin, G. and Gnanzou, D. (2015), "The International Journal of Production Economics How 'big data' can make big impact: Findings from a systematic review and a longitudinal case study", *International Journal of Production Economics*, Vol. 165, pp. 1–23, doi: <http://dx.doi.org/10.1016/j.ijpe.2014.12.031>.
- Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J. fan, Dubey, R. and Childe, S.J. (2017a), "Big data analytics and firm performance: Effects of dynamic capabilities", *Journal of Business Research*, Elsevier, Vol. 70, pp. 356–365, doi: 10.1016/J.JBUSRES.2016.08.009.
- Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J. fan, Dubey, R. and Childe, S.J. (2017b), "Big data analytics and firm performance: Effects of dynamic capabilities", *Journal of Business Research*, Elsevier Inc., Vol. 70, pp. 356–365, doi: 10.1016/j.jbusres.2016.08.009.
- Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J. fan, Dubey, R. and Childe, S.J. (2017c), "Big data analytics and firm performance: Effects of dynamic capabilities", *Journal of Business Research*, Elsevier Inc., Vol. 70, pp. 356–365, doi: 10.1016/j.jbusres.2016.08.009.
- Wang, H., Feng, J., Zhang, H. and Li, X. (2020a), "The effect of digital transformation strategy on performance: The moderating role of cognitive conflict", *International Journal of Conflict Management*, Emerald Group Publishing Ltd., Vol. 31 No. 3, pp. 441–462, doi: 10.1108/IJCMA-09-2019-0166.

- Wang, H., Feng, J., Zhang, H. and Li, X. (2020b), "The effect of digital transformation strategy on performance: The moderating role of cognitive conflict", *International Journal of Conflict Management*, Emerald Group Holdings Ltd., Vol. 31 No. 3, pp. 441–462, doi: 10.1108/IJCMA-09-2019-0166.
- Wang, H., Feng, J., Zhang, H. and Li, X. (2020c), "The effect of digital transformation strategy on performance: The moderating role of cognitive conflict", *International Journal of Conflict Management*, Emerald Group Holdings Ltd., Vol. 31 No. 3, pp. 441–462, doi: 10.1108/IJCMA-09-2019-0166.
- Warner, K.S.R. and Wäger, M. (2019), "Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal", *Long Range Planning*, Pergamon, Vol. 52 No. 3, pp. 326–349, doi: 10.1016/J.LRP.2018.12.001.
- Wessel, L., Baiyere, A., Ologeanu-Taddei, R., Cha, J. and Jensen, T.B. (2021), "Unpacking the difference between digital transformation and it-enabled organizational transformation", *Journal of the Association for Information Systems*, Association for Information Systems, Vol. 22 No. 1, pp. 102–129, doi: 10.17705/1jais.00655.
- Winby, S. and Worley, C.G. (2014), "Management processes for agility, speed, and innovation", *Organizational Dynamics*, Vol. 43, pp. 225–234, doi: 10.1016/j.orgdyn.2014.08.009.
- Xu, M., Duan, Y., Cao, G., Ong, V. and Dietzmann, C. (2022), "Understanding the challenges and perceived roles of artificial intelligence in information processing by UK managers", 1 September.
- Xu, M., Duan, Y., Ong, V. and Cao, G. (2022), "Managerial information processing in the era of big data and AI - a conceptual framework from an evolutionary review", Springer, 16 October.
- Yalcin, A.S., Kilic, H.S. and Delen, D. (2022), "The use of multi-criteria decision-making methods in business analytics: A comprehensive literature review", *Technological Forecasting and Social Change*, Elsevier Inc., Vol. 174, doi: 10.1016/j.techfore.2021.121193.
- Yeow, A., Soh, C. and Hansen, R. (2017), "Aligning with new digital strategy : A dynamic capabilities approach", *Journal of Strategic Information Systems*, Vol. 27 No. February 2015, pp. 1–16, doi: 10.1016/j.jsis.2017.09.001.
- Yeow, A., Soh, C. and Hansen, R. (2018a), "Aligning with new digital strategy: A dynamic capabilities approach", *Journal of Strategic Information Systems*, Elsevier B.V., Vol. 27 No. 1, pp. 43–58, doi: 10.1016/j.jsis.2017.09.001.
- Yeow, A., Soh, C. and Hansen, R. (2018b), "Aligning with new digital strategy: A dynamic capabilities approach", *The Journal of Strategic Information Systems*, North-Holland, Vol. 27 No. 1, pp. 43–58, doi: 10.1016/J.JSIS.2017.09.001.
- Zhang, K.Z.K., Benyoucef, M. and Zhao, S.J. (2015), "Electronic Commerce Research and Applications Building brand loyalty in social commerce : The case of brand microblogs", *Electronic Commerce Research and Applications*, Vol. 15 No. December, pp. 14–25, doi: 10.1016/j.elerap.2015.12.001.
- Zhang, X., Xu, Y.Y. and Ma, L. (2023), "Information technology investment and digital transformation: the roles of digital transformation strategy and top management", *Business Process Management Journal*, Emerald Publishing, Vol. 29 No. 2, pp. 528–549, doi: 10.1108/BPMJ-06-2022-0254.
- Zhou, J., Mavondo, F.T. and Saunders, S.G. (2019), "The relationship between marketing agility and financial performance under different levels of market turbulence", *Industrial Marketing Management*, Elsevier Inc., Vol. 83, pp. 31–41, doi: 10.1016/j.indmarman.2018.11.008.