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Strategic Alignment of Big Data Analytics: Leveraging Operational and Market Capabilities for Organisational Performance

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Abstract:
Although the emergence of big data analytics (BDA) has stimulated enormous investments from contemporary businesses, empirical evidence tends to remain limited about how firms should leverage their BDA initiatives. There is also a need to understand how BDA integrates with organisational capabilities to drive performance gains. We draw on the strategic alignment framework grounded in dynamic capabilities theory to examine combinations of BDA dimensions with other organisational resources, such as internal competencies and external integration with supply chain actors to drive operational and market competitiveness in realising performance. Our hypotheses find support in a combination of primary and secondary data gathered from 207 dyads of business and IT executives. Our results suggest that simply implementing BDA tools and techniques do not automatically translate into financial gains. Instead, it must align with the firm's strategic integration capabilities to leverage operational and market capabilities. Our research delineates the mechanisms by which the business value of BDA capability is realised and provides useful guidance to managers and consultants in implementing BDA.

Keywords: big data analytics, strategic integration capability, strategic alignment framework, operational competitiveness, market competitiveness, Tobin's Q, financial performance, dynamic capabilities theory, business value of IT

1 INTRODUCTION

Big data analytics (BDA) capability is the approach of managing, processing, and analysing large volumes of data to gain meaningful insights by strategically utilising data, technology, and talent across an organisation (Mikalef and Krogstie, 2020). Research suggests that BDA has become a vital source for commercial competitiveness (Zeng and Glaister, 2018), and firms are making substantial investments to harness big data (Sena et al. 2019). The International Data Cooperation (IDC) predicts that global investment in BDA will reach $70.7 billion in the Asia Pacific region alone by 2026 (IDC 2023). The ultimate success of any big data project, however, lies in realising strategic business value that provides a competitive advantage (Grover et al. 2018).

Despite massive investments, many firms fail to generate value from their BDA initiatives (Hasan et al. 2024). Such investments can even disrupt firms if they fail to implement key mechanisms to translate BDA initiatives into business performance. For instance, Bean (2022) argues that ordinary big data analytic capability and mere possession of big data are more likely to create conditions for business failure. The failure of Primera Air to terminate its operations was mainly due to "*its inability to develop and capitalise on BDA*" (Amankah-Amoah and Adomako, 2019; p. 208). This evidence suggests a fundamental disconnect between acquiring BDA capabilities and achieving performance gains, highlighting a problem that requires a deeper theoretical explanation (Yu et al. 2019). Firms face several specific challenges in attempting to leverage and generate value from BDA initiatives, including managing large data, data formats, complexity, high inflows, high variability, extracting value, and governance (Cappa et al., 2021). Empirical evidence from Vidgen et al. (2017) highlights that these challenges particularly relate to how BDA is leveraged for improved decision-making and creating a big data and business analytics strategy. These persistent challenges underscore the need for a more indepth understanding of how BDA creates value (Yeh et al., 2025).

Given these persistent challenges, it is important to examine the theoretical assumptions underlying current BDA research. The prevailing research on the business value of information technology, drawing heavily from the resource-based view, has established a dominant logic: that firm-specific, valuable, and rare capabilities like BDA should lead to superior performance (Arshad et al., 2024; Yeh et al., 2025). This perspective has guided a significant body of literature that seeks to demonstrate a direct, positive relationship between BDA investment and organisational outcomes. This dominant view tends to rest on a fundamental assumption that BDA is a standalone capability that generates direct performance returns. We argue this assumption is problematic and can be increasingly incommensurable with the widespread real-world BDA project failures (Amankwah-Amoah and Adomako 2019; Hasan et al. 2024; Wamba et al. 2017). The assumption can be challenged for two primary reasons. First, it treats BDA as a monolithic “black box”, a higher-order construct that ignores the distinct roles of its managerial, technological, and human components (Müller et al. 2018). While BDA in companies is largely tech-driven, its relationship to an organization's IT capability needs clarity. Mandal (2018), referencing Wamba et al. (2015), suggests that BDA manages unique data dimensions like volume and velocity more holistically than just IT. Additionally, BDA factors in the human dimension of decision-making, a point highlighted by Mikalef et al. (2020). Second, it presumes a direct-effects logic that is inconsistent with the reality that technology is often a commodity (Haenssgen and Ariana, 2018). Sustained advantage comes not from possessing a technology, but from its complex integration with other resources (Teece 2018), a view that aligns with theoretical arguments that technological innovation requires combination with other assets to be profitable, i.e., transformative effect (Haenssgen and Ariana, 2018).

In this paper, we go beyond the dominant view by building upon an alternative assumption that BDA is a contingent enabler, not a direct driver, of performance. We posit that its value is latent and is only actualized when it is strategically aligned with complementary organizational capabilities (Wamba et al., 2020). The value of BDA, therefore, is not inherent in the capability itself, but emerges from its synergistic combination with other firm resources (Kohli and Grover, 2008).

This framing presents a theoretical tension between two competing views. If the dominant assumption holds, BDA capabilities should have a direct, positive effect on firm performance. If our alternative assumption holds, any such direct effect will be minimal or non-existent, and the value of BDA will instead be revealed through indirect pathways contingent upon other factors. Our central contribution is to empirically adjudicate between these competing assumptions. By doing so, we aim to provide a more robust explanation for why BDA initiatives succeed or fail, moving the conversation from if BDA creates value to how it creates value (Mandal, 2018; Agarwal and Dhar, 2014). This reconceptualization addresses calls from researchers who highlight the need to explore BDA's transformative potential through integration with operational capabilities (Sheng and Amankwah-Amoah, 2021; Batistič and van der Laken, 2019; Yeh et al., 2025). From a practical standpoint, these insights could potentially improve the success rate of BDA investments and help managers avoid costly misperceptions around resource integration (Hirschheim, 2021).

To conduct this critical test, we adopt a strategic alignment framework (Henderson and Venkatraman, 1993) grounded in dynamic capabilities theory (Flynn et al. 2010; Teece et al. 1997; Wong et al. 2011). This approach builds on the strategic IT alignment perspective, which views alignment as a state of congruence between IT and business strategies that enhances firm performance and as a capability that leverages IT resources more effectively to create value (Venkatraman et al., 1993; Sabherwal et al., 2019). We develop and examine a model where the performance effects of BDA's core dimensions (management, technology, and talent) are mediated by operational and market competitiveness (Teece et al. 1997). Operational competitiveness is the ability of a firm in responding to competition based on production cost and product quality, while market competitiveness is the ability of a firm in responding to competition based on delivery speed and production flexibility (Flynn et al. 2010; Wong et al., 2011). Crucially, we model these effects as being contingent on the firm's strategic integration capability (SIC). SIC is defined as the ability of an organisation to harmonise internal and external functions (Flynn et al. 2010, Wong et al. 2011, Akhter et al. 2019; Wiener et al. 2020).

For instance, Amazon's success in leveraging BDA lies not just in its predictive analytics but in the integration of this analytic capability with its strategic supply chain partnerships and logistics management (Sanders 2016), allowing it to anticipate customer demand, optimise inventory, and maintain high levels of efficiency.

Our hypotheses are therefore formulated not as incremental additions to an existing model, but as a direct empirical test of our alternative, indirect-effects assumption. Finding that the direct BDA-performance path is non-significant while the mediated paths are significant would provide strong support for our alternative assumption over the dominant view.

This study contributes to the literature in the following ways. First, we move beyond the monolithic view of BDA by providing a fine-grained analysis of how its distinct dimensions—BDA management, technology, and talent capabilities—contribute to value creation (Wamba et al. 2024). Second, we uncover the indirect mechanisms through which BDA creates value. We reveal that the value of BDA is fully mediated through operational competitiveness (OC) and market competitiveness (MC), with no statistically significant direct effect on performance (Mandal 2018). Third, we provide a novel theoretical framework by integrating Dynamic Capabilities theory with the Strategic Alignment Model (SAM). This synthesis demonstrates that BDA's effectiveness is contingent upon its strategic alignment with SIC (Flynn et al. 2010). Fourth, we offer robust empirical validation using objective performance data (Sales and Tobin's Q) from the Capital IQ and Bloomberg Professional databases, providing reliable and differentiated evidence in a field that often relies on perceptual measures (Ferraris et al. 2019, Rialti et al. 2019b, Sun and Liu 2020, Awan et al. 2022).

2 THEORY AND HYPOTHESES

2.1 BDA dimensions

To create an organisational capability that is difficult to imitate and transfer, Grant (1991) categorises three types of resources that are jointly required: tangible (e.g., physical and financial resources), human skills (e.g., employee skills and knowledge), and intangible (e.g., organisational culture and learning). While Grant's (1991) seminal work predates the emergence of big data analytics, his fundamental resource categorisation provides a valuable theoretical lens for understanding the types of assets required for modern digital capabilities like BDA. Following this adapted application of Grant's (1991) categorisation, prior studies have adopted numerous typologies for the dimensions of BDA. For instance, Barton and Court (2012) identify talent management, IT infrastructure, and front-line employees' expertise, whereas Wixom et al. (2013) recognise BDA capabilities in terms of strategy, data, and people.

Drawing on the emerging literature on BDA (Arshad et al., 2024; Huy and Phuc, 2024; Wamba et al., 2017), we argue that the dimensions of BDA can be understood as contemporary manifestations of Grant's resource categories: BDA Management capability represents intangible resources (encompassing planning, coordination, and control processes); BDA Technology capability embodies tangible resources (including hardware, software, and technical infrastructure); and BDA Talent capability reflects human resources (comprising analytics skills, technical knowledge, and business acumen) (Wamba et al., 2017). This theoretical adaptation allows us to structure our understanding of BDA capabilities within an established resource-based framework while acknowledging the unique characteristics of data-driven technologies (Arshad et al., 2024). These commonly used and well-accepted typology are defined in Table 1.

Table 1: Overview of BDA Dimensions

BDA dimensions	Explanation
BDA Management Capability	Refers to the planning, management, and control of the BDA platform to ensure knowledgeable decision-making (Akhtar et al. 2016; Wamba et al. 2017).
BDA Technology Capability	Reflects the flexibility and modularity of the BDA platform, allowing data scientists to develop, deploy, and support a firm's resources rapidly (Akhtar et al. 2016).
BDA Talent Capability	Refers to the analytics skills and knowledge of professionals, enabling them to support business goals efficiently in a big data environment (Akhtar et al. 2016).

Existing empirical research tends to have predominantly treated BDA as a singular, higher-order construct, thereby overlooking its multifaceted nature (Chen et al. 2015; Muller et al.

2018). While these studies acknowledge the overarching value of BDA capabilities, they fall short in delineating the nuanced roles and impacts of its specific sub-dimensions and, therefore, do not fully address how individual BDA influence firm performance (Yeh et al., 2025). It is analogous to listening to an orchestra solely as a collective sound rather than appreciating the unique contribution of each instrument. To truly harness the potential of BDA, it becomes imperative to investigate the granular effects and roles of its sub-dimensions and aligning these with complementary organisational resources, rather than solely investigating direct relationships with performance. For instance, Mikalef et al. (2019) demonstrate that specific BDA capabilities individually contribute to innovation performance, but these effects significantly amplify when strategically aligned with dynamic capabilities such as sensing and seizing opportunities. Su et al. (2022) further reinforce the need for exploring indirect mechanisms by highlighting that BDA impacts organisational performance through mediating roles of dual innovation (process and product), which remain obscured if viewed as a single higher-order construct. Vesterinen et al., (2025) empirically illustrate how marketing agility mediates the relationship between BDA capabilities and firm performance, underscoring the value of understanding strategic alignment. A comprehensive meta-analysis by Liu et al., (2025) confirms organisational agility as a consistent mediator, validating the argument that misalignment among BDA sub-dimensions weakens overall performance outcomes. Similarly, Wamba et al. (2020) reveal conditional benefits of BDA, suggesting that supply chain ambidexterity moderates the impact on performance, which highlights the necessity for strategic integration of distinct analytics capabilities. Lastly, the systematic review by Ciampi et al. (2022) explicitly calls for more granular exploration of BDA dimensions, advocating for research to move beyond simplistic direct linkages and instead examine nuanced and combinatory routes to performance.

In this regard, the dynamic capabilities provide an invaluable lens to understand the strategic alignment of the sub-dimensions of BDA within a firm's resources (Mikalef et al., 2019). This perspective can guide firms in determining how distinct BDA sub-dimensions fit, function, and potentially synergise with existing firm resources, thereby shedding light on potential combinations for optimised value creation (Sabherwal et al. 2019). While BDA helps in gaining insights into large and complex datasets, the strategic alignment that aids BDA workflows is of utmost importance.

2.2 Dynamic Capabilities

Organisational capabilities, defined as the reliable performance of specific activities (Helfat and Winter, 2011), are distinct from dynamic capabilities, which involve modifying a firm's resource base to create significant change (Helfat et al., 2007; Lin and Wu, 2014). Teece (2007) outlines a framework for dynamic capabilities consisting of sensing, seizing, and reconfiguring. Sensing involves observing the external environment (Augier and Teece, 2009), seizing entails evaluating and investing in resources (Wilden et al., 2013; Helfat and Peteraf, 2015), and reconfiguring focuses on recombining resources to optimise complementarities (Sirmon et al., 2011; Teece, 2012). These components are interrelated and collectively drive organisational outcomes (Danneels, 2015; Teece, 2007).

Effective reconfiguration requires both sensing and seizing to align resource bundles with external conditions (Drnevich and Kriauciunas, 2011; Wilden et al., 2013). From this perspective, strategic IT alignment plays a crucial role in facilitating dynamic capabilities, as it ensures that IT investments contribute to an organisation’s ability to sense, seize, and reconfigure resources in response to changing market conditions. Thus, aligning organisational competencies with dynamic capabilities is key to enhancing their strategic value (Schilke, 2014).

2.3 Strategic IT Alignment

Strategic IT alignment has evolved from early organisational and strategic management literature that recognised the role of IS in enhancing firm performance and efficiency (Scott-Morton, 1991). Venkatraman and Henderson (1993) expanded this concept into the Strategic Alignment Model (SAM), which remains a widely adopted framework in both academic research and organisational practice (Avison et al., 2004; Renaud et al., 2016).

SAM conceptualises organisations across four domains: business strategy, business infrastructure, IT strategy, and IS infrastructure, which operate at two levels—external strategy and internal infrastructure (Renaud et al., 2016). Business strategy determines how the organisation competes in its marketplace and includes business scope, distinctive competencies, and governance mechanisms. Business infrastructure focuses on organisational structure, business processes, and required business skills to implement strategies effectively. IT strategy defines how an organisation positions itself within the IT marketplace, encompassing IT scope, systemic competencies, and IT governance. Finally, IS infrastructure refers to the portfolio of technological assets, key IS processes, and necessary IS skills that support business operations (Avison et al., 2004).

Strategic IT alignment tends to go beyond ensuring congruence between IT and business strategies to developing a capability that enables firms in leveraging IT resources effectively (Sabherwal and Chan, 2001; Baker et al., 2011). The alignment between IT and business strategy has been shown to directly influence firm performance, reinforcing the view that IT investments, when strategically integrated, contribute to superior business outcomes (Tallon and Pinsonneault, 2011). Additionally, alignment serves as a dynamic capability by enabling organisations to integrate IT resources with other assets, thereby enhancing adaptability and responsiveness to market changes (Sabherwal et al., 2019).

2.4 Dynamic Capabilities and the Need for Strategic Alignment

Dynamic capabilities provide a theoretical foundation for understanding how firms reconfigure resources in response to evolving market conditions (Helfat et al., 2007; Teece, 2012). However, the complexity of integrating BDA with existing organisational resources necessitates a complementary framework. This is where the SAM becomes critical. The strategic alignment of BDA can ensure that data-driven insights are not only generated but also effectively embedded into the firm's strategic and operational frameworks.

The integration of BDA with other organisational capacities, such as strategic integration capabilities (SIC), can enhance the ability to transform data insights into actionable strategies, improving operational efficiency and market competitiveness. BDA requires significant investment in infrastructure, skills, and expertise to reach its full potential (Chen et al. 2015). By leveraging strategic IT alignment, organisations can ensure that BDA is integrated into a dynamic framework that continuously adapts to new data sources and analytical tools. This integration may reinforce the organisation's ability to sense opportunities, seize resources, and reconfigure processes, strengthening its dynamic capabilities (Wamba et al 2107).

The synergy between dynamic capabilities and strategic IT alignment can maximise the value of BDA. While dynamic capabilities provide the mechanisms for continuous adaptation, strategic IT alignment ensures that these capabilities are embedded within the organisation's IT and business strategies (Sabherwal et al. 2019). This synthesis strengthens the contribution of our research by bridging the gap between IT alignment, data-driven decision-making, and dynamic capabilities, offering an in-depth understanding about how organisations adapt and compete in data-intensive environments. Table 2 provides an overview of conceptual model.

Table 2: Conceptualization and overview of conceptual framework

Theory/Concept	Key Insight	This study's conceptual framework
Dynamic Capabilities	Sensing: Continuous observation of the external environment to identify opportunities and threats (Augier and Teece, 2009). Seizing: Evaluation and investment in resources to capture opportunities (Wilden et al., 2013; Helfat and Peteraf, 2015).	Essential for BDA to adapt and evolve with new data sources and analytics tools, ensuring relevance and competitiveness. BDA requires substantial investment in infrastructure, skills, and expertise to harness its full potential.

	Reconfiguration: Recombination of resources to optimize internal and external complementarities (Sirmon et al., 2011; Teece, 2012).	BDA integration involves flexible and scalable solutions to continuously adapt and optimize resource utilisation.
Strategic Alignment Model	Congruence: Alignment between IT and business strategies to achieve superior performance (Venkatraman et al., 1993; Tallon and Pinsonneault, 2011). Capability: strategic alignment as a capability that enables the firm to leverage IT resources more effectively (Schwarz et al., 2010; Baker et al., 2011).	Strategic alignment of BDA ensures that data-driven insights are effectively available for decision making and enhancing competitiveness. The integration of BDA and SIC not only aligns IT and business strategies but also enhances the firm's dynamic capability to adapt and reconfigure resources in response to changing organisational requirements, leading to improved performance.

2.5 SIC and BDA

SIC encompasses the coordination of both internal and external functions within a firm that can foster alliances among supply chain members (Flynn et al., 2010). Internally, SIC can ensure that departments and units within the organisation work cohesively to process information and meet customer demands, while externally, it can facilitate integration with suppliers and customers to enhance overall performance (Rosenzweig et al., 2003; Itani et al., 2024).

From a dynamic capabilities' perspective, the integration of SIC and BDA may enhance sensing, seizing, and reconfiguring activities by ensuring real-time information flows that support rapid decision-making. From the SAM perspective, BDA requires structured data exchange, and SIC may serve as the foundational mechanism that can align IT capabilities with business strategy. The integration of SIC with BDA can foster strategic agility, enabling firms to extract insights, anticipate market trends, and optimise performance (Chen et al., 2021; Awan et al., 2021). For example, Netflix's use of BDA to analyse vast amounts of customer reviews and tailor content recommendations illustrates how strategic IT alignment between BDA and SIC can lead to improved customer experiences (Xu et al., 2016). Supermarkets using a data driven digital transformation approach for dynamic pricing (Syed et al., 2024). Similarly, Marriott hotels use BDA, collected through what they call IoT guestroom, integrating with their room service and consequently adjusting the room environmental aspects for the customers for a comfortable stay (Buhalis and Leung, 2018).

Despite theoretical examples, there is limited empirical research on the impact of integrating BDA and SIC on business performance. Our study aims to explore how aligning these capabilities can create synergistic effects that drive competitive advantage. This perspective shifts the focus from examining isolated effects to understanding the alignment and interaction between these capabilities, rather than solely focusing on direct causal relationships.

2.6 BDA and Performance

The growing interest in assessing the business value of BDA has unearthed critical challenges that may undermine or even reverse its potential (Kiron 2017). Interestingly, these challenges have little to do with the technology itself, but rather with how firms leverage BDA initiatives and align them with business strategies (Vidgen et al. 2017). A new stream of studies argues that BDA can develop valuable and idiosyncratic organisational capabilities that realise organisational performance, such as dynamic capabilities (Wamba et al. 2017, Mikalef et al. 2019), ambidextrous capabilities (Rialti et al. 2019b, Wamba et al. 2020), and entrepreneurial orientation (Ciampi et al. 2020). These studies acknowledge the indirect influence of BDA, arguing for the existence of intermediating links.

Aligned with the view that underscores the importance of complementary organisational resources when leveraging new digital technologies (Joshi et al. 2010; Guo et al. 2022), we argue that operational competitiveness (OC), i.e., cost reduction and quality enhancement, along with market competitiveness (MC), i.e., delivery speed and flexibility, serve as the crucial intermediary links to leverage the synergised effect of the BDA and SIC on overall firm performance. The combined effect of BDA and SIC can enhance OC through driving down costs while elevating product and service quality with efficient supply chain coordination, enabling optimised resource allocation, streamlined processes, and informed decision-making (Chen et al. 2021; Akhtar et al., 2022). Similarly, the combined effect of BDA and SIC capabilities may support MC by facilitating rapid response to changing demands, shorter lead times, and adaptable supply chain configurations (Dubey et al. 2019a; Dubey et al., 2019b). The improved operational and market strategies, in turn, can improve firm performance. These theoretical expectations are further explained as mediation hypotheses and are represented in our hypothesized model in Figure 1.

2.7 Hypotheses

We argue that the integration of BDA with SIC can significantly enhance organisational performance by improving both operational (OC) and market competitiveness (MC). These hypotheses are grounded in the theoretical frameworks of dynamic capabilities and the SAM, highlighting the mediating role of OC and MC in the relationship between BDA-SIC integration and firm performance.

BDA management capability can play a crucial role in enabling firms to process, analyse, and interpret large datasets, enabling data-driven decision-making and resource optimisation (Akter et al., 2016). However, the effectiveness of BDA management capability could be significantly enhanced when it is strategically combined with strategic integration capability (SIC)—a firm's ability to coordinate and align internal functions, suppliers, and customers to ensure seamless information flow and operational synergy (Flynn et al., 2010). SIC, as measured through customer integration, supplier integration, and internal integration, facilitates a high level of information sharing, collaborative decision-making, and synchronised operations across the supply chain (Flynn et al., 2010; Wong et al., 2011). For instance, customer integration can ensure that firms actively engage with customers through market information exchange, product development collaboration, and continuous feedback loops. This may allow BDA-driven insights to be leveraged in shaping demand forecasts and improving customer-centric innovation.

Similarly, supplier integration can strengthen strategic partnerships with key suppliers by fostering transparency in production schedules, inventory levels, and capacity planning.

This helps firms to optimise procurement, reduce uncertainty, and align supply chain processes with real-time data analytics. Finally, a firm's internal integration can ensure that cross-functional teams and integrated systems facilitate seamless internal communication, enabling different departments to collectively utilise data insights for improvement and innovation.

Whilst BDA management capability can provide the technical foundation for extracting insights, it is the strategic alignment enabled by SIC that could allow firms to translate these insights into operational execution and performance gains. Vidgen et al. (2017) argue that firms with strong BDA management capability can effectively convert data insights into business value, but the extent of this value realisation depends on their ability to integrate insights into decision-making and execution. While SIC enhances data-driven collaboration across business functions, its performance benefits can signify when firms possess the OC to act on insights. From a dynamic capabilities' perspective, OC can enable firms to reconfigure resources, streamline operations, and enhance agility (Wong et al., 2011), making it a key mechanism through which SIC and BDA management capability could drive firm performance (Teece et al., 1997; Bahrami & Shokouhyar, 2022). Furthermore, past research has identified OC as a key determinant of firm performance, reflecting a firm's ability to efficiently manage resources, streamline processes, and enhance productivity (Ou et al., 2010; Qrunfleh & Tarafdar, 2014). A strong OC driven by data analytics can enable firms to deliver high-quality products, reduce costs, and improve responsiveness, ultimately contributing to sustained competitive advantage in dynamic markets (Wong et al., 2011). Thus, we argue that OC mediates the relationship, ensuring that SIC and BDA management capability translate into tangible operational efficiencies and performance gains.

Hypothesis 1a (H1a): OC mediates the relationship between the integration of SIC and BDA management capability on firm performance.

BDA technology capability can provide the infrastructure and tools necessary for real-time data collection, processing, and analysis, enabling firms to enhance decision-making and operational agility (Akhter et al., 2016). However, its effectiveness is argued to depend on SIC, which can ensure that BDA technology is leveraged for demand forecasting, process automation, and supply chain synchronisation, reducing inefficiencies and enhancing operational visibility (Gunasekaran et al., 2017; Gupta et al., 2020). For instance, customer integration could enable real-time demand sensing, supplier integration optimises inventory and procurement, and internal integration facilitates cross-functional collaboration for process efficiency (Tseng, 2023). Lin et al. (2024) argue that firms with strong BDA technology capability can ensure business resilience and transparency by effectively collecting, processing, and analysing vast datasets. This can improve visibility into operations, optimised inventory levels, accurate safety stock planning, and demand prediction, thereby preventing issues like inventory overproduction or stock shortages.

While SIC can facilitate the adoption of BDA technology across operations, OC could be the key enabler that transforms data-driven insights into efficiency improvements, agility, and responsiveness. The SITA framework suggests that aligning IT resources with business processes enhances strategic outcomes (Popovič et al., 2018), but these outcomes can be realised through OC that integrate insights into workflows and decision-making (Wong et al., 2011). OC can effectively mediate this relationship by ensuring that insights generated by BDA technology are translated into operational efficiencies. Thus, we hypothesise:

*Hypothesis 1b (H1b)***:** *OC mediates the relationship between the integration of SIC and BDA technology capability on firm performance.*

BDA talent capability, which refers to the expertise of data scientists and analysts in extracting actionable insights, can enhance decision-making and operational efficiency (Akhter et al., 2016). However, we argue that its effectiveness depends on SIC, which can ensure that data-driven insights are embedded into business processes across internal operations, suppliers, and customers (Bag et al., 2022; Behl et al., 2022; Wamba and Akter, 2019). SIC can enable firms to translate analytical insights into strategic actions, fostering process innovation, cost reduction, and quality enhancement (Shamim et al., 2019; Freije et al., 2022). However, these benefits could materialise only when there are operational structures to effectively leverage BDA insights. From a dynamic capabilities' perspective, human expertise may help firms sense opportunities, reconfigure resources, and adapt processes, which makes OC a critical factor in realising performance improvements (Teece, 2007). Thus, rather than a direct effect, the combined impact of SIC and BDA talent on firm performance is argued to occur through OC, which ensures insights are systematically integrated into operational workflows. Thus, we propose:

Hypothesis 1c (H1c): *OC mediates the relationship between the integration of SIC and BDA talent capability on firm performance.*

Beyond operational efficiencies, the strategic alignment of BDA management capability with SIC can also strengthen a firm's market responsiveness and competitive positioning by enabling firms to leverage real-time data for rapid decision-making, demand forecasting, and customer adaptation, strengthening their MC (Chen et al., 2015).

However, these benefits may not materialise directly. MC can serve as the key enabler to plan product adjustments, empower competitive pricing, and build targeted marketing campaigns (Wong et al., 2011), where the insights from BDA and SIC could be effectively translated into market-driven actions. From a dynamic capabilities' perspective, aligning BDA with SIC can enhance a firm's ability to sense market trends, seize opportunities, and reconfigure strategies (Teece, 2007). MC approaches, such as delivery speed and product flexibility, are evidenced to enhance firm performance through optimised resource utilisation, rapid response to customer demands, and maintain flexibility in dynamic environments (Jacobs et al., 2011). Thus, we argue that MC mediates the relationship between the integration of SIC and BDA management capability to enhanced market positioning and responsiveness. Therefore, we propose:

*Hypothesis 2a (H2a)**:** MC mediates the relationship between the integration of SIC and BDA management capability on firm performance.*

The synergy between BDA technology capability and SIC can strengthen a firm's ability to analyse market data, anticipate shifts, and respond swiftly to changing conditions (Benzidia et al., 2021). According to the SAM perspective, aligning IT resources with business processes enhances a firm's agility and market adaptability, both of which are key aspects of MC (Sabherwal et al., 2019). For example, Song et al. (2022) observed that an increasing number of SMEs are focusing on establishing digital customer profiles to track buying behaviors, predict demand patterns, and personalize offerings. This illustrates how integrating BDA technology with strategic processes may enhance a firm's ability to adjust marketing strategies, optimise customer engagement, and maintain competitive agility. MC can play a pivotal role in ensuring that firms can capitalize on data-driven insights to refine their market strategies, optimize resource allocation, and enhance customer responsiveness. By bridging the gap between technological capabilities and strategic execution, MC could facilitate the transformation of digital capabilities into competitive market advantages. We, therefore, propose the following hypothesis:

*Hypothesis 2b (H2b)**:** MC mediates the relationship between the integration of SIC and BDA technology capability on firm performance.*

The integration of BDA talent with SIC can enable firms to generate nuanced insights that enhance market strategies (Chen et al., 2012). Human expertise, as highlighted by dynamic capabilities theory, can be critical for sensing market opportunities and reconfiguring resources to meet customer demands (Teece, 2007; Chatterji and Patro, 2014). By leveraging insights from BDA talent, firms can anticipate market trends, optimise product offerings, and improve customer experiences, thereby enhancing MC (Bradlow et al., 2017). Therefore, the presence of skilled BDA talent and strong integration mechanisms could benefit strongly from MC in realising organisational performance. MC could offer a mediating role, ensuring that data-driven insights could be effectively translated into competitive market actions. Through enhanced responsiveness, targeted decision-making, and improved strategic alignment, MC can facilitate the transformation of BDA-driven intelligence into sustained market success. Therefore, we propose:

Hypothesis 2c (H2c): *MC mediates the relationship between the integration of SIC and BDA talent capability on firm performance.*

Figure 1 presents our hypothesised model.

Figure 1: Hypothesised Research model

3 METHODOLOGY

3.1 Data collection

This research consisted of two data collection stages. Initially, online surveys were utilised, designed for matched-pair data to enhance content validity and response rates, as suggested by Podsakoff et al. (2003). This included choosing senior managers as respondents, ensuring anonymity and confidentiality to respondents, assuring respondents that there is no right or wrong answer to the survey to avoid socially desirable responses, and mixing the order of predictor and criterion variables to control for priming effect. A market research firm facilitated these surveys for IT and operational executives in UK-based companies within specific NAICS 2007 industry classification codes 31, 32, 33, 44, 51, 52, 54, and 55. The UK was chosen due to its high-tech investments and innovations (KPMG 2019). Using a random stratified sampling method, 1,000 medium-to-large firms were selected, as they typically invest more in strategic endeavours (Lee et al. 2015) and have superior archival data records than smaller companies.

The data were collected from IT and operations executive dyads. Two questionnaires were developed: the first was related to BDA capability and targeted senior IT executives, while the second was related to SIC, OC, and MC which targeted senior business or operations directors. In firms where one executive within the dyad was unapproachable, the other executive was asked to identify an alternative senior executive in their firm with relevant information. This approach helped us identify knowledgeable respondents and is consistent with prior information systems (IS) studies (i.e., Syed et al. 2021). We used criteria questions, such as "*our firm continuously collects and analyses data in decision-making*," to ensure the data were collected from firms with data analytics capabilities. Further, only respondents who gave the required answers to criteria questions concerning their knowledge were allowed to access the questionnaires. Survey links were independently e-mailed to each type of respondent. Before the formal data collection, the questionnaires were pre-tested with 23 postgraduate students and five IS academic professionals to assess the items' face and content validity.

The matched-pair respondents in each firm were further verified by checking that two distinct IP addresses had been logged by the online survey tool. After three rounds of follow-up reminders, 227 matched responses were collected between September and December 2019. The collected responses were screened for missing values, lack of distinct IP addresses, and disengagement (low completion time or zero variance across responses). Six matched responses were excluded following data screening, leaving 221 valid responses: the 22.10% response rate is comparable with that of other matched surveys in the IS literature (Lee et al. 2015).

In the second phase, data were collected on model variables for the 221 firms giving valid responses in the first phase. The Capital IQ database was primarily used to collect data on sales and Tobin's Q values and was complemented by the Bloomberg Professional database for any missing values. Fourteen firms were further removed from our sample due to missing data for performance measures, leaving 207 firms for analysis. To smooth out performance fluctuations attributable to unusually good or bad quarters, we measured averages of sales and Tobin's Q for the quarters in the year 2019. Table 3 provides an overview of our sample firm characteristics. Appendix sections B1 and B2 further explain our checks on statistical power and response bias.

Table 3: Characteristics of sample firms

	Frequency	Percentage
Firm size		
Medium (50–249 full-time employees)	81	39.13%
Large (≥250full-time employees)	126	60.87%
Firm age		
5–10 years	23	11.11%
11–15 years	75	36.23%
≥15 years	109	52.66%
Industry		
Food, beverage, and tobacco product manufacturing	18	8.70%
Information and communication	15	7.25%
Apparel manufacturing	6	2.90%
Printing and related support activities	4	1.93%
Computer and electronics	40	19.32%
Appliance and equipment manufacturing	37	17.87%
Health, scientific, and personal care services	23	11.11%
Data processing, hosting, and related services	22	10.63%
Insurance carrier, financial investments, and securities activities	14	6.76%
Professional, scientific, and technical activities	28	13.53%

3.2 Construct operationalisation

We used subjective measures for some of our constructs because objective measures were not readily available. A robustness check with alternative measures of BDA capability produces results that are consistent with our main findings. All constructs in our conceptual model are operationalised by adopting scales that have been tested and validated in the literature. Table

A1 in the Appendix provides an overview of the scales used and their psychometric properties. All items were measured on seven-point Likert scales with anchors ranging from "strongly disagree" (1) to "strongly agree" (7). We checked the degree of variance for all second-order constructs to be explained by their respective first-order constructs. All path coefficients were found significant at $p<0.01$ (Appendix, Table A2).

Firm performance is operationalised using two models: financial performance, measured by sales, and market value, measured by Tobin's Q. Financial performance reflects short-term impacts of BDA strategies, using sales data from 2019. However, it could be limited as it represents past performance and ignores future risks (Bardhan et al. 2013; Dos Santos et al. 2012). In contrast, market value offers a long-term perspective, incorporating future benefits of IT strategies (Mithas & Rust 2016). It was calculated using the 2019 average of Tobin's Q, which compares a firm's market value to its asset replacement cost. A Tobin's Q above 1 suggests the firm's market value surpasses its asset value.

Control variables are detailed in the Appendix, Section A3. Appendix Sections B1 to B5 provide methodological checks on biases in detail. Table 4 provides an overview of construct operationalisations with references to prior studies and data sources.

Table 4: Overview of variables operationalisation

Variable	Operationalisation
BDA management	BDA planning, control, investment, and coordination (Akter et al. 2016; Wamba et al. 2017). Survey completed by senior IT executives. Survey measurement items are included in the Appendix. Secondary data: BDA-related announcements sourced from the Lexis-Nexis database.
BDA technology	BDA connectivity, compatibility, and modularity (Akter et al. 2016; Wamba et al. 2017). Survey completed by senior IT executives. Survey measurement items are included in the Appendix. Secondary data: BDA-related announcements sourced from the Lexis-Nexis database.
BDA talent	BDA technology management knowledge, technical knowledge, business knowledge, and relational knowledge (Akter et al. 2016; Wamba et al. 2017). Survey completed by senior IT executives. Survey measurement items are included in the Appendix. Secondary data: BDA-related announcements sourced from the Lexis-Nexis database.
SIC	Internal integration, supplier integration, and customer integration (Flynn et al. 2010; Wong et al. 2011). Survey completed by senior Operations Manager. Survey measurement items included in the Appendix.
OC	Quality conformance and cost-effectiveness (Wong et al. 2011). Survey completed by senior Operations Manager. Survey measurement items included in the Appendix.
MC	Delivery speed and process flexibility (Wong et al. 2011). Survey completed by senior Operations Manager. Survey measurement items included in the Appendix.
Sales	Average sales in four quarters for the year 2019. Data source Capital IQ and Bloomberg professional.

Tobin's Q	The market value of the firm is divided by the replacement cost of assets (Mithas and Rust 2016), where the firm's market value is calculated by adding the market value of its common equity, the liquidated value of its preferred stock, and the total debt. Data source Capital IQ and Bloomberg professional.
Firm size	Logarithmic value of the total number of full-time employees. Data source Capital IQ and Bloomberg professional.
Firm age	logarithmic value of the total number of years the firm has been in business. Data source Capital IQ and Bloomberg professional.
R&D expense	The ratio of R&D expenses to total assets. Data source Capital IQ and Bloomberg professional.
Advert. Expense	The ratio of advertising expenses to total assets. Data source Capital IQ and Bloomberg professional.
Tangible assets	The ratio of tangible assets to sales Data source Capital IQ and Bloomberg Professional.
Env. dynamism	Market unpredictability (Wong et al. 2011). Survey completed by senior Operations Manager.
Industry dummy	Industry type – manufacturing, services, and financial industries.

4 ECONOMETRIC CONSIDERATIONS AND MODEL ESTIMATION

We used the ordinary least squares to estimate the direct effects of the interaction term on the dependent variables, as well as its indirect effects through the mediators. To test our hypotheses, we estimate the following equations.

Y_1 *= f (BDA management, BDA technology, BDA talent, SIC, BDA management x SIC, BDA technology x SIC, BDA talent x SIC, control variables)*

Y_2 *= f (BDA management, BDA technology, BDA talent, SIC, BDA management x SIC, BDA technology x SIC, BDA talent x SIC,* Y_1*, control variables)*

Where Y_1 is the mediating variable (MC and OC) and Y_2 is the dependent variable (Sales and Tobin's Q). To account for the potential endogeneity, we used Garen's (1984) and two-stage least square approaches. First, we used Garen's (1984) two-step residual analysis approach for selection bias (Saldanha et al. 2017, 2022) which firms may self-select into integrating BDA based on observable or unobservable factors. In the first step, we regressed two additional variables that were likely to influence the firm's use of BDA on our independent variables, BDA $_{\text{dimensions}}$ SIC. In the second step, we used residuals from the first-stage equation and included η˜ and the interaction term η˜ × BDA $_{\text{dimensions}}$ SIC. η̃ corrects for selection bias and η̃ × BDA $_{\text{dimensions}}$ SIC accounts for unobserved heterogeneity (Garen, 1984). We conducted several tests to assess instrument validity. Appendix Section B explains these approaches and corresponding results. Table 5 presents the descriptive statistics of key variables.

Table 5: Descriptive statistics

	Mean (Std.)	1	2	3	4	5	6	7	8

1. BDA Management	4.24 (1.31)	1.000							
2. BDA Technology	4.36 (1.28)	0.324**	1.000						
3. BDA Talent	4.11 (1.16)	0.274**	0.233**	1.000					
4. SIC	4.42 (0.84)	0.102*	0.137*	0.017	1.000				
5. OC	4.29 (0.75)	0.230**	0.122*	0.084	0.336***	1.000			
6. MC	4.63 (0.88)	0.058	0.168*	0.116*	0.130*	0.372***	1.000		
7. Sales	10.52 (7.54)	0.082	0.102*	0.063	0.032	0.122*	0.246**	1.000	
8. Tobin's Q	1.63 (1.30)	0.043	0.057	0.089	0.166*	0.285**	0.119*	0.113*	1.000

*** $p<0.01$, ** $p<0.05$, * $p<0.1$, SIC= strategic integration capability, OC= operational competitiveness, MC= market competitiveness

5 MODEL RESULTS

The study used Baron and Kenny's (1986) method to test mediation hypotheses. The analysis (Table 6) shows that OC fully mediates the relationship between various dimensions of BDA and SIC with firm performance metrics (Sales and Tobin’s Q). Initial models (1-2) found no direct effect of BDA and SIC on Sales and Tobin’s Q. However, significant positive impacts are observed of BDA dimensions interacting with SIC on OC (Model 3), which in turn significantly affect Sales and Tobin’s Q (Model 4&5), confirming Hypotheses H1a, b, & c.

We repeated the approach for Hypotheses H2 a, b, & c, focusing on MC. While initial models (Table 7) show insignificant effects of BDA and SIC on Sales, significant direct effects were noted on Tobin’s Q. Further, BDA dimensions interacting with SIC significantly impact MC (Model 3), which then significantly influenced Sales and Tobin’s Q (Model 4&5). This confirms that MC fully mediates the relationship between BDA dimensions and SIC with Sales and Tobin’s Q, thus supporting/validating H2 a, b, & c. Our robustness checks with mediation analysis further supported these findings, detailed in Appendix Section C1 (Chen et al. 2012; Chiang et al. 2018).

Among the control variables, the study found that environmental dynamism negatively affects OC and MC, while firm size, age, and tangible assets positively influence these capabilities, supporting the idea that resources aid in developing complex capabilities under stable conditions. In Model 5, R&D expense, tangible assets, firm size, and age significantly influenced Tobin's Q, consistent with Bardhan et al. (2013). Additionally, firm size and advertising expenses positively impacted Sales (Model 4), corroborating prior literature.

Table 6: Results for the mediation effect of OC

	Model 1 Direct treatment effect	Model 2 Direct treatment effect	Model 3 First stage-mediation link	Model 4 Second stage – mediation link	Model 5 Second stage – mediation link
	DV: Sales without mediator	DV: Tobin's Q without mediator	DV: OC	DV: Sales with OC mediator	DV: Tobin's Q with OC mediator
BDA Management	0.024	0.065	0.147*	0.032	0.062
BDA Technology	0.017	0.083*	0.221**	0.016	0.078*
BDA Talent	0.001	0.009	0.072	0.011	0.001
SIC	0.082*	0.011	0.102*	0.085*	0.014
BDA Management x SIC	0.067	0.089*	0.104**	0.075	0.082
BDA Technology x SIC	0.012	0.078*	0.135**	0.011	0.066
BDA Talent x SIC	0.037	0.054	0.078*	0.035	0.053
OC				0.132**	0.201**
Firm size	0.159*	0.089*	0.130*	0.162*	0.083*
Firm age	0.023	0.136**	0.165*	0.029	0.137**
R&D expense	0.079	0.131*	0.055	0.077	0.128*
Advert. expense	0.124*	0.084	-0.079	0.121*	0.082
Tangible assets	0.048	0.211**	0.136*	0.039	0.196**
Env. dynamism	-0.045	-0.078	-0.123*	-0.042	-0.075
Industry dummy	Included	Included	Included	Included	Included
Sample (N)	207.00	207.00	207.00	207.00	207.00
Adj. R^2	0.205	0.236	0.405	0.242	0.258
F-Statistic	2.884***	3.235***	0.465***	2.984***	3.276***

*p<0.10; **p<0.05; ***p<0.01; SIC= strategic integration capability, OC= operational competitiveness; $\chi2$ (df) = 94.38 (32) = 2.9; RMSEA (90% CI) = 0.038 (0.032, 0.047); CFI = 0.96; IFI = 0.92; NCP (90% CI) =88.54 (72.54, 103.86). The interaction terms were also tested one at a time and found substantively similar results (omitted for brevity).

Table 7: Results for the mediation effect of MC

	Model 1 Direct treatment effect	Model 2 Direct treatment effect	Model 3 First stage-mediation link	Model 4 Second stage – mediation link	Model 5 Second stage – mediation link
	DV: Sales without mediator	DV: Tobin's Q without mediator	DV: MC	DV: Sales with MC mediator	DV: Tobin's Q with MC mediator
BDA Management	0.024	0.065	0.088	0.028	0.064
BDA Technology	0.017	0.083*	0.115*	0.015	0.083*
BDA Talent	0.001	0.009	0.246**	0.002	0.004
SIC	0.082*	0.011	0.124*	0.087*	0.012
BDA Management x SIC	0.067	0.089*	0.091*	0.072	0.085
BDA Technology x SIC	0.012	0.078*	0.112*	0.008	0.072
BDA Talent x SIC	0.037	0.054	0.135**	0.032	0.056
MC				0.296***	0.098*
Firm size	0.159*	0.089*	0.044	0.155*	0.088*
Firm age	0.023	0.136**	0.100*	0.018	0.135**
R&D expense	0.079	0.131*	0.098	0.078	0.092
Advert. expense	0.124*	0.084	0.120*	0.126*	0.069
Tangible assets	0.048	0.211**	0.066	0.045	0.224**
Env. dynamism	-0.045	-0.078	-0.028	-0.012	-0.001
Industry dummy	Included	Included	Included	Included	Included

Sample (N)	207.00	207.00	207.00	207.00	207.00
Adj. R^2	0.205	0.236	0.354	0.230	0.266
ΔF-Statistic	2.884***	3.235***	0.478***	3.334***	3.571***
*p<0.10; **p<0.05; ***p<0.01; SIC= strategic integration capability, MC= market competitiveness; χ2 (df) = 96.55 (32) = 3.01; RMSEA (90% CI) = 0.03 (0.039, 0.046); CFI = 0.96; IFI = 0.94; NCP (90% CI) = 88.74 (72.29, 102.66). The interaction terms were also tested one at a time and found substantively similar results (omitted for brevity).					

We plotted the interaction terms to validate the synergistic effects of BDA dimensions and SIC on OC and MC. The graphical representations (Figures 2,3, & 4) show a higher impact for the interaction effect with the higher level of BDA and SIC capabilities. We tested the robustness of our findings through various checks, including alternate measures of mediation effect assessments, and measurement methods detailed in Appendix, Section C.

Figure 2: The interaction effect of BDA Management and SIC on OC and MC

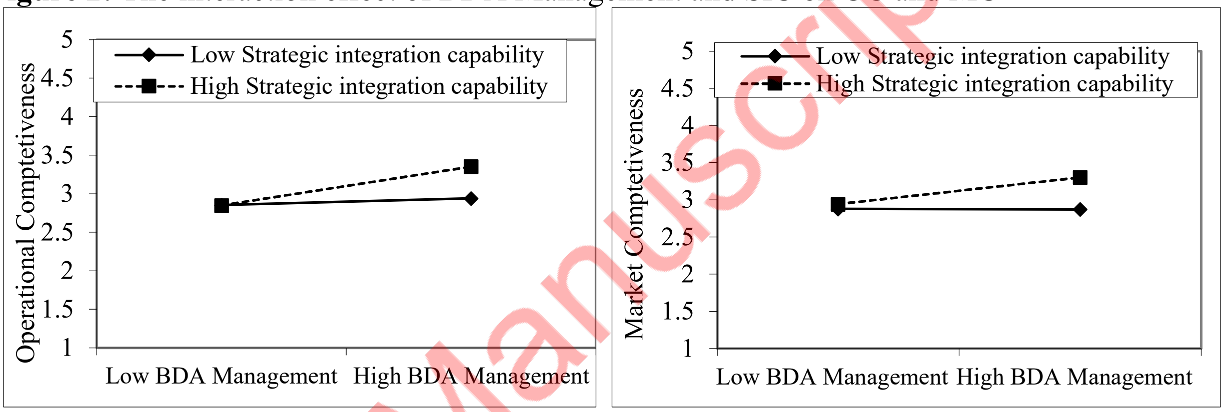


Figure 3: The interaction effect of BDA Technology and SIC on OC and MC

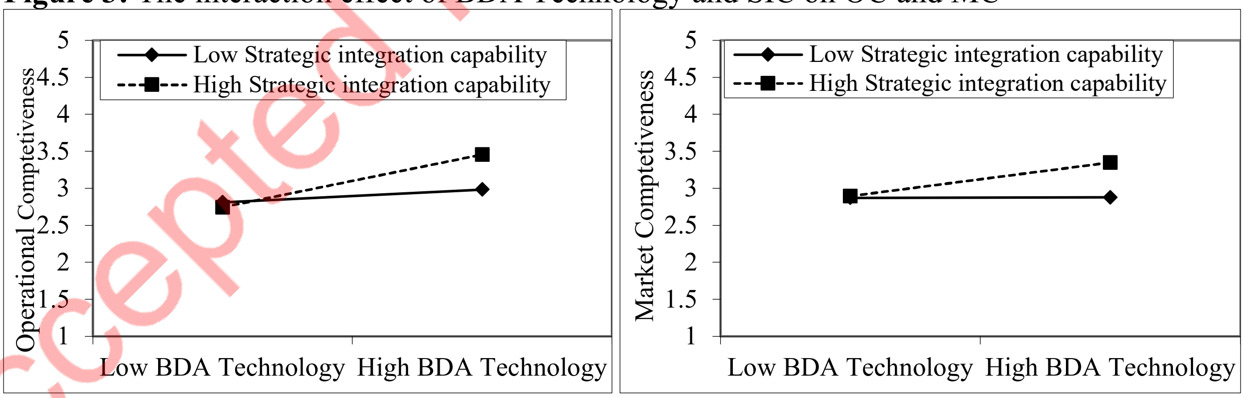
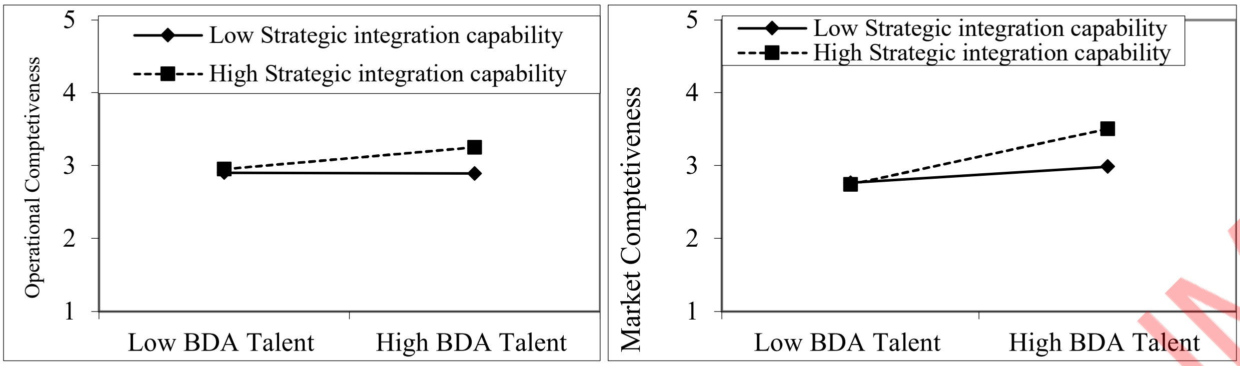


Figure 4: The interaction effect of BDA Management and SIC on OC and MC



6 DISCUSSION AND CONCLUSIONS

The integration of the strategic alignment model (SAM) and dynamic capabilities theory guided our research design by positing that the strategic bundling of resources, such as BDA sub-dimensions and SIC, is crucial for achieving competitive performance. This perspective shifts the focus from investigating isolated effects to understanding complex interactions and configurations that drive performance outcomes.

Our research explores the combined impact of BDA dimensions (BDA management capability, BDA technology capability, and BDA talent capability) with strategic integration capability (SIC), on firm performance, mediated by operational and market competitiveness. We theoretically argue and empirically demonstrate that BDA capabilities integrated with SIC can enhance a firm's operational and market competitiveness. Our findings suggest that BDA management capability, which relates to the strategic-level decisions in the implementation of BDA, such as planning, investment, coordination, and control, coupled with SIC can provide a strategic-level guide to improve value proposition (Chen et al., 2022). Our findings are in line with past research, highlighting that BDA technology capability can improve a firm's operation mediated by value addition on both the operational and market levels. This is due to BDA infrastructure's ability to adapt to different situations, and gathered data may help exploit new opportunities, resulting in increased operational and market competitiveness (Lu and Ramamurthy, 2011). Finally, BDA talent capability allows personnel to possess skills needed to identify the right data obtained from SIC to draw the right conclusions, thus creating a competitive advantage (Wamba et al., 2017; McAfee and Brynjolfsson, 2012).

Altogether, our results reinforce the theoretical proposition based on SAM and dynamic capabilities theory that BDA does not directly influence performance, but instead integrates with existing organisational capabilities, SIC, to realise performance. Second, in contrast to prior studies, which reported the direct influence of BDA capability on firm performance, our results are not statistically significant for the direct effects of BDA on neither market value nor financial performance. Finally, we find that both operational and MC fully mediate the impact of the interaction of BDA dimensions and SIC on organisational performance. These findings have important implications for IS research and practice.

6.1 Key contributions and theoretical implications

This research makes several contributions to the BDA literature by addressing the four key gaps identified in our introduction. First, we challenge the monolithic conceptualization of BDA. As Sousa and Voss (2008) argue, once a concept's general importance is established, research must focus on its nuances to provide deeper, actionable insights. In this spirit, while much of the existing research treats BDA as a single higher-order construct (e.g., Chen et al. 2015; Muller et al. 2018; Wamba et al. 2017), our study demonstrates the importance of examining its sub-dimensions. Just as one appreciates each instrument in an orchestra, our fine-grained analysis reveals how BDA Management, BDA Technology, and BDA Talent capabilities each play distinct roles in value creation, thereby pointing to promising avenues for future work that explores these specific impacts.

Second, we reveal the indirect pathways of BDA value creation. Addressing calls in the literature to understand the mechanisms through which BDA creates value (Agarwal and Dhar 2014; Mikalef et al. 2019; Vidgen et al. 2017), our findings break the stereotypical view of BDA's direct impact. We show that BDA does not directly influence financial performance.

Instead, its value is realized through operational and market competitiveness, which fully mediate the relationship. This finding clarifies the mechanisms through which the business value of BDA capability is realised (Zeng et al., 2018), offering a more nuanced explanation of its role.

Third, we advance theory by demonstrating that BDA must be strategically aligned with a firm's dynamic capabilities to realize performance gains. We position BDA as a strategic enabler that functions as a '*digital complementary asset*' (Rosemann et al., 2011). By embedding BDA within a broader digital business strategy (Bharadwaj et al., 2013), our research extends the IT alignment literature (Coltman et al., 2015), showing that integrating BDA with Strategic Integration Capability (SIC) is a core component of digital ecosystems. This synthesis extends Teece's (1986, 2018) argument that technological innovation must be combined with existing assets to create sustained value.

Fourth, we strengthen empirical rigor through objective performance measures. Addressing a noted weakness in the BDA literature, where empirical studies using objective measures have been scarce (Tambe 2014, Müller et al. 2018), our research employs archival data from Capital IQ and Bloomberg Professional databases. This approach provides more reliable evidence than the self-reported perceptual measures commonly used in prior studies (Ferraris et al. 2019, Rialti et al. 2019b, Sun and Liu 2020, Awan et al. 2022).

Altogether, these contributions refine the current understanding of BDA's impact and pave the way for more nuanced future explorations. Our findings show that BDA has no direct influence on financial performance, breaking the stereotypical view (e.g., Wamba et al. 2017, Raguseo and Vitari 2018, Ferraris et al. 2019, Rialti et al. 2019b) and providing a more novel resource integration perspective of BDA. In this light, BDA can be considered to provide a digital platform that facilitates enhancing operational and market capabilities, which in turn realise performance improvements. Our research supports the expanding role of IT capabilities in contemporary organisations, which goes beyond a remit "*simply to support operations*" to being "*the heart of operations*" (Hayes et al. 2005, p. 175).

6.2 Managerial implications

Our findings provide several actionable insights for managers aiming to leverage BDA for enhanced organisational performance. First, managers should focus on integrating BDA with existing capabilities, such as SIC, rather than relying on BDA as a standalone solution. This integration can optimise resource allocation and coordination, leading to improved operational and market competitiveness. Second, managers must recognise the multidimensional nature of BDA and tailor their approaches to utilise specific sub-dimensions effectively. By doing so, they can create more granular strategies that align with their organisational context. Third, adopting a proactive and strategic approach to BDA implementation is essential. Managers should ensure that BDA capabilities are complemented by other organisational resources to maximise their potential. Finally, the emphasis should be on building robust mechanisms for BDA to interact with existing capabilities, thereby facilitating the realisation of business value. This involves continuous evaluation and reconfiguration of resources to adapt to the dynamic market environment, ensuring sustained competitive advantage.

6.3 Limitations and future research avenues

This study has several limitations that may provide foundations for further work. Although the alternative approaches used (i.e., endogeneity test, reverse causality checks) confirm our key findings, we cannot formally ascertain causality due to the cross-sectional nature of the analysed data. Our use of cross-sectional data limits our insights to immediate effects and doesn't reflect the evolving dynamics of BDA on firm performance over longer periods. Moreover, this study's findings are derived from data on British firms only, which may limit their generalisability.

Another limitation of this study is the potential presence of double-barrelled questions, even though all survey items were adopted from established studies, and prior research using the same scale has reported no issues. For instance, the survey question, “In our organisation, business analysts and line people meet frequently to discuss important issues both formally and informally,” combines two contexts—formal and informal meetings—which may lead to ambiguous responses if one type occurs more frequently than the other. While the study applies Garen’s (1984) two-stage estimation approach and conducts robustness tests in line with Saldanha et al. (2017, 2022) to address endogeneity and selection bias (see Section B5), these methods do not fully eliminate measurement errors arising from double-barrelled items. Future research may consider measuring each construct separately to mitigate this issue.

While our sample spans multiple industries and includes both medium and large organisations, we acknowledge that this diversity may introduce sector-specific variation in data maturity, resource availability, and operational contexts. Although our modelling controls for industry effects, the findings should be interpreted with caution when generalising across sectors with heterogeneous digital capabilities. Additional studies using data from dispersed geographical locations or cultures may help to assess the generalisability of our findings. Our findings acknowledge the still often neglected multidimensionality of BDA, thereby pointing to promising avenues for future work at the first-order constructs for the BDA construct. A strategic integration approach to dynamic capabilities offers a theoretical lens for other scholars to study BDA’s impact on resource management, i.e., comparing BDA's integration with other strategic resources, enabling comparative studies to provide meaningful practical insights (Jan et al. 2019). The present study measures firm performance by focusing on short-term (financial performance) and long-term measures (market value performance). Future work could examine whether BDA, SIC, OC, and MC play similar roles in other dimensions of firm success (e.g., new product development) and whether there are any trade-offs in the effects of these capabilities on various dimensions of firm success, potentially resulting from industry-specific contexts.

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APPENDIX

Section A: Construct operationalization

Table A1: Measurement scales and psychometric properties.

	Mean (SD)	Loading
BDA Management (CR= 0.89, AVE= 0.67)		
BDA planning (Wamba et al. 2017)		
We enforce adequate plans for the introduction and utilization of big data analytics.	4.16 (1.24)	0.75
We perform big data analytics planning processes in systematic and formalized ways.	5.33 (1.03)	0.82
We frequently adjust big data analytics plans to better adapt to changing conditions.	3.34 (1.11)	0.88
BDA Investment Decision-Making (Wamba et al. 2017)		
In making BDA investment decisions, we consider and project how much these options will help end-users make quicker decisions.	4.57 (1.08)	0.67
In making BDA investment decisions, we think about and estimate the cost of training that end-users will need.	5.55 (0.91)	0.72
In making BDA investment decisions, we consider and estimate the time managers will need to spend overseeing the change.	3.89 (2.34)	0.77
BDA Coordination (Wamba et al. 2017)		
In our organization, business analysts and line people meet frequently to discuss important issues both formally and informally.	5.13 (0.91)	0.66
In our organization, business analysts and line people from various departments frequently attend cross-functional meetings.	4.55 (1.23)	0.78
In our organization, business analysts and line people coordinate their efforts harmoniously.	4.37 (1.33)	0.65
BDA Control (Wamba et al. 2017)		
We are confident that big data analytics project proposals are properly appraised.	4.98 (1.01)	0.73
We constantly monitor the performance of the big data analytics function.	4.15 (1.42)	0.66
Our analytics department is clear about its performance criteria.	3.88 (2.03)	0.85
BDA Technology (CR= 0.88, AVE= 0.66)		
BDA Connectivity (Akter et al. 2016)		
All remote, branch, and mobile offices are connected to the central office for analytics.	4.02 (1.18)	0.82
Our organization utilizes open systems network mechanisms to boost analytics connectivity.	4.67 (0.98)	0.74
There are no identifiable communications bottlenecks within our organization when sharing analytics insights.	3.95 (1.46)	0.75
BDA Compatibility (Akter et al. 2016)		
Software applications can be easily transported and used across multiple analytics platforms.	5.29 (0.59)	0.73
Our user interfaces provide transparent access to all platforms and applications.	4.78 (1.12)	0.65
Analytics-driven information is shared seamlessly across our organization, regardless of the location.	4.63 (0.86)	0.66
BDA Modularity (Akter et al. 2016)		
Reusable software modules are widely used in new analytics model development.	5.03 (0.94)	0.77
End-users utilize object-oriented tools to create their own analytics applications.	4.96 (1.12)	0.84
Applications can be adapted to meet a variety of needs during analytics tasks.	4.65 (1.22)	0.86
BDA Talent (CR= 0.85, AVE= 0.64)		
BDA Technical Knowledge (Wamba et al. 2017)		
Our analytics personnel are very capable in terms of programming skills.	4.52 (1.27)	0.77
Our analytics personnel are very capable in the areas of data and network management and maintenance.	4.88 (1.16)	0.73
Our analytics personnel create very capable decision-support systems driven by analytics.	5.19 (0.95)	0.69
BDA Technology Management Knowledge (Wamba et al. 2017)		
Our analytics personnel show superior understanding of technological trends.	4.57 (1.37)	0.76
Our analytics personnel show superior ability to learn new technologies.	4.88 (1.25)	0.79
Our analytics personnel are very knowledgeable about the critical factors for the success of our organization.	5.07 (0.98)	0.83
BDA Business Knowledge (Wamba et al. 2017)		

Our analytics personnel understand our organization's policies and plans at a very high level.	4.65 (1.02)	0.75
Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions.	4.18 (1.27)	0.77
Our analytics personnel are very knowledgeable about business functions.	3.98 (1.45)	0.76
BDA Relational Knowledge (Wamba et al. 2017)		
Our analytics personnel are very capable in terms of planning, organizing, and leading projects.	5.11 (0.89)	0.83
Our analytics personnel are very capable in terms of planning and executing work in a collective environment.	4.87 (1.15)	0.73
Our analytics personnel are very capable in terms of teaching others.	3.98 (1.78)	0.82
Strategic Integration Capability (CR= 0.76, AVE= 0.66)		
Customer Integration (Flynn et al. 2010; Wong et al. 2011)		
We have a high level of information sharing with our major customers about the market.	4.11 (1.32)	0.76
Our customers are involved in our product development processes.	4.44 (1.27)	0.65
We regularly follow-up with our major customer for feedback.	4.07 (1.46)	0.76
Supplier Integration (Flynn et al. 2010; Wong et al. 2011)		
We have a high degree of strategic partnership with suppliers.	4.78 (0.97)	0.77
Our major supplier shares their production schedule with us.	4.55 (1.07)	0.76
Our major supplier shares their production capacity with us.	4.51 (1.22)	0.78
\We share our inventory levels with our major supplier.	4.07 (1.46)	0.65
Internal Integration (Flynn et al. 2010; Wong et al. 2011)		
We have an integrated system across functional areas under plant control.	4.49 (1.38)	0.76
We use cross-functional teams in process improvement.	4.28 (1.21)	0.72
We use cross-functional teams in new product development.	4.33 (1.16)	0.71
Dynamism (CR= 0.79, AVE= 0.56) (Wong et al. 2011)		
Our suppliers' performance is unpredictable.	5.11 (0.87)	0.67
Our competitors' actions regarding marketing promotions are unpredictable.	4.64 (1.19)	0.73
Our firm uses core production technologies that often change.	4.33 (2.01)	0.72
Operational competitiveness (CR= 0.74, AVE= 0.57)		
Product/Service Quality (Wong et al. 2011)		
Our products/services meet established standards (i.e., conformance quality).	4.55 (1.28)	0.72
Our products/services have lower probability of malfunctioning or failing within a specified time (i.e., product/service reliability).	5.12 (1.01)	0.68
Our products/services offer primary operating characteristics (i.e., performance quality).	4.34 (1.20)	0.71
Product Cost (Wong et al. 2011)		
We offer lower-priced products than our competitors.	4.19 (1.39)	0.75
We manufacture similar products at a lower cost than our competitors.	4.15 (1.46)	0.69
Market competitiveness (CR= 0.72, AVE= 0.52)		
Delivery Speed (Flynn et al. 2010)		
We provide fast-response deliveries from order to end customer.	4.29 (1.19)	0.72
We have faster order fulfilment time than our competitors.	4.38 (1.18)	0.76
We have faster order delivery than our competitors.	4.57 (1.32)	0.68
Process Flexibility Speed (Flynn et al. 2010)		
Our firm has the ability to rapidly change production volumes.	4.51 (1.33)	0.74
Our firm has a broad product mix within the same manufacturing and process facilities.	4.37 (1.29)	0.66
Our firm has the ability to rapidly modify methods for materials.	4.46 (1.17)	0.69

Table A2: Assessment of higher-order models

	Latent constructs	**AVE**	**CR**	**Dimensions**	**B**	**R^2**	**t-stat**
Second-order constructs	BDA Management	0.658	0.890	BDAPL	0.922	0.785	25.642
				BDAID	0.945	0.772	68.815
				BDACO	0.897	0.82	45.834
				BDACT	0.901	0.805	54.956
	BDA Technology	0.664	0.878	BDACN	0.894	0.814	26.333
				BDACM	0.910	0.825	29.723
				BDAMD	0.886	0.813	15.786

	BDA Talent Capability	0.637	0.846	BDATM	0.842	0.788	24.275
				BDATK	0.835	0.765	32.114
				BDABK	0.865	0.774	20.656
				BDARK	0.894	0.806	17.334
	Strategic Integration Capability	0.655	0.755	Customer integration	0.825	0.754	26.442
				Supplier integration	0.884	0.767	35.083
				Internal integration	0.806	0.723	25.420
	Operational Competitive	0.566	0.735	Product quality	0.776	0.743	15.890
				Product cost	0.794	0.725	17.225
	Market Competitive	0.524	0.719	Delivery speed	0.824	0.768	24.624
				Process flexibility	0.884	0.799	22.119
Notes: $\chi2$ (df) = 82.39 (29) = 2.8; RMSEA (90% CI) = 0.03 (0.034, 0.041); CFI = 0.97; IFI = 0.94; NCP (90% CI) = 89.33 (77.55, 107.94).							

Table A3: Discriminant validity results based on AVE-SE (Fornell-Larker criterion)

	1	2	3	4	5	6	7	8
1. BDA Planning	**0.842**							
2. BDA Investment Decision-Making	0.130	**0.885**						
3. BDA Coordination	0.102	0.144	**0.774**					
4. BDA Control	0.078	0.109	0.168	**0.798**				
5. BDA Connectivity	0.152	0.068	0.130	0.036	**0.823**			
6. BDA Compatibility	0.176	0.012	0.044	0.048	0.058	**0.745**		
7. BDA Modularity	0.084	0.048	0.026	0.020	0.130	0.194	**0.755**	
8. BDA Technology Management Knowledge	0.130	0.123	0.102	0.053	0.058	0.014	0.023	**0.923**
9. BDA Technical Knowledge	0.116	0.096	0.063	0.044	0.078	0.023	0.078	0.336
10. BDA Business Knowledge	0.176	0.116	0.084	0.036	0.096	0.012	0.063	0.212
11. BDA Relational Knowledge	0.068	0.084	0.048	0.068	0.109	0.026	0.102	0.194
12. Customer Integration	0.058	0.058	0.137	0.058	0.194	0.020	0.020	0.053
13. Supplier Integration	0.044	0.053	0.123	0.078	0.176	0.044	0.032	0.036
14. Internal Integration	0.036	0.032	0.078	0.176	0.203	0.053	0.048	0.068
15. Product Quality	0.020	0.102	0.168	0.144	0.084	0.096	0.032	0.116
16. Delivery Speed	0.026	0.130	0.123	0.102	0.058	0.084	0.053	0.044
17. Product Flexibility	0.063	0.116	0.090	0.137	0.017	0.116	0.048	0.063
18. Product Cost	0.084	0.137	0.078	0.212	0.044	0.078	0.032	0.102

	9	10	11	12	13	14	15	16	17	18
9. BDA Technical Knowledge	**0.881**									
10. BDA Business Knowledge	0.230	**0.844**								
11. BDA Relational Knowledge	0.176	0.152	**0.753**							
12. Customer Integration	0.109	0.102	0.176	**0.784**						
13. Supplier Integration	0.123	0.084	0.137	0.017	**0.741**					
14. Internal Integration	0.102	0.130	0.194	0.116	0.152	**0.727**				
15. Product Quality	0.026	0.090	0.063	0.096	0.176	0.212	**0.764**			
16. Delivery Speed	0.032	0.058	0.048	0.026	0.063	0.116	0.078	**0.742**		
17. Product Flexibility	0.023	0.032	0.044	0.020	0.048	0.044	0.048	0.058	**0.774**	
18. Product Cost	0.040	0.078	0.036	0.058	0.058	0.102	0.032	0.023	0.063	**0.737**
Note: Bold values represent AVE values.										

Section A1: Control variables

Control variables were included to minimize spurious effects. Firm size may affect our results because larger firms have more slack resources, which can facilitate implementation of CCC and limit any adverse effects on business performance. Firm size was measured as the logarithmic value of the total number of full-time employees. Firm age may affect our results because older firms tend to have developed competencies and established processes that may support building new capabilities but may also act as key rigidities (Syed et al., 2020). Firm age was measured as the logarithmic value of the total number of years the firm has been in business. We also controlled for environmental dynamism because a higher level of environmental dynamism requires a greater amount of information to be processed by decision-makers to achieve a given level of operational and business performance (Syed et al., 2020). Following prior studies (Bardhan et al. 2013; Kohli et al. 2012), we controlled for variables that may influence sales and Tobin's Q. In particular, we controlled for the ratio of advertising expenses to total assets, the ratio of R&D expenses to total assets, and the ratio of tangible assets to sales. Beyond firm-level controls, we controlled for industry type (manufacturing, services, or financial), because the diverse nature of firms in different industries may lead to different performance implications (Chae et al. 2014; Syed et al., 2024). Three dummy variables were created, one for each industry type, taking the value 1 if the firm was in that industry and 0 otherwise: Industry 1, Industry 2, and Industry 3 represent the manufacturing, services, and financial industries, respectively. Experimental tests with further industry-based dummy variables showed high correlation, so these were truncated in the analysis.

Section B: Methodological checks

Section B1: Priori statistical power analysis

A priori statistical power analysis was performed to estimate the minimum sample size required for a good estimate of our proposed model (Benitez et al. 2018). Keeping a medium effect size ($f^2 = 0.150$), using seven predictors (the maximum number of structural links received by sales and Tobin's Q), a confidence level of 0.05, and a desired statistical power level of 0.80, the proposed model required a minimum sample size of 98 (Cohen 1988). The sample size of 207 in this study is, therefore, adequate to estimate the proposed model. In other words, our sample should have sufficient statistical power to detect significant effects (Cohen 1988).

Section B2: Response bias

To check for late-response bias, a comparison was performed of the demographics of the first wave of respondent firms (early respondents) and the last wave of respondent firms (late respondents). T-tests showed no statistically significant differences between the two groups. We also performed a comparison of the demographics of the respondent sample and non-respondent firms to check for non-response bias. Again, t-tests revealed no pattern of statistically significant differences between the two groups of firms based on average sales, firm age, and industry type.

Section B3: Measure validation and reliability

We performed an exploratory factor analysis that evidences the items were loaded on their respective components (see Appendix – Table A1). Following the methodological recommendation of Gefen et al. (2011), all factor loadings on the intended latent variables were tested and found to be higher than 0.70 (for all first order and second-order constructs) and the average variance extracted (AVE) from each variable exceeded 0.50 (Appendix, Table A2), evidencing convergent validity (Fornell and Larcker 1981). Discriminant validity was assessed by performing the AVE-SV test, which compares the AVE estimate for each construct to the shared variance (i.e., squared correlation) between the construct and all other constructs in the model. To achieve discriminant validity, a construct's AVE should be greater than the shared variance between it and all other constructs (Fornell and Larcker 1981, Voorhees et al. 2016). Appendix, Table B6, provides the results of our AVE-SV test, which suggest there is no overlap between the constructs (Voorhees et al. 2016). In addition, for each construct, the factor loadings were much higher than the cross-loadings on other constructs, confirming the sufficiency of discriminant validity (Hair et al. 2013).

Multicollinearity was tested by checking the correlation coefficients between the constructs. Table 5, presents the descriptive statistics for our key variables. The highest correlation coefficient between key constructs is 0.372, well below the threshold of 0.80. Variance inflation factor scores ranged from 1.067 to 4.255, sufficiently below recommended thresholds (Hair et al. 2013). Further details on common method bias checks are included in the Appendix (Section C1).

The model fit of the structural model was assessed using confirmatory factor analysis (CFA), checking chi-squared ($\chi 2$) / degrees of freedom (df), comparative fit index (CFI), goodness of fit index (GFI), Tucker-Lewis index (TLI), root mean squared error approximation (RMSEA), and standardized root mean square residual (SRMR). The CFA revealed $\chi 2$/df (82.39/29) = 2.841; RMSEA = 0.037; SRMR = 0.03; CFI = 0.972; GFI = 0.985; TLI = 0.969. All model fit indices were above the recommended thresholds (Hu and Bentler 1999), indicating that the measures of the model variables in this study were acceptable.

Section B4: Common method bias checks

The data collection approach used, featuring two respondents, a single method, and an online questionnaire survey, could potentially lead to common method bias. Accordingly, three tests were conducted to ensure common method bias is minimal in this study. First, Harman's one-factor test was performed. The analysis generated distinct expected factors with the largest factor accounting for 22.73% of the total variance (72.35). Second, a CFA marker variable approach was employed to observe the shared variance between a marker variable and hypothesized variables (Serrano Archimi et al. 2018; Williams et al. 2010), as adopted in prior IS studies (Liang et al. 2007). A single-scale item was identified as a marker variable that was theoretically unrelated to the variables in our conceptual model. The chi-squared statistic difference ($\Delta\chi^2$) test was performed via CFA to check for statistically significant differences between a basic measurement model that included only hypothesized variables and an extended measurement model that also included the theoretically irrelevant marker (Serrano Archimi et al. 2018). The analysis revealed that there was no statistically significant improvement in the series of fit indices. Results for the basic model and the extended model, respectively, are as follows: $\chi 2/df = 82.39/29$ vs. 117.85/30, CFI = 0.972 vs. 0.913, GFI = 0.985 vs. 0.947, and TLI = 0.969 vs. 0.945. Moreover, there was no statistically significant difference in the chi-squared values ($\Delta\chi 2 = 1.087$; $p > 0.1$) between the measurement models, indicating that common method bias can be ruled out (Williams et al. 2010). Third, following the recommendation of Lindell and Whitney (2001), the second smallest positive correlation among measurement items (r=0.008) was selected as a conservative estimate of common method variance, and all between-item correlations were adjusted by partialling out the common method variance estimate. The results showed only a slight change in the magnitude of correlations and no change in statistical significance, suggesting that common method variance is unlikely to be a concern.

Section B4-2: Results of Hypotheses

Hypothesis	Results
Hypothesis 1a (H1a): OC mediates the relationship between the integration of SIC and BDA management capability on firm performance.	supported
*Hypothesis 1b (H1b)**:** OC mediates the relationship between the integration of SIC and BDA technology capability on firm performance.*	supported
*Hypothesis 1c (H1c)**:** OC mediates the relationship between the integration of SIC and BDA talent capability on firm performance.*	supported
*Hypothesis 2a (H2a)**:** MC mediates the relationship between the integration of SIC and BDA management capability on firm performance.*	supported
*Hypothesis 2b (H2b)**:** MC mediates the relationship between the integration of SIC and BDA technology capability on firm performance.*	supported
*Hypothesis 2c (H2c)**:** MC mediates the relationship between the integration of SIC and BDA talent capability on firm performance.*	supported

Section B5: Endogeneity Test

Following prior studies (such as (Saldanha et al. 2017, 2022)), we applied Garen's (1984) two-stage estimation approach to correct for endogeneity and selection bias. In the first stage, we estimate the interaction term of BDA dimensions and SIC by including additional variables that may influence BDA use. These include the *industry intensity of BDA use* and *mechanistic structure.* The industry intensity (measured as the average use of BDA in the industry) is likely to drive the BDA use in the focal firm but is unlikely on its own to improve operational, market, or organizational performance. This is consistent with the prior literature that uses industry IT intensity as an instrument for firm IT use (e.g., (Kleis et al. 2012; Saldanha et al. 2020)). The mechanistic structure measures the extent to which a firm tends to be more bureaucratic and employs the common characteristics of institutionalized rules, policies, and routines to define how tasks are accomplished (Kang and Snell 2009). The mechanistic structure is argued to provide greater clarity, transparency, and objectivity, especially when tasks are complex, stable, and routine, such as BDA capability. It is measured using a 3-items scale (Table B1). We regress the industry intensity and mechanistic structure factors and then calculate residuals ($\tilde{\eta}$) from the first-stage equations and include $\tilde{\eta}$ and the interaction term $\tilde{\eta} \times$ BDA $_{\text{dimensions}}$ SIC as endogeneity correction terms in the second-stage equation. $\tilde{\eta}$ corrects for selection bias and $\tilde{\eta} \times$ BDA $_{\text{dimensions}}$ SIC accounts for unobserved heterogeneity (Garen 1984).

The first stage of the two-stage model identified significant coefficients of the instrument variables, thereby satisfying the condition that the instrument is significantly correlated with the potentially endogenous variable (Table B2). In addition, the correlations of the instrument with the OC and MC dependent variables are not significant ($p > 0.10$). The correlation between the instrument and the interaction terms of BDA dimensions and SIC is significant ($p < 0.05$). In the over-identifying restrictions tests, neither the Sargan (*p=.523*) nor Bassman (*p=.454*) test is statistically significant at a 95% level, so we appear to have valid instrumental variables (Bellamy et al. 2014). Moreover, the partial F statistic suggests that the instrumental variables are strong (Wooldridge 2010). In the second stage, we regress OC and MC as the dependent variable on the interaction terms of BDA dimensions and SIC capability and included the residuals ($\tilde{\eta}$) from the first-stage equation and the interaction term $\tilde{\eta} \times$ BDA $_{dimensions}$ SIC (Garen 1984). Tables B3 and B4 present our findings for the corrected model with the endogeneity correction terms, showing results are substantively retained, implying robustness to endogeneity.

Table B1: Measurement scales and psychometric properties of instrumental variable

Mechanistic structure (CR=0.85, AVE=0.78)	Mean (SD)	Loadings
Written rules and procedures occupy a central place in the organizational unit	3.46 (1.42)	0.881^{***}
Firm adheres strong emphasis on getting personnel to follow formal procedures	3.29 (2.16)	0.714^{***}
Quality control and cost control procedures of operations are well documented	3.33(1.99)	0.865^{***}

Table B2: First stage results for the Garen's two-stage model

	BDA $_{management}$ x SIC	BDA $_{technology}$ x SIC	BDA $_{talent}$ x SIC
Mechanistic structure	0.184^{**}	0.133^{**}	0.098^{*}
Industry intensity of BDA	0.224^{***}	0.176^{**}	0.325^{***}
Firm size	-0.045	0.058^{*}	0.164^{**}
Firm age	0.122^{*}	0.096^{*}	0.114^{**}
R&D expense	0.063	0.102	0.056
Advert. expense	-0.038	0.096	0.112
Tangible assets	0.122^{*}	0.254^{***}	0.095^{*}
Env. dynamism	-0.011	-0.054	0.034
Industry 1	0.036	0.001	0.000
Industry 2	0.012	0.005	0.002
Industry 3	0.091	0.010	0.000
Adj. R^2	0.314	0.235	0.224
F-statistics	5.127^{***}	3.645^{***}	3.489^{***}
N	207.00	207.000	207.00

$^{***}p < .01$; $^{**}p < .05$; $^{*}p < .10$; $p \leq 0.000$ for F-statistics values; SIC= strategic integration capability

Table B3: Robustness Test for Endogeneity - Second stage 2SLS results for OC

	Model 1 Direct treatment effect	Model 2 Direct treatment effect	Model 3 First stage-mediation link	Model 4 Second stage – mediation link	Model 5 Second stage – mediation link
	DV: Sales without mediator	DV: Tobin's Q without mediator	DV: OC	DV: Sales with OC mediator	DV: Tobin's Q with OC mediator
BDA Management	0.012	0.067	0.124*	0.032	0.062
BDA Technology	0.009	0.072	0.181**	0.016	0.078*
BDA Talent	0.001	0.001	0.014	0.011	0.001

SIC	0.085*	0.006	0.098	0.085*	0.014
BDA Management x SIC	0.068	0.085*	0.100*	0.075	0.082
BDA Technology x SIC	0.095	0.062*	0.097*	0.011	0.066
BDA Talent x SIC	0.021	0.006	0.065	0.035	0.053
OC				0.132**	0.201**
$\tilde{\eta}_a$	0.037	0.075	0.084	0.021	0.004
$\tilde{\eta}_a$ × BDA $_{management}$ x SIC	0.005	0.069	0.121*	0.086	0.075
$\tilde{\eta}_b$	0.012	0.044	0.095	0.005	0.001
$\tilde{\eta}_b$ × BDA $_{technology}$ x SIC	0.115	0.058	0.214*	0.001	0.082
$\tilde{\eta}_r$	0.044	0.015	0.065	0.039	0.075
$\tilde{\eta}_r$ × BDA $_{talent}$ x SIC	0.001	0.032	0.182*	0.054	0.068
Firm size	0.132*	0.088*	0.145*	0.114*	0.095*
Firm age	0.010	0.132**	0.087	0.007	0.100**
R&D expense	0.054	0.096	0.002	0.054	0.078*
Advert. expense	0.125*	-0.051	-0.044	0.087*	0.052
Tangible assets	0.013	0.202**	0.089*	0.016	0.155**
Env. dynamism	-0.005	-0.010	-0.111*	-0.035	-0.001
Industry dummy	Included	Included	Included	Included	Included
Sample (N)	207.00	207.00	207.00	207.00	207.00
Adj. R2	0.216	0.258	0.486	0.264	0.297
F-Statistic	3.335***	3.874***	4.756***	3.979***	4.132***
*p<0.10; **p<0.05; ***p<0.01; SIC= strategic integration capability, OC= operational competitiveness; The terms containing $\tilde{\eta}$ are endogeneity-correction terms calculated from the first stage (Garen 1984). The interaction terms were also tested one at a time and found substantively similar results (omitted for brevity).					

Table B4: Robustness Test for Endogeneity - Second stage 2SLS results for MC

	Model 1 Direct treatment effect	Model 2 Direct treatment effect	Model 3 First stage-mediation link	Model 4 Second stage – mediation link	Model 5 Second stage – mediation link
	DV: Sales without mediator	DV: Tobin's Q without mediator	DV: MC	DV: Sales with MC mediator	DV: Tobin's Q with MC mediator
BDA Management	0.012	0.067	0.084	0.009	0.062
BDA Technology	0.009	0.072	0.103*	0.015	0.088*
BDA Talent	0.001	0.001	0.187**	0.003	0.002
SIC	0.085*	0.006	0.102	0.098	0.015
BDA Management x SIC	0.068	0.085*	0.091*	0.050	0.079
BDA Technology x SIC	0.095	0.062*	0.106*	0.007	0.063
BDA Talent x SIC	0.021	0.006	0.085*	0.034	0.005
MC				0.304***	0.097*
$\tilde{\eta}_a$	0.037	0.075	0.024	-0.052	0.023
$\tilde{\eta}_a$ × BDA $_{management}$ x SIC	0.005	0.069	0.075	-0.003	0.064
$\tilde{\eta}_b$	0.012	0.044	0.146*	0.084*	0.059
$\tilde{\eta}_b$ × BDA $_{technology}$ x SIC	0.115	0.058	0.221**	0.075	0.101*
$\tilde{\eta}_r$	0.044	0.015	0.105*	0.013	0.064
$\tilde{\eta}_r$ × BDA $_{talent}$ x SIC	0.001	0.032	0.082	0.008	0.071
Firm size	0.132*	0.088*	0.011	0.152**	0.084*
Firm age	0.010	0.132**	0.094**	0.014	0.162**
R&D expense	0.054	0.096	0.086*	0.098*	0.102
Advert. expense	0.125*	-0.051	0.054	0.132*	0.001
Tangible assets	0.013	0.202**	0.004	0.016	0.210**
Env. dynamism	-0.005	-0.010	-0.027	-0.053	-0.012
Industry dummy	Included	Included	Included	Included	Included
Sample (N)	207.00	207.00	207.00	207.00	207.00
Adj. R2	0.216	0.258	0.354	0.275	0.312
F-Statistic	3.335***	3.874***		4.016***	4.525***
*p<0.10; **p<0.05; ***p<0.01; The terms containing $\tilde{\eta}$ are endogeneity-correction terms calculated from the first stage (Garen 1984). The interaction terms were also tested one at a time and found substantively similar results (omitted for brevity).					

Section C: Robustness tests

Several robustness checks were performed to ascertain the sensitivity of our estimation results to differences in estimation methodologies and model specifications.

Section C1: Mediation effect

To further ascertain the mediating effect, we conducted Sobel's (1982) standard error test. It tests the hypothesis that the mediator (M) carries the influence of the independent variable (X) to the dependent variable (Y). Specifically, it evaluates the significance of the indirect effect of X on Y through M using the following equation.

$$\text{Test statistics } (z) = \frac{a\ X\ b}{\sqrt{b^2 X\ s_a^2 + a^2 X\ s_b^2}}$$

a is the effect of the independent variable on the mediator. *b* is the effect of the mediator on the dependent variable, controlling for the independent variable. s_a and s_b are the standard errors of a and b, respectively. The resulting z-value is then compared against a standard normal distribution. If the absolute value of z is large (typically $|z| > 1.96$ for a significance level of 0.05), it suggests that the mediation effect is significant. Our findings for both mediators (OC and MC) confirmed that the absolute value of z is significant and larger than 1.96, suggesting a significant mediation effect.

Section C2: Alternate measure for Tobin's Q

An alternative measure of Tobin's Q was estimated following Lang and Maffett (2011), calculated as the value of a firm's total assets plus the market value of equity minus the book value of equity scaled by total assets. The structural model was retested using this alternative measure of Tobin's Q. The findings obtained for the alternative measure of Tobin's Q replicated the results for the original model, suggesting a lack of sensitivity to the alternative method of calculating Tobin's Q, which is consistent with the results of prior studies (e.g., (Bardhan et al. 2013)).

Section C3: Secondary data for BDA

Although survey data collected to measure BDA are valuable, surveys can be susceptible to common method bias. Therefore, secondary data about firms' BDA initiatives were also collected based on an extensive examination of news articles from multiple data sources—an approach found to be feasible in prior IS studies (e.g., (Joshi et al. 2010; Sabherwal and Sabherwal 2007)). We screened the LexisNexis database, which includes more than 4,000 news sources and major computer journals, such as ComputerWorld, InformationWeek, and eWeek (Sabherwal and Sabherwal 2007), to identify BDA-related announcements concerning the sample firms. A list of keywords was developed based on a literature review of BDA articles. The list of keywords was further refined and validated by discussion with three IS academics and are reported in Table C1. Finally, a thorough content analysis of news announcements related to the sample firms was conducted covering the past three years (to allow a lag for BDA capability development and implementation). An independent researcher collected 596 BDA-related news articles for 119 of our sample firms from the years 2015 (178 articles), 2016 (194 articles), and 2017 (224 articles). Figure C1 presents an overview of the key steps in this process. The authors and the independent researcher completed the news coding by carefully reading the news articles (with containing keywords) to decide whether the firm applied BDA. BDA dimensions were measured as a first-order construct using codes (1, 0) based on the keywords in the news articles (see also Joshi et al. (2010) & Castillo et al. (2021)). The three BDA dimensions measured using secondary data showed a medium to strong correlation (r= 0.72, r=0.78, r=0.68) with the BDA dimensions measured using the corresponding firms' survey data. We re-ran our model using 119 firms with secondary measures of BDA dimensions. Although the beta values were small, the results did not show differences in the statistical significance or directions of influence.

Figure C1: An overview of the process followed for secondary data analysis.

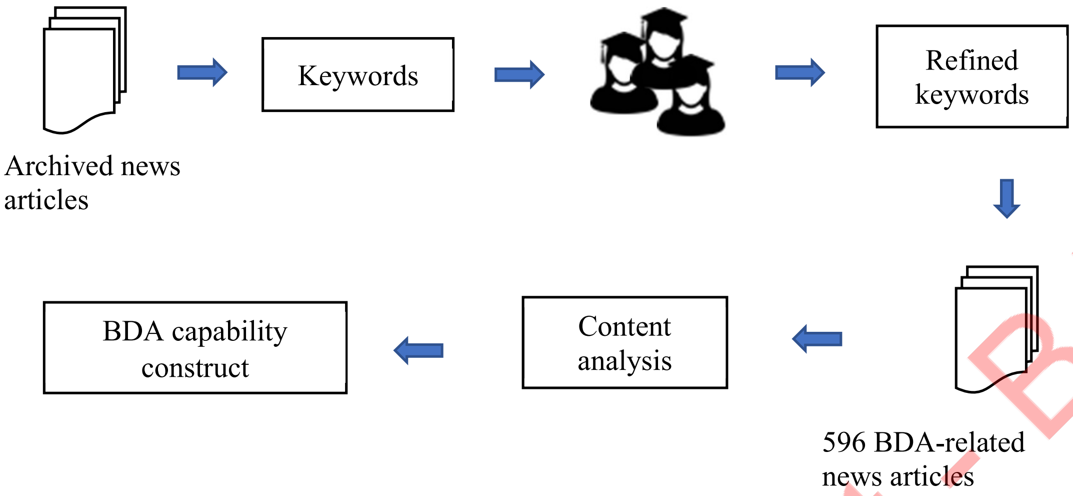

Table C1: Key search terms used for structured content analysis

Big data analytics technology	BDA connectivity; BDA network system; BDA shared insights; BDA platforms; BDA software applications; BDA user interface; BDA compatibility; BDA integration; BDA adaptation; digital dashboard; data visualization; analytical software.
Big data analytics management	BDA planning; BDA systemization; BDA formalization; BDA centrality; BDA regulations; BDA coordination; BDA responsibility; BDA accessibility; BDA monitoring; BDA control; BDA management system.
Big data analytics talent	BDA technical knowledge; analytics skills; BDA technical solutions; BDA networking skills; BDA maintenance skills; BDA upgradation; BDA utilization; BDA business solutions; BDA functionality command; BDA training; BDA business knowledge; BDA technology management knowledge.

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