



Unveiling the path to innovation: Exploring the roles of big data analytics management capabilities, strategic agility, and strategic alignment

Zahid Sarwar^a, Zhi-hong Song^{a,*}, Syed Tauseef Ali^b, Muhammad Asif Khan^c, Farman Ali^d

^a Institute of Management and Decision, School of Economics and Management, Shanxi University, Taiyuan, Shanxi 030006, PR China

^b School of Accounting and Finance, Hong Kong Polytechnic University (PolyU), Kowloon, Hong Kong

^c Department of Business and Economics Studies, University of Naples Parthenope, Naples, Italy

^d College of Business, King Faisal University, Al Ahsa, Kingdom of Saudi Arabia

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ABSTRACT

Big data are known to improve operational efficiency, competitiveness, and performance. Despite these unprecedented benefits, the understanding of how big data transform organizational processes remains limited. To address this gap, this research empirically investigates how big data analytics management capabilities (BDAMC) influence innovation performance. This study bases its assumptions on the dynamic capability and knowledge-based views. A PLS-SEM analysis of 199 firms reveals that establishing BDMC is essential for fostering organizations' innovation performance. This study advances knowledge by demonstrating that BDMC enhances organizations' strategic agility, which subsequently boosts innovation performance. Moreover, the empirical findings reveal that developing BDMC is crucial for achieving strategic alignment, which in turn reinforces innovation performance. These unique findings hold significant practical value for managers and consultants seeking to leverage big data-related systems within organizations.

Introduction

The introduction of the most sophisticated technological systems in terms of big data, artificial intelligence (AI), and the internet of things (IoT) has revolutionized the landscape of collecting, storing, analyzing, and visualizing data (Fu et al., 2023; Iyer & Bright, 2024). This paradigm shift has laid the foundation of the current “age of data,” where new data are being generated at an exceptional rate (de Haan et al., 2024; Jum'a et al., 2024), resulting in a huge amount of data known as big data (Gao & Sarwar, 2024). Big data serve as a crucial source of first-hand information (de Haan et al., 2024; Fantazy & Tipu, 2024; Fu et al., 2023). The significance of big data is increasingly being acknowledged by researchers and practitioners, who emphasize that data are now more valuable than oil (Acciarini et al., 2023). This has inspired numerous organizations to invest in big data-related technologies to achieve their strategic objectives (M. Zhang et al., 2024b). Therefore, the value of the big data market is growing exponentially. It is estimated to reach 103 billion dollars by 2027, up from the current worth of 55 billion dollars (Acciarini et al., 2023). Organizations are focusing on efficiently leveraging these technologies at the ground level, as 87 % of firms

believe that big data will serve competitiveness, while 89 % believe that if they do not operationalize big data technologies in the coming few years, they will lose a massive market share (Akter et al., 2016). However, routinizing these technologies is a complex process that requires organizational capabilities (Acciarini et al., 2023; Elia et al., 2022; Sivarajah et al., 2024; M. Zhang et al., 2024b). Accordingly, the study advocates the development of big data analytics management capabilities (BDAMC), which can lead organizations toward achieving their intended outcomes.

Big data are enormous (volume), diverse (variety), accurate (veracity), valuable (value), and fast-paced (velocity) data residing in diverse databases (Owolabi et al., 2024; Sivarajah et al., 2024; Taherdoost, 2024). Big data analytics (BDA) enables organizations to transform unstructured raw data into valuable knowledge resources, fueling strategic management processes (Gao & Sarwar, 2024). These knowledge resources facilitate decision making (Fantazy & Tipu, 2024; Fu et al., 2023), serve strategic agility (Sarwar et al., 2024; Shams et al., 2021), enhance dynamism (Sarwar et al., 2024; Sivarajah et al., 2024), and enable organizations to create business value (de Haan et al., 2024). For instance, “Southwest Airlines” effectively operationalizes BDA to

* Corresponding author.

E-mail addresses: zahidsarwar13@gmail.com (Z. Sarwar), songzhong@sxu.edu.cn (Z.-h. Song), tauseefali_shah3@yahoo.com (S.T. Ali), asif_marwat1439@yahoo.com (M.A. Khan), fqayum@kfu.edu.sa (F. Ali).

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assimilate structured and unstructured information about customer behaviors to improve customer satisfaction. The airline utilizes BDA to examine its interactions with customers to better understand and anticipate their needs. It also gathers customer opinions on its services, competitors, and industry through social media. This enables the airline to reconfigure its existing processes to enhance customer satisfaction (Erevelles et al., 2016). Accordingly, adopting BDA processes can save 66 billion dollars over 15 years for general engineering (Ward, 2014). Rapid acquisition of sophisticated data is more relevant in the current super-competitive, complex, and dynamic market environment (Gao & Sarwar, 2024; Wamba et al., 2017). Indeed, prior research has highlighted BDA as a frontier for productivity, innovativeness, and competitiveness (Manyika et al., 2011). Despite being a promising prospect and presenting prominent significance, researchers report that only 25 % of firms have achieved their intended outcomes from big data (Ghasemaghaei & Calic, 2020). Recent studies have reported that a considerable number of firms have failed to fully exploit big data and extract befitting value from them (Gao & Sarwar, 2024; Wamba et al., 2017). The major reasons for this failure are scarce big data understanding in the organizational context and lack of essential organizational-level capabilities to leverage them effectively (Elia et al., 2022; Günther et al., 2017). In this context, consistent with the studies of M. Zhang et al., 2024b, McAfee et al. (2012), we argue that organizations need to establish big data-related management capabilities to leverage big data up to their befitting potential. Thus, this study advocates the development of BDAMC. It possesses the potential to elevate an organization's competency to reconfigure its existing processes and enable it to achieve the value-creation target of innovation performance.

In the current dynamic business environment, innovation is the principal strategic objective of an organization (Sarwar et al., 2024). It is the organizational potential to acquire and assimilate new knowledge resources to develop, implement, and routinize new ideas or concepts (Calantone et al., 2002). This enables them to better position themselves for a substantial competitive edge and is a core formula for success (Sarwar et al., 2024; Sivarajah et al., 2024). Scholars have identified next-generation digital technological systems, such as BDA, as a crucial source of innovation (Fu et al., 2023; Zhang & Xu, 2023; C. Zhang et al., 2024a). They argue that BDA improves organizations' competencies to efficiently scan the external market for prospective business opportunities and threats. It facilitates the acquisition and processing of external market information to better understand customer priorities, which are core factors in innovation performance (Acciarini et al., 2023; Ghasemaghaei & Calic, 2020). For instance, Procter & Gamble extensively implement BDA to develop unique insights into customer data. They obtain data through interactions with customers via social media, digital platforms, research and development (R&D) activities, and websites. Such valuable information places companies in a better position to satisfy customers by introducing products and services according to their needs (Elia et al., 2022). Regarding the significance of big data, previous research has found that big data contribute to decision making (Awan et al., 2021d; Fu et al., 2023; Ji et al., 2024), competitive advantage (Cadden et al., 2023; Mikalef et al., 2020), knowledge creation (Lin et al., 2024), value creation (Elia et al., 2022), and performance (Sivarajah et al., 2024; Wamba et al., 2017). Research has also highlighted the potential of big data to increase organizations' transformation competencies (Cadden et al., 2023; Elia et al., 2022; Ghasemaghaei & Calic, 2020). The cited scholars have called for further empirical assessment as the association between big data and innovation is anecdotally understood. In response to the call, scholars have linked big data with service innovation (Shamim et al., 2021), cooperative innovation (Ji et al., 2024), supply chain innovation (Bhatti et al., 2024), and innovation ambidexterity (Sivarajah et al., 2024). However, the association between big data, particularly BDAMC, and overall innovation performance is underexplored. Therefore, the primary objective of this study is to explore this relationship empirically. To achieve this goal, we adopted a totalistic approach consistent with the studies by Elia

et al. (2022), Mikalef et al. (2020), Awan et al. (2021d).

Apart from the totalistic approach, this research advances the body of knowledge suggesting that technology-based capabilities leverage intended outcomes through other capabilities (Cadden et al., 2023; Elia et al., 2022; Shamim et al., 2020b; Sivarajah et al., 2024; C. Zhang et al., 2024a). Consistent with this notion, scholars including Awan et al. (2021d), Ravichandran (2018), Yunis et al. (2018) claim that technology-based competencies leverage desired outputs through other organizational-level competencies. Building on this argument, prior research has explored the indirect roles of the flexibility of supply chain (Bag et al., 2023), knowledge development (Fantazy & Tipu, 2024), supply chain innovation capabilities (Jum'a et al., 2024), knowledge integration (Cadden et al., 2023), supply chain agility and adaptability (Bhatti et al., 2024), and exploratory and exploitative innovation (Sivarajah et al., 2024), between BDA and outcomes constructs. However, it remains unclear whether strategic alignment and agility indirectly affect the association between big data and innovation performance. Thus, we contribute to this research stream by proposing that big data, in terms of BDAMC, foster innovation performance through strategic alignment and strategic agility. Strategic alignment emphasizes achieving a strategic fit between business and information system strategies (Sarwar et al., 2024; Shao, 2019). Meanwhile, strategic agility is an organization's ability to adapt to changes that occur in the external business environment (Khan & Tao, 2022; Shams et al., 2021). Organizations are surfing various prospects to achieve them as they facilitate performance and boost competitive advantage (Sarwar et al., 2024; Shams et al., 2021; Shao, 2019). Strategic alignment and agility are both continuous processes fueled by first-hand information. In this context, we argue that BDAMC provides the required information and knowledge resources to foster strategic alignment and agility, which, in turn, may enhance innovation performance. In addition, the literature presents contrasting outcomes concerning the relationship between investments in the latest technologies, such as BDA, and productivity. Some scholars have reported a positive relationship (Barua et al., 1995; Brynjolfsson & Hitt, 2000), whereas others have reported no association between them (Devaraj & Kohli, 2003; Irani, 2010; Solow, 1987; Strassmann, 1990). Therefore, examining the association between BDAMC and innovation performance, particularly through strategic alignment and agility, is valuable. This study asserts that strategic agility and strategic alignment are crucial organizational-level dynamic capabilities that have the potential to mediate the connection between BDAMC and innovation performance. This discussion brings us to the second objective of this study, which is to explore the indirect roles of strategic agility and strategic alignment between BDAMC and innovation performance.

To achieve the study objectives and address the highlighted research gaps, this study explores the following research questions: Does BDAMC have a direct influence on an organization's innovation performance? How does BDAMC facilitate strategic alignment and strategic agility? Do strategic alignment and strategic agility mediate the relationship between BDAMC and innovation performance? This study employs the PLS-SEM approach using data collected from 199 manufacturing firms operating in Pakistan to test the proposed conceptual model presented in Fig. 1. This model is conceptualized based on the knowledge-based view (KBV) and dynamic capability view (DCV).

The current study makes significant theoretical contributions to the body of knowledge on big data and innovation performance (Acciarini et al., 2023; Ghasemaghaei & Calic, 2020; Mikalef et al., 2020; Taherdoost, 2024) by empirically finding that BDAMC substantially enhances organizations' innovation performance. This research extends extant knowledge by indicating that BDAMC elevates organizational capabilities to generate and implement new ideas, leading organizations toward improved innovation performance. This is among the primary studies to investigate the direct and indirect (strategic agility and strategic alignment) associations between big data in terms of BDAMC and innovation performance. Moreover, unlike previous research, which has limited

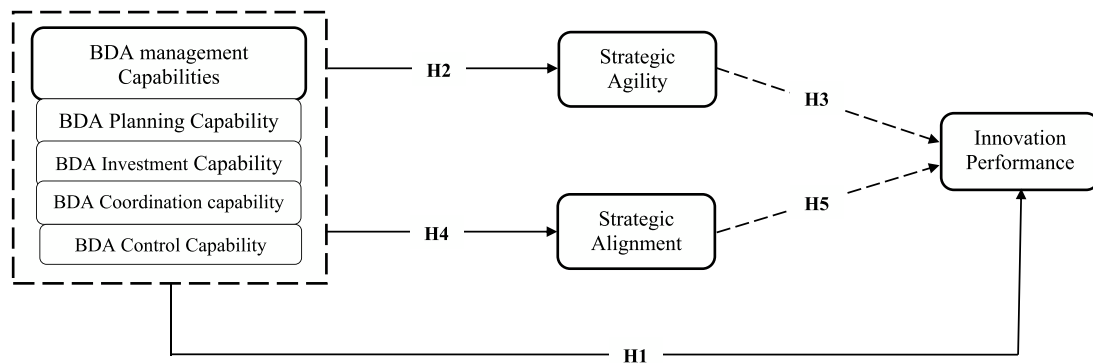


Fig. 1. Conceptual model.

Note: Mediation effects are represented via dotted lines: BDA; Big data analytics.

itself to a single perspective of either the principle-agent theory, dynamic capability theory, organizational learning theory, absorptive capacity theory, systems theory, or resource-based view (RBV) (Awan et al., 2021d; Bag et al., 2023; Cadden et al., 2023; de Haan et al., 2024; Ghasemaghahi & Calic, 2020; Jum'a et al., 2024; C. Zhang et al., 2024a), the study adopts the unique approach of synergizing the KBV and DCV to draw relationships among constructs and empirically explore these associations. This integration provides robust underpinnings to the framework, demonstrating how organizations can leverage BDAMC to accomplish the value creation target of innovation performance. Furthermore, BDA processes enable organizations' access to valuable knowledge resources, helping them foresee opportunities and threats and swiftly adapt their processes accordingly (strategic agility), which subsequently enhances their innovation performance. Similarly, BDAMC rapidly provides authentic data and related management capabilities to initiate, formulate, and implement strategically aligned strategies, leading to improved innovation performance. We derive these conclusions from our findings, which reveal that strategic agility and alignment partially mediate the connection between BDAMC and innovation performance.

Background and literature review

Theoretical background

The DCV is an extended form of the RBV, which posits that organizations' integration and transformation abilities cannot be easily replicated, yielding a profound competitive advantage (Teece et al., 1997). It stresses how organizations acquire and employ strategic resources to achieve competitiveness and beat competition (Teece, 2007). In this context, the KBV manifests knowledge as one of the preliminary strategic resources of firms that bring about economic outcomes (Grant, 1996). The DCV asserts that organizations should strive to develop the related capabilities of efficiently acquiring and utilizing resources (Teece, 2014). These views are complementary and jointly focus on achieving competitive advantage and economic outcomes. Thus, the current study integrates these views to offer a comprehensive theoretical underpinning for studying the influence of big data on innovation performance. An organization's competency in fortifying big data-related analytical capabilities, especially management capabilities, contributes to its superior business performance (Awan et al., 2021b; Olabode et al., 2022; M. Zhang et al., 2024b). Furthermore, firms with superior management capabilities for exploring and exploiting big data possess a greater potential to achieve a competitive edge (Gao & Sarwar, 2024; Shamim et al., 2021). In this context, BDAMC provides the required set of knowledge and competencies that enable organizations to create imitable outcomes (Elia et al., 2022; Olabode et al., 2022). Consistent with this perspective and based on the DCV and KBV, this study posits that BDAMC enables organizations' access to valuable knowledge

resources and managerial competencies. Doing so increases their potential to transform existing processes, generate new ideas, and create unique outcomes (Li et al., 2022; M. Zhang et al., 2024b). Previous research also supports the application of an integrative approach, suggesting that no single view covers all the aspects of a strategy (Acosta et al., 2018; Gao & Sarwar, 2024). Recently, Shamim et al. (2021), Shamim et al. (2020a) utilized an integrative approach to explore the emerging research topic of big data. The literature recognizes big data as a crucial prospect that enhances performance, service innovation, decision-making quality, online ratings, and ambidexterity (Ji et al., 2024; Li et al., 2022; Taherdoost, 2024; Zhang & Xu, 2023; C. Zhang et al., 2024a). However, the direct relationship between big data, specifically BDAMC, and innovation performance remains underexplored, warranting further empirical investigation. Moreover, whether strategic alignment and strategic agility mediate this association also requires empirical investigation. Thus, drawing on the KBV and DCV, this study fills the abovementioned research gaps by empirically investigating the direct and indirect (strategic agility and strategic alignment) relationships between BDAMC and innovation performance. A brief graphical representation of these underexplored associations is shown in Fig. 1.

Big data analytics management capability (BDAMC)

The introduction of state-of-the-art technologies, such as big data, fundamentally impacts organizations' operational processes (Taherdoost, 2024). It revolutionizes the processes of knowledge acquisition and assimilation (Zhang & Xu, 2023). BDA constitutes groundbreaking innovations that drive organizational transformation competencies (Cadden et al., 2023). Scholars refer to them as frontiers of knowledge and innovation (Gao & Sarwar, 2024; Manyika et al., 2011). However, big-data-related structures are complex in nature. The efficient operationalization of these structures requires individual- and organizational-level dynamic competencies (Fantazy & Tipu, 2024; Ji et al., 2024; Mikalef et al., 2020; Shamim et al., 2019; Sivarajah et al., 2024). This has motivated researchers and practitioners to explore big data in organizational contexts. Research indicates that big data play a critical role in solving contemporary management problems and diverse ecological challenges (Gao & Sarwar, 2024; C. Zhang et al., 2024a). Big data are a considerable volume of unstructured data available in various databases (Wamba et al., 2017). Their effective application in the context of organizations is inevitable, as they play a momentous role in an organization's success, productivity, and value creation (Acciarini et al., 2023; Fu et al., 2023).

Initially, big data were characterized by their rapid generation (velocity), large amount (volume), and diversity (variety), collectively referred to as the 3Vs (Akter et al., 2020; Awan et al., 2021d). Scholars have found that developing big data-related capabilities significantly boosts an organization's ability to achieve competitive advantage (Alkhatib & Valeri, 2024; Olabode et al., 2022). Supporting this view,

Gao and Sarwar (2024) emphasize that the establishment of effective processes and related capabilities helps to transform big data into valuable information, ultimately facilitating problem-solving and decision-making processes (Fu et al., 2023; Ghasemaghahi & Calic, 2019a; Li et al., 2022). However, identifying, acquiring, and assimilating large amounts of data make the transmutation process even more challenging. It requires productive data mining, which includes identifying, visualizing, storing, and analyzing data on an enormous scale and at a brisk pace (Gao & Sarwar, 2024; Hilbert, 2016). Later, Rumsfeld et al. (2016), Yin and Kaynak (2015) included two more Vs (value and velocity) in their characterization of big data, making big data operationalization even more challenging.

Although big data bring complexities and challenges, they also present unprecedented advantages. Scholars and practitioners equally acknowledge the potential of big data to bring value to organizations. Recent studies have focused on the topic of establishing technical competencies to extract value from big data, shaping a comprehensive body of knowledge on the subject (Acciarini et al., 2023; Babu et al., 2024; Bhatti et al., 2024; Elia et al., 2022; Fantasy & Tipu, 2024; Owolabi et al., 2024; Sivarajah et al., 2024; Taherdoost, 2024; C. Zhang et al., 2024a). These studies indicate that big data-related technical competencies enable organizations to decrease operational costs and increase efficiency, productivity, and customer satisfaction. These competencies stimulate prominent improvements in business model innovation (Acciarini et al., 2023). The cited scholars underscore the development of BDA-related capabilities to overcome challenges involving big data implications. BDA enables organizations to rapidly obtain and process large amounts of data (Dong & Yang, 2020), elevating their potential to achieve superior performance (Olabode et al., 2022; Owolabi et al., 2024). Employing BDA facilitates organizations' efforts to outperform competitors and enhance their overall organizational performance (Suoniemi et al., 2020). For instance, Liu (2014) states that they increase organizations' profitability by 8 % while reducing their operational costs by 47 %. Further, Amazon employs BDA to provide customers with online purchase suggestions, which increases their sales by 47 %. Similarly, general engineering industries have saved 66 billion dollars within a short span of 15 years by employing BDA processes (Gao & Sarwar, 2024).

However, along with technical competencies, contemporary research has also focused on developing big data-related management competencies. This is because only 18 % of organizations have successfully yielded big data to their full potential (de Haan et al., 2024). In this regard, scholars argue that obtaining the intended outcomes from big data requires not only developing technical competencies but also management competencies (Akhtar et al., 2019; Gao & Sarwar, 2024; M. Zhang et al., 2024b). Supporting this argument, Shamim et al. (2019) report that creating value from big data greatly depends on developing related management capabilities (Shamim et al., 2019). McAfee et al. (2012) also highlighted the crucial role of management competencies in yielding the intended outcomes from big data. Consistent with this view, the current study focuses on fortifying big data-related management capabilities such as BDAMC. In accordance with Gao and Sarwar (2024), Shamim et al. (2020a), we argue that big data itself cannot generate the intended outcomes unless organizations establish related management capabilities. Accordingly, Barton and Court (2012) note that the BDA environment and business management capabilities are critical for boosting decision-making quality, which may foster organizations' transformation capabilities. This study conceptualizes BDAMC as a second-order construct of BDA investment decisions, planning, control, and coordination. It views BDAMC as a core source of knowledge resources and managerial competencies that may lead organizations toward improved innovation performance.

Hypotheses formulation

BDAMC and innovation performance

Generally, the term innovation refers to "out-of-the-box thinking." It is the process of generating and implementing new ideas to produce unique products and services (Dodgson et al., 2013; Gao & Sarwar, 2024). Similarly, Cadden et al. (2023) stated that it is the introduction of new technology, ideas, products, services, or managerial innovations emphasizing cost reduction and the development of superior products (Chatterjee et al., 2024; Sarwar et al., 2024). Both modern and classic research acknowledges its significance in achieving efficiency and competitiveness (Baregheh et al., 2009; Bhatti et al., 2024; Cohen & Levinthal, 1990; Griffin & Page, 1993; Ji et al., 2024; Sivarajah et al., 2024). This underscores the importance of developing collective processes among internal and external stakeholders, guiding organizations toward the development of new products and services (Chesbrough, 2003; Khan & Tao, 2022; Zhang & Xu, 2023). The core of innovation is to introduce and implement the concepts of unique product and process development, which greatly depends on the organization's ability to innovate (Ji et al., 2024; Sarwar et al., 2024; 2021). Previous research has correlated organizational innovation with financial performance, efficiency, productivity, competitive edge, social performance, knowledge transfer activities, value creation, and productivity (Awan et al., 2021a; Awan et al., 2021c; Cadden et al., 2023; Ghasemaghahi, 2019; Parteka & Kordalska, 2023; Sivarajah et al., 2024). As discussed, the benefits of innovation are obvious; however, achieving improved innovation performance in a real-time business environment is challenging.

Being innovative in today's world is even more challenging because of the threats of climate change and environmental degradation. Consumers are well aware of these threats and are more open to utilizing socially acceptable and environment-friendly products and services (Awan et al., 2019). In addition, the current volatile, dynamic, and super-competitive market environment makes it challenging for organizations to improve their innovation performance (Sarwar et al., 2024; Shams et al., 2021). Accordingly, shorter product life cycles and swiftly changing consumer demands add to these challenges (Gao & Sarwar, 2024; Sarwar et al., 2024; 2021; Shams et al., 2021). To cope with the challenges and be more innovative than others, organizations need authentic data, knowledge resources, and related dynamic capabilities (Ghasemaghahi & Calic, 2020; Lin et al., 2024; Shamim et al., 2020b; Zahoor et al., 2022). In this regard, consistent with the foundations of Shamim et al. (2021), Gao and Sarwar (2024), this study emphasizes that developing BDAMC is crucial as it presents sufficient amount of first-hand data and related management capabilities to yield value from them. Rumsfeld et al. (2016), in accordance with the study by Yin and Kaynak (2015), acknowledge the essentialness of big data and related analytics in improving knowledge management within and outside the organization. BDAMC rapidly provides authentic information on a large scale for efficient decision making (Awan et al., 2021d), facilitating competitiveness and performance gains (Mikalef et al., 2020; Suoniemi et al., 2020). In this context, the DCV and KBV highlight the importance of establishing capabilities and accumulating knowledge resources. These views suggest that scanning the environment for potential opportunities and acquiring knowledge resources create a more precise framework for strategic alternatives and performance gains (Elia et al., 2022; Shamim et al., 2021; 2019; Zahoor et al., 2022). The DCV reports that firms' competitiveness and dynamism depend on their capabilities to acquire and deploy resources (Teece, 2007). This process begins by identifying potential opportunities and gathering essential information to capitalize on them (Teece, 2018). These views (DCV and KBV) propose that organizational transformation and adaptation depend on the acquisition of unique and authentic information. The literature points to a positive association between knowledge and innovation (Kim & Lee, 2013; Shamim et al., 2021). Researchers such as McAfee et al. (2012)

identify that, along with their access to big data, organizations need to develop related management capabilities to exploit them to their full potential (Gao & Sarwar, 2024; Shamim et al., 2019). BDAMC has the potential to revolutionize the innovation paradigm by establishing a suitable fit between market demands and product specifications (Gao & Sarwar, 2024; Johnson et al., 2017). It bolsters organizations' capabilities to create new and transform already established procedures to introduce inimitable products and services. This may lead them toward improved innovation performance. We hypothesize this association as follows:

H1. BDAMC will increase organizations' innovation performance.

Role of strategic agility

Strategic agility consists of a set of actions that organizations take to obtain value in a continuously changing business environment (Shams et al., 2021; Weber & Tarba, 2014). It is a continuous process of systematic changes that an organization incorporates into its products, processes, and structures (Weill et al., 2002). These incorporations are intended to align with the changes in the external business environment. Goldman et al. (1995) refers to it as an organization's adaptive capacity in an uncertain business environment. Comprehensive investigations in the strategy and technology management fields indicate that strategic agility is an essential success predictor (Doz & Kosonen, 2010; Khan & Tao, 2022; Zahoor et al., 2022). It plays a significant role in improving organizational performance (Ahhammad et al., 2021). It is conceptualized as an organization-level dynamic capability of proactiveness, quickness, and flexibility in realizing opportunities and avoiding threats (McCann et al., 2009). Conclusively, strategic agility can be operationalized as an organization's capability to avail opportunities and mitigate threats through adaptability, swiftness, and assurance (Kotter, 2012). It hugely depends on organizations' potential to accumulate the required resources and efficiently assimilate them to proactively adapt to changes in the external environment (Weber & Tarba, 2014). Strategic agility includes accumulating resources and developing capabilities to utilize them in a timely manner (Shams et al., 2021). It is an essential capability that facilitates a quick organizational response and enables the organization to stay on track toward achieving its objectives (Brueller et al., 2014). However, acting quickly and correctly at the same time is a critical operational challenge. In this context, consistent with the study by Shams et al. (2021), this research advocates the development of BDAMC to operationalize strategic agility. BDAMC provides sufficient knowledge resources and necessary dynamic capabilities to support strategic agility.

Additionally, the exponentially growing significance of strategic agility has stimulated recent research to study it from the standpoints of management (Arbussa et al., 2017), strategy (Doz & Kosonen, 2010), internationalized business (Ahhammad et al., 2021; Boojihawon et al., 2021), and information technology (Tallon et al., 2019). Moreover, prior research has explored strategic agility across diverse fields and settings. Examples include the service sector (Kale et al., 2019), mergers and acquisitions (Khan et al., 2020), internationalization (Clauss et al., 2019; Shams et al., 2021), small and medium enterprises (Zahoor et al., 2022), and manufacturing sectors (Khan & Tao, 2022). Despite its critical role in serving business innovation, capabilities development, and opportunity seizing (Hock et al., 2016; Vaillant & Lafuente, 2019), there are limited studies on the antecedents that facilitate strategic agility, especially in the context of big data. In this regard, the current research presents BDAMC as a vital prospective predictor that may influence strategic agility. It provides reliable information that enables firms to implement fundamental changes based on market demands (Buhalis et al., 2019) and enhance their adaptive capabilities. BDAMC elevates organizational capabilities to use knowledge resources efficiently and extract economic value from big data (Shamim et al., 2021), leading organizations toward the identification of new opportunities. According

to Shamim et al. (2019), BDAMC serves dynamism by enabling organizations to foresee threats and potential opportunities. Furthermore, BDA enables organizations to swiftly transmute an enormous amount of unstructured raw data into precious information resources, facilitating problem-solving, quick decision-making, and strategy formulation and implementation processes (Awan et al., 2021d; Hagel, 2015). Following the fundamentals of the DCV and KBV, BDAMC provides access to huge amounts of first-hand data and analyzes them for patterns, enabling firms to create unique knowledge. All the above mentioned prospects that BDAMC serves, such as authentic information, adaptiveness, quickness, dynamism, and opportunity and threat identification, are fundamental to a strategically agile organization. Accordingly, we present the following hypothesis:

H2. BDAMC will increase organizations' strategic agility.

In the big data context, fortifying BDAMC is crucial as it triggers firms' capacities to detect undiscovered gaps and opportunities (Popović et al., 2018). It fosters firms' capabilities to identify emerging opportunities and unseen threats (Mikalef et al., 2020; Shamim et al., 2021; M. Zhang et al., 2024b). It serves agility by acquiring data from various sources, transforming them into valuable information, and enhancing decision-making performance (Awan et al., 2021d; Ji et al., 2024; Shamim et al., 2019). Further, BDAMC bolsters strategic agility by facilitating knowledge management processes throughout the organization and external market environment. In addition to a direct and positive connection between BDAMC and strategic agility, strategic agility has the potential to have an indirect (mediating) influence on BDAMC and organizations' innovation performance. The literature has yet to establish an extensive understanding of the indirect role of strategic agility (Kale et al., 2019), especially in the context of big data. Consistent with the studies conducted by Tallon and Pinsonneault (2011), Kale et al. (2019), the current study posits that strategic agility mediates the association between BDAMC and innovation performance. This is because BDAMC provides valuable information resources, related analytics, and managerial capabilities, enabling firms to systematically adapt to changes that occur in the external market environment (Kale et al., 2019; Olabode et al., 2022), which in turn may enhance organizations' transformation potential. In the modern, complex, and super-competitive market environment, researchers and practitioners prioritize achieving strategic agility because timely and rapid adaptation is key to success (Arbussa et al., 2017; Tallon et al., 2019), which enhances an organization's potential to innovate (Shams et al., 2021; Zahoor et al., 2022). Thus, we argue that firms rely significantly on BDAMC and strategic agility to acquire knowledge resources and efficiently deploy them to adapt to changes and transform their processes, which may ultimately boost innovation performance. We propose this association in the following hypothesis:

H3. Strategic agility will mediate the association between BDAMC and innovation performance.

Role of strategic alignment

In today's digitalized world, organizations are surfing various prospects that may serve performance and competitiveness. The go-to option for most of them is to implement the latest digital technological and information systems (Bag et al., 2023; Ji et al., 2024; Jum'a et al., 2024; Owolabi et al., 2024; Sarwar et al., 2024; Sivarajah et al., 2024; M. Zhang et al., 2024b). However, investments in these latest digital systems do not necessarily yield the intended outcomes, as several organizations have failed to successfully operationalize them at the ground level, resulting in substantial financial losses (de Haan et al., 2024; Elia et al., 2022; Gao & Sarwar, 2024; Sarwar et al., 2024). Comprehensive research has highlighted that the major cause of failure is the absence of strategic alignment (Majhi et al., 2021; Nassani & Aldakhil, 2021; Sarwar et al., 2024; Shao, 2019). The strategic alignment model is the

foundation of this notion, which comprises technological strategies, infrastructure, business strategies, and technological processes (Gao & Sarwar, 2024; Henderson & Venkatraman, 1999; 1989). Strategic alignment is based on strategic management characteristics. It is conceptualized as strategic harmony among an organization's information systems infrastructure, processes, and business strategies (Panda, 2021; Sarwar et al., 2024; Shao, 2019). It is the process of finding an optimal strategic fit between organizational business strategies and information system strategies (Sarwar et al., 2024; Xu et al., 2019). The basic purpose of achieving strategic alignment is to operationalize technological systems in a way that supports business goals, objectives, vision, and missions (Gao & Sarwar, 2024; Shao, 2019; Yayla & Hu, 2012). Achieving strategic alignment is an essential prospect that ultimately serves dynamism, innovativeness, performance, and a competitive edge (Gao & Sarwar, 2024; Gerow et al., 2014; Sarwar et al., 2024). The cited studies suggest that in the contemporary uncertain and volatile market environment, achieving strategic alignment has become a top priority for organizations. Strategic alignment is critical at the operational and strategic levels, as it extracts strategic value for organizations (Henderson & Venkatraman, 1999). Thus, how to achieve strategic alignment is a critical research question in the domain of strategic management. To address this question, we argue that establishing BDAMC can foster firms' strategic alignment, as it provides information resources to support organizations' strategic initiation, formulation, and implementation processes (Sarwar et al., 2024). In addition, it enables timely access to data and aids management in formulating complementary and aligned strategies (Shamim et al., 2021). Moreover, through BDA, organizations develop unique insights into data, enabling them to foresee the need for necessary future change and develop strategically aligned strategies to adapt to it (Gao & Sarwar, 2024). It also facilitates firms' efforts to establish a culture where they formulate and alter strategies based on data, thereby enhancing decision-making quality (Awan et al., 2021d). Finally, BDAMC, combined with rapid, accurate, and valuable information, provides the necessary capabilities to formulate, implement, monitor, and adjust strategies, ensuring strategic harmony between information systems strategies and business strategies (Gao & Sarwar, 2024; Sarwar et al., 2024). Based on the above discussion, we propose the following hypothesis:

H4. BDAMC will increase organizations' strategic alignment.

Recent research underscores the growing importance of strategic alignment (Majhi et al., 2021; Panda, 2021; Sarwar et al., 2024; Shao, 2019). It plays a vital role in guiding organizations toward performance enhancement, creativity, and innovativeness (Gao & Sarwar, 2024; Nassani & Aldakhil, 2021; Panda, 2021). These studies emphasize that the synergy between information systems and business strategies is essential for improving profitability and competitiveness. This synergy in the shape of strategic alignment is critical for achieving a competitive advantage (Chen & Zhang, 2014; Gao & Sarwar, 2024). It is an organizational process of aligning its structure, business strategies, and information system strategies to proactively adapt to changes in the external environment. For this purpose, BDAMC harmonizes the concerned departments of an organization by strengthening the communication and coordination among them. This makes it easy to adapt to the change (Barki & Pinsonneault, 2005). BDAMC fosters strategic alignment by facilitating decision-making quality and strategic management processes (Aral & Weill, 2007; Shamim et al., 2020b), which subsequently may influence innovation performance. BDAMC also promotes knowledge management among stakeholders, such as partner firms, customers, and suppliers, which is key to formulating strategically aligned strategies (Panda, 2021; Sarwar et al., 2024). Furthermore, BDAMC and strategic alignment enhance firms' capabilities to redesign products and services according to market demand, thereby elevating their transformation capabilities (Gao & Sarwar, 2024; Mikalef et al., 2020). Based on the above discussion, we assert that BDAMC provides

the necessary inputs in terms of knowledge resources and capabilities that may influence strategic alignment, which may subsequently elevate an organization's capacity to transform existing processes, products, and services. Thus, we hypothesize this association as follows:

H5. Strategic alignment will mediate the influence of BDAMC on innovation performance.

Methodology

This study adopted a survey (questionnaire) approach to empirically investigate the hypothesized relationships among the constructs of BDAMC, strategic agility, strategic alignment, and innovation performance. It is a recommended approach to solve the generalizability problem, facilitate replicability, and enable concurrent testing of several constructs (Sarwar et al., 2024). In this context, two questionnaires, A and B, forming one complete survey, were circulated among manufacturing firms operating in Pakistan. This two-questionnaire approach, known as the "matched-pair" approach, was also employed by Gao and Sarwar (2024) and recommended by Podsakoff et al. (2012) as a "procedural remedy" for common-method variance. According to Podsakoff et al. (2012), this approach involves collecting feedback on endogenous and exogenous variables from different sources to reduce the likelihood of common method variance in the data collection stage.

Questionnaire A consisted of 21 item-statements related to the exogenous construct of BDAMC, while Questionnaire B contained 13 item-statements related to the mediating and endogenous constructs of strategic agility, strategic alignment, and innovation performance. Statements pertaining to firm attributes were also included in Questionnaire B. Additionally, an extensive 7-point Likert-scale, ranging from 1 (strongly disagree) to 7 (strongly agree) was used for all item-statements. A pilot study with 20 responses was conducted to assess the content validity and clarity of the questionnaires. The suggested changes were incorporated into the final version of the questionnaires.

Constructs measurement

The exogenous variable, BDAMC, is a second-order variable comprising four sub-dimensions adopted from the studies by Gao and Sarwar (2024), Wamba et al. (2017). These sub-dimensions, referred to as BDA investment decision, planning, coordination, and control capabilities, were measured using five, four, four, and eight item-statements, respectively. The mediating constructs of strategic agility and strategic alignment were first-order constructs of five and three item-statements, respectively, and were adopted from the studies by Demir et al. (2021), Sarwar et al. (2024). The strategic agility construct originated from the study by Tallon and Pinsonneault (2011). Finally, the endogenous construct of innovation performance consisted of six item-statements adopted from the study by Sarwar et al. (2024), Gunday et al. (2011). Conclusively, the measures of all constructs under investigation were adopted from the latest studies published in high-end journals. The complete details of the tested and validated measures are provided in Appendix A.

Sample selection and data collection

The sole purpose of our research is to explore whether BDAMC, directly and indirectly, influences an organization's innovation performance. Population and sample selection were crucial to ascertain the applicability of this study. This study selected the manufacturing sector as the population because, first, the manufacturing sector produces tangible products, which is an essential component of innovation performance (Sarwar et al., 2024). Second, it adds 14 % to the GDP of the country (Ministry of Finance, 2020; Gao & Sarwar, 2024). Third, it plays a significant role (13.8 %) in creating employment (Sarwar et al., 2024). Further, firms were included in the sample based on four criteria. First, a

firm must have a formal organizational culture. Second, a firm must be recognized by the Sialkot Chamber of Commerce, the Pakistan Stock Exchange, and the database of the industry association of Pakistan. Third, a firm must practice big data approaches. Fourth, the contact details and address of a firm must be available. Based on these criteria, we selected 430 firms located in four industrial hubs in Pakistan.

This study followed subsequent measures to collect feedback from the sample. First, one complete questionnaire (Questionnaire A and Questionnaire B) was physically distributed to each firm. Second, following Obeidat et al. (2020), the study adopted the drop-off and pick-up approach, an offline data collection process that yields a higher response rate (Bryman, 2016). Third, at least three representatives were appointed to collect feedback from each hub. Fourth, questionnaire A targeted respondents who were chief officers in the technical and information departments. Questionnaire B targeted respondents who were chief executive officers and chief operation officers. Finally, each questionnaire, A and B, was sent to the potential respondents with an attached cover letter explaining the academic purpose of the research, response confidentiality, and voluntary participation. After removing outliers, extreme responses, incomplete response treatment, and follow-up rounds (three) via calls, 199 matched-pair (questionnaires A and B) responses were collected, at a rate of 46 %. The 199 matched responses from an equal number of manufacturing firms exceeded the 20-times rule proposed by Kline (2015) for determining the appropriate number of survey responses. Consistently, Hair et al. (2019, 2022) recommended applying the 10-times rule to determine the appropriate number of responses. They forwarded this rule for analysis in the PLS-SEM, according to which 40 responses will yield highly applicable results in the case of this particular study. Thus, the above discussion clarifies that the responses of the 199 manufacturing firms will produce highly valid outcomes.

Analysis tool and findings

This research utilized Smart-PLS version 3.3.3 and the statistical package for social science (SPSS) version 25 to analyze the feedback collected from 199 manufacturing firms. This study used the PLS-SEM approach for the following reasons. First, the PLS-SEM is a recommended and extensively used approach in the fields of strategy and technology management (Henseler et al., 2015). Second, it has the potential to simultaneously assess multiple constructs (Hair et al., 2022; Sarwar et al., 2024; Sarwar & Song, 2023). Third, it is a more appropriate approach for exploring second-order variables (Gao & Sarwar, 2024; Hair et al., 2019; Henseler et al., 2016). Fourth, it is a promising prediction approach (Henseler et al., 2016). Finally, the latest studies of a similar nature use this approach: Cadden et al. (2023), Ghasemaghahi and Calic (2020), Sarwar et al. (2024), Shamim et al. (2019), Awan et al. (2021d). Thus, the discussion above concludes that PLS-SEM is a highly suitable method for assessing the study's hypothesized relationships. Before conducting the reliability and validity assessment, the data were analyzed for common method variance.

Common method variance

This study employed the recommended approaches to mitigate potential common method variance. Specifically, we followed suggested "procedural remedies," such as ensuring the clarity of item statements, volunteer partaking, response confidentiality, response anonymity, and collecting feedback on exogenous and endogenous constructs from different sources. Podsakoff et al. (2012) recommended that these procedures negate the potential existence of common method variance in the research design and feedback collection stages. In addition, the current study followed the recommended statistical tools to ensure that common-method variance did not contaminate the data. First, Kock (2015) recommended collinearity analysis in terms of the variance inflation factor (VIF) as the most authentic tool to test collinearity

(Sarwar & Song, 2023). The Smart-PLS's outcomes of the VIF lie within the upper-bound limit of 3.3 (Sarwar et al., 2021; Sarwar & Song, 2023). The detailed VIF values are listed in Table 1. Moreover, the SPSS v25 results (32 %) of Harman (1976) single-factor test were within the upper-bound limit of 50 %. These results further confirm that common method variance was not a problem in this study.

The subsequent analysis focuses on the attributes of the responding firms. It shows that out of 199 responses, the maximum feedback (22.6 %) was obtained from textile firms, followed by pharmaceuticals (16.6 %), food and beverages (16.6 %), fertilizers (12.1 %), cement (10.1 %), electronics (9.5 %), and chemicals (7.5 %). Furthermore, the proposed model is reflective. In line with the studies by Sarwar et al. (2021, 2024), Hair et al. (2022), we followed the guidelines of Hair et al. (2019) to present the findings of reflective measurement and structural model assessments, as discussed below.

Measurement model analysis

In this section, we assess the reliability and validity of the latent constructs and their statements by analyzing content validity, convergent validity, internal consistency, and discriminant validity. We ensured the content validity of the indicators through factor loadings. The factor loadings of all indicators fell above the lower-bound limit of 0.708 (Hair et al., 2022), excluding IP1 (0.629). However, along with the mentioned source, Sarwar et al. (2024) also report that factor loadings above 0.4 are adequate and acceptable. These outcomes indicate that the latent constructs investigated explain more than 50 % of the variance in the related indicators (Gao & Sarwar, 2024; Hair et al., 2019; Sarwar et al., 2024). Moreover, in accordance with the study by Sarwar et al. (2021), this research employed composite reliability and Cronbach's alpha to analyze the internal consistency of the latent variables. This refers to the mutual consistency among indicators of the same constructs (Gao & Sarwar, 2024). The composite reliability and Cronbach's alpha outcomes ranged between 0.906–0.873 and 0.875–0.806, respectively. These outcomes are above the lower-bound limit of 0.7 (Cohen, 2013; Sarwar & Song, 2023). Furthermore, the research ensured the convergent validity of the latent constructs through the average variance extracted (AVE). This refers to the degree to which a construct congregates to elucidate variations among indicators of the same construct (Sarwar et al., 2024). The outcomes of AVE range between 0.532 and 0.758, which falls above the lower-bound threshold of 0.5 (Hair et al., 2022). This means that the latent constructs elucidate at least 50 % of the variation among the related indicators (Gao & Sarwar, 2024). The outcomes of these assessments (content, convergence, and internal consistency) verified the reliability and validity of the collected data. Detailed outcomes are presented in Table 1.

Furthermore, following the guidelines of Hair et al. (2022), this research assesses the constructs' discriminant validity via the heterotrait-monotrait (HTMT) ratio and Fornell and Larcker criterion. Sarwar et al. (2024) report that discriminant validity refers to the degree to which the constructs examined are different from each other. The research applies the HTMT method to analyze the constructs' discriminant validity during this assessment. The HTMT ratio of all constructs falls below the upper threshold of 0.85, as suggested in the studies conducted by Gao and Sarwar (2024), Hair et al. (2022). The extensive details of the HTMT assessment are presented in Table 2. Additionally, we ensured that the latent constructs are distinct from each other through the criterion developed by Fornell and Larcker (1981), known as the Fornell and Larcker criterion. This criterion compares the square root of a construct AVE with the correlations of other constructs. The higher AVE values than correlations depict that the constructs are adequately different from each other (Hair et al., 2022; Sarwar et al., 2024). The comprehensive outcomes of this criterion are provided in Table 3. The bold values in Table 3 represent the square root of each construct's AVE, which is higher than the correlations among the constructs, indicating adequate discriminant validity. These assessments

Table 1
Measurement model analysis.

Statement code	Constructs	α	CR	AVE	F. L	t-val	VIF
BDA management capabilities (BDAMC)							
BDA Planning capability (PLNC)		0.806	0.873	0.632			
PLNC1					0.794	22.963	1.636
PLNC2					0.818	26.509	1.746
PLNC3					0.757	15.255	1.561
PLNC4					0.809	28.017	1.725
BDA Investment capability (INVC)		0.866	0.903	0.652			
INVC1					0.785	24.341	1.771
INVC2					0.815	32.080	1.906
INVC3					0.851	32.445	2.364
INVC4					0.745	17.112	1.653
INVC5					0.838	34.771	2.238
BDA Coordination capability (COOC)		0.818	0.88	0.647			
COOC1					0.825	34.170	1.924
COOC2					0.809	26.627	1.844
COOC3					0.833	30.968	1.946
COOC4					0.749	17.381	1.656
BDA Control capability (CONCA)		0.874	0.901	0.532			
CONC1					0.701	16.300	1.804
CONC2					0.713	14.248	1.847
CONC3					0.725	16.884	2.005
CONC4					0.762	21.406	1.921
CONC5					0.766	26.242	1.941
CONC6					0.716	17.765	1.838
CONC7					0.737	19.177	1.770
CONC8					0.712	16.890	1.802
Strategic agility (SAG)		0.862	0.901	0.646			
SAG1					0.783	21.223	1.785
SAG2					0.735	17.286	1.697
SAG3					0.842	31.688	2.437
SAG4					0.845	46.432	2.525
SAG5					0.809	30.284	1.920
Strategic alignment (SA)		0.841	0.904	0.758			
SA1					0.892	60.008	2.093
SA2					0.845	29.855	1.924
SA3					0.876	36.628	1.980
Innovation performance (IP)		0.875	0.906	0.619			
IP1					0.629	9.095	1.421
IP2					0.823	35.710	2.210
IP3					0.839	33.712	2.700
IP4					0.808	27.852	2.248
IP5					0.800	24.694	1.978
IP6					0.802	22.316	1.970

Note: VIF: Variance inflation factors; AVE: Average Variance Extracted; CR: Composite Reliability; α : Cronbach's Alpha; t-value: t statistics of statements; F.L: Factor Loadings; VIF values of all item statements are within the threshold of 3.3.

Table 2
HTMT ratio (Discriminant validity).

Latent Construct	1	2	3	4	5	6	7
1 BDA Planning capability							
2 BDA Investment capability	0.733						
3 BDA Coordination capability	0.737	0.726					
4 BDA Control capability	0.358	0.309	0.402				
5 Strategic agility	0.260	0.488	0.491	0.617			
6 Strategic alignment	0.212	0.338	0.353	0.722	0.718		
7 Innovation performance	0.234	0.394	0.407	0.799	0.796	0.774	

Note: BDA; Big data analytics; Constructs' HTMT values are below the upper-bound threshold of 0.85.

Table 3
Fornell-Larcker criterion (Discriminant validity).

Latent Construct	1	2	3	4	5	6	7
1 BDA Planning capability	0.795						
2 BDA Investment capability	0.614	0.808					
3 BDA Coordination capability	0.602	0.615	0.805				
4 BDA Control capability	0.311	0.276	0.348	0.729			
5 Strategic agility	0.222	0.424	0.414	0.54	0.804		
6 Strategic alignment	0.178	0.294	0.295	0.623	0.611	0.871	
7 Innovation performance	0.193	0.342	0.339	0.697	0.696	0.672	0.787

Note: Bold values represent constructs' square root of average variance extracted (AVE); Nonbold values are the correlations among constructs.

clarify that the study has established satisfactory discriminant validity.

Structural model analysis

This analysis comprises assessing the collected data for R^2 , Q^2 , and the path coefficient. During this assessment, we also tested the significance of path coefficients among endogenous and exogenous constructs. However, before this analysis, we assessed the collinearity of the collected data using VIF to ensure that it did not affect the regression analysis. Hair et al. (2019) recommend this approach to guard against collinearity issues. The outcomes of the collinearity assessment in the form of VIF values fell under the upper-bound threshold of 3.3, indicating that this study is free of collinearity problems (Hair et al., 2022; Sarwar & Song, 2023). Next, the study moved toward the bootstrapping process to assess the significance of path coefficients. For this purpose, the bootstrapping function of Smart-PLS at a subsample of 5000 was performed. The comprehensive details of hypotheses and path coefficient (β) assessments are presented in Table 4 and Fig. 2. At the same time, the model fitness was assessed through R^2 , Q^2 , and goodness of fit (GoF), discussed under “analysis of model fit.”

The bootstrapping results reveal that BDAMC has a significantly positive influence on organizations’ innovation performance with ($\beta = 0.181$; p -val = 0.003; and t -val = 3.024), providing support to H1. Further, the outcomes unveil that BDAMC positively and significantly influences strategic agility with ($\beta = 0.558$; p -val = 0.000; and t -val = 9.074) and strategic alignment with ($\beta = 0.505$; p -val = 0.000; and t -val = 7.127). These outcomes lend support to H2 and H4.

Mediation analysis

This study hypothesizes that strategic agility and strategic alignment indirectly (mediate) impact the connection between BDAMC and innovation performance. To examine the mediating role of a construct in PLS-SEM, the recommended approach is to first analyze the direct relationship between exogenous and endogenous constructs (Preacher & Hayes, 2008; Sarwar et al., 2024). In the case of this study, the results of the direct relationship were positive and significant with ($\beta = 0.389$; p -val = 0.000; and t -val = 8.342). Moving forward, the results of the mediation assessment, which were obtained in the second stage, reveal that strategic agility with ($\beta = 0.214$; p -val = 0.000; and t -val = 4.460) and strategic alignment with ($\beta = 0.175$; p -val = 0.000; and t -val = 4.039), partially mediate the association between BDAMC and innovation performance. Therefore, these outcomes provide evidence in support of H3 and H5. Table 4 presents the results of this analysis.

Analysis of model fit

Our study ensured the model’s fitness through variance (R^2), predictive relevance (Q^2), and GoF. The R^2 values of the endogenous

constructs of innovation performance, strategic agility, and strategic alignment are 60.3, 31.1, and 25.5 %, respectively. This implies that the endogenous variables have good explanatory power for the exogenous variables (Hair et al., 2019). Furthermore, our study analyzed the model fitness via Q^2 because model assessment based on a single approach is not recommended (Hair et al., 2022; Radović-Marković et al., 2017). To achieve this, we initiated the blindfolding function of Smart-PLS at an omission distance of 7. The results revealed that Q^2 values of the endogenous constructs for innovation performance, strategic agility, and alignment were 0.363, 0.193, and 0.186, respectively. According to the criteria set by Chin (2009), these values of Q^2 fall into the large, medium, and medium categories, respectively. Hence, the Q^2 outcomes show that the exogenous constructs have adequate predictive relevance for the endogenous constructs. Additionally, this study utilized GoF to guard the model’s fitness. The details of the GoF calculations are presented in Table 5. According to the criteria recommended by Wetzels et al. (2009), the GoF value of the current model, which is 0.50, falls in the “large category.” This demonstrates the adequacy and acceptability of the proposed model. Comprehensive details of this analysis in terms of R^2 , Q^2 , and GoF are provided in Table 5.

Discussion and conclusion

Organizations are surfing various prospects to achieve efficiency and superior outcomes in the modern hyper-competitive business world. For this, organizations’ access to unique and authentic information resources is crucial (Lin et al., 2024; Zhang & Xu, 2023). In this regard, the current research emphasizes the significance of implementing next-generation digital technologies, such as AI, big data, and IoT, in the organizational context (Ardito et al., 2021; Babu et al., 2024; Iyer & Bright, 2024; Meng & Wang, 2023; Sarwar et al., 2024; Wang et al., 2024). Among these, big data are considered an essential source of authentic and inimitable information resources (Acciarini et al., 2023; Jum’a et al., 2024; Owolabi et al., 2024; Sivarajah et al., 2024; Taherdoost, 2024; M. Zhang et al., 2024b). Furthermore, the significance of big data is continuously growing as they facilitate firms’ introduction of new ideas and help them achieve competitive advantage (Cadden et al., 2023; Gao & Sarwar, 2024; Mikalef et al., 2020). Accordingly, contemporary studies acknowledge their imperativeness in creating business value, and consider big data a paradigm of business model innovation (Acciarini et al., 2023; Elia et al., 2022; Meng & Wang, 2023; Taherdoost, 2024). Since big data present remarkable advantages and efficiency in firms’ processes by improving decision-making (Fu et al., 2023; Ji et al., 2024), business value (Dong & Yang, 2020; Shamim et al., 2020a), data-driven insights (Awan et al., 2021d), innovativeness (Cadden et al., 2023; Jum’a et al., 2024), dynamic capacities (Gao & Sarwar, 2024; Mikalef et al., 2020), agility (Awan et al., 2021b), and business performance (Fantazy & Tipu, 2024; Sivarajah et al., 2024), many organizations are investing in big data-related digital technological systems (Ghasemaghaei & Calic, 2020). However, research shows that only a limited number of firms have achieved their intended outcomes through these investments (de Haan et al., 2024; Gao & Sarwar, 2024). Thus, the conditions and mechanics through which these investments guide businesses toward desired outcomes have attracted the attention of practitioners and researchers (Acciarini et al., 2023; Akter et al., 2020; Awan et al., 2021b; Elia et al., 2022; Gao & Sarwar, 2024; Ghasemaghaei & Calic, 2020; Suoniemi et al., 2020). Research highlights that the pathways and mechanics through which big data produce intended outcomes is a critical research question that requires further empirical exploration (Mikalef et al., 2020). In line with the studies of M. Zhang et al. (2024b), McAfee et al. (2012), Gao and Sarwar (2024), this study suggests that the development of related management competencies is a prerequisite for leveraging big data to their full potential. This research acknowledges that big data are an essential resource; however, to yield the desired outcomes from big data, firms need to develop related management capabilities, such as BDAMC.

Table 4
Hypotheses evaluation.

Hypothesized Path	Path (β)	t-test	Significance (p)	Result
Total effect				
BDAMC ->IP	0.389	8.342	0.000	
Direct effect				
H1 BDAMC ->IP	0.181	3.014	0.003	Accepted
H2 BDAMC ->SAG	0.558	9.074	0.000	Accepted
H4 BDAMC ->SA	0.505	7.127	0.000	Accepted
Mediation effect				
H3 BDAMC ->SAG ->IP	0.214	4.460	0.000	Mediation (Partial)
H5 BDAMC -> SA ->IP	0.175	4.039	0.000	Mediation (Partial)

Note: IP: Innovation performance; SA: Strategic alignment; SAG: Strategic agility; BDAMC: Big data analytics management capabilities.

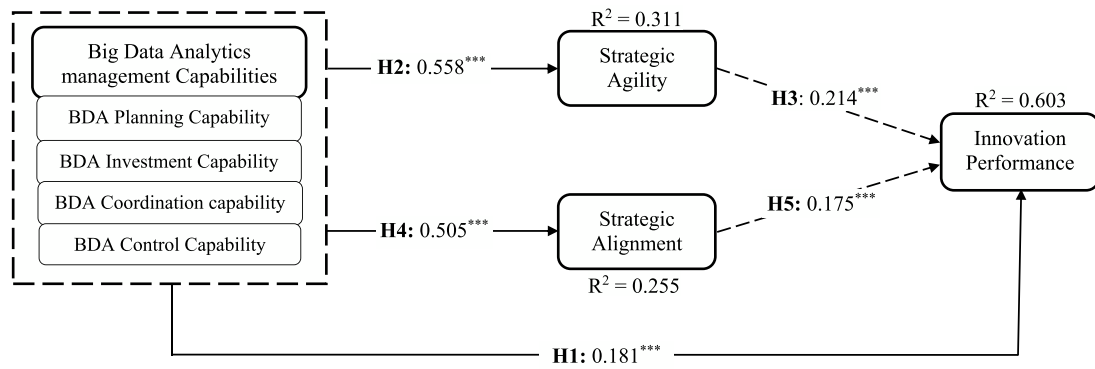


Fig. 2. Structural model assessment.

Note: Mediation effects are represented via dotted lines; *** significance at $p < 0.001$; * significance at $p < 0.05$

Table 5

Analysis of model fit.

Constructs	R ²	Q ²	Status	AVE	Status
BDAMC					
BDA Planning capability				0.632	
BDA Investment capability				0.652	
BDA Coordination capability				0.647	
BDA Control capability				0.532	
Strategic agility	0.311	0.193	Medium	0.646	
Strategic alignment	0.255	0.186	Medium	0.758	
Innovation performance	0.603	0.363	Large	0.619	
GoF = Avg of AVE *Avg of R ²				0.641 × 0.39	
GoF = $\sqrt{(AVE \times R^2)}$				0.50	Large

Note: BDA: Big data analytics.

This study drew inspiration from recent research, paying significant attention to big data and their role in transforming product and service development processes (Cadden et al., 2023; Sivarajah et al., 2024; Taherdoost, 2024). Scholars have identified big data as a frontier of innovation and have associated them with performance (Awan et al., 2021b; Mikalef et al., 2019; Wamba et al., 2017). However, limited empirical evidence proves whether big data influence organizations' innovation performance. Prior research by Ghasemaghaei and Calic (2020), Gao and Sarwar (2024) also supports this argument, stating that the connection between big data and innovation performance is intuitively understood. Thus, there is a need to empirically explore the relationship between big data in terms of BDAMC and innovation performance. Therefore, it is imperative to understand whether this association is mediated by other constructs (Elia et al., 2022; Suoniemi et al., 2020). Expanding on current knowledge, we propose a second-order research model based on the foundations of the KBV and DCV. In the research model presented in Fig. 1, we hypothesize a direct association between BDAMC and innovation performance. We also hypothesize that this association occurs through strategic agility and strategic alignment. Empirical exploration of these associations was the primary objective of this study.

This study provides nuanced insights into the association between BDAMC and innovation performance. We formulated five hypotheses and tested them using primary data collected through a questionnaire administered to Pakistani manufacturing firms. We ensured reliability and validity of the data in the measurement model assessment. The model fit assessment also confirmed the quality of the proposed research model. The exogenous construct explains 25.5 % of the variance in strategic alignment, 31.1 % in strategic agility, and 60.3 % in innovation performance. Accordingly, Q^2 and GoF also proved the adequacy of the proposed model. Moving forward, the PLS-SEM outcomes of 199

manufacturing firms revealed that developing BDAMC is vital for enhancing innovation performance. We infer this from the results for H1, which show that BDAMC has a significant and positive influence on innovation performance. These outcomes facilitated the achievement of the primary objectives of this study. Further, the results revealed that BDAMC fuels strategic agility by enabling organizations' access to first-hand data, which subsequently boosts innovation performance. We derive this from the results for H2 and H3, which prove that strategic agility partially mediates the relationship between BDAMC and innovation performance. Moreover, the results revealed that BDAMC provides sufficient knowledge resources and management capabilities to achieve a strategic fit between information systems and business strategies. This strategic fit in terms of strategic alignment then facilitates innovation performance. We conclude this from the results for H4 and H5, which show that strategic alignment partially mediates the association between BDAMC and innovation performance. The results for H2, H3, H4, and H5 helped achieve the second major objective of this research. Additionally, the results also depict that the mediating role of strategic agility between BDAMC and innovation performance is stronger with ($\beta = 0.214$) compared to the strategic alignment with ($\beta = 0.175$). Finally, the PLS-SEM outcomes clarify that among four sub-constructs of BDAMC, BDA coordination capability contributes more to BDAMC, followed by investment capability, planning capability, and control capability with ($\beta = 0.796$), ($\beta = 0.793$), ($\beta = 0.763$), and ($\beta = 0.711$), respectively. The findings of this study have nuanced theoretical and practical implications, as discussed below.

Theoretical implications

Compared with traditional data analytics techniques, the application of BDA significantly enhances an organization's chances of success (Jum'a et al., 2024). Efficient utilization of big data facilitates value creation (Elia et al., 2022), knowledge management (Zhang & Xu, 2023), innovativeness (Cadden et al., 2023), decision making (Ji et al., 2024), dynamism (Gao & Sarwar, 2024), business model innovation (Acciarini et al., 2023), and performance (Sivarajah et al., 2024). Recognizing the potential of big data and related analytics, organizations have begun to operationalize them at the ground level. However, this is a complex process that may not necessarily yield the desired outcomes (Gao & Sarwar, 2024; Wamba et al., 2017). Highlighting this issue, contemporary research calls for further investigation of the pathways through which big data produce outcomes (Acciarini et al., 2023; Mikalef et al., 2020). Research also highlights the issue of limited big data understanding, especially their effect on organizations' transformation capabilities (Ghasemaghaei & Calic, 2019b; 2020). This study attempts to fill the gaps in the literature by providing nuanced insights into the relationships between BDAMC, strategic agility, strategic alignment, and innovation performance. The results of this study offer

several theoretical contributions, which are discussed below.

First, the study integrated the KBV and DCV to conceptualize a BDAMC model. The adoption of this unique integrative approach is essential for the field of strategic management to comprehensively study all aspects of strategy (Acosta et al., 2018) rather than focusing on a single perspective of either the RBV, systems view, or organizational learning view (Dong & Yang, 2020; Ghasemaghaei & Calic, 2019a; Mikalef et al., 2020). Scholars recommend using an integrative approach, arguing that no single perspective can encompass all aspects of a strategy (Acosta et al., 2018; Ferreira et al., 2016). In today's complex and dynamic business environment, integrating diverse approaches is becoming increasingly relevant (Ferreira et al., 2016), especially because the emergence of dynamic capabilities and knowledge-based views as standalone theoretical bases does not provide a sufficient explanation. For instance, the RBV stresses acquiring diverse resources, but does not elaborate on their utilization (Sarwar et al., 2024). In contrast, the KBV and DCV, along with the assimilation of diverse resources, also focus on the deployment of these resources to achieve dynamism, competitiveness, and performance (Gao & Sarwar, 2024). Doing so enhances the organization's transformation capacity to cope with a continuously changing external market environment. Research supports this perspective, arguing that, along with identification and acquisition, efficient deployment of resources is compulsory to accomplish the intended business objective (Gao & Sarwar, 2024; Teece et al., 1997). Accordingly, scholars argue that in a dynamic and swiftly evolving market environment, a firm's transforming capacity depends heavily on top management's potential to efficiently deploy organizational resources (Gutierrez-Gutierrez et al., 2018). Building on the studies of Gao and Sarwar (2024), Shamim et al. (2021), M. Zhang et al. (2024b), this study significantly extends current knowledge by integrating the KBV and DCV to establish relationships between the constructs of BDAMC, strategic agility, strategic alignment, and innovation performance.

Second, this study is among the first to examine the influence of BDAMC on innovation performance. Prior research has emphasized the development of technological capabilities to leverage innovation. For instance, Elia et al. (2022) linked BDA capabilities to product and service innovation in terms of transparency, access, proactive adaptation, and discovery. Cadden et al. (2023) explored big data connections with innovation through knowledge integration. The literature shows an association between BDA and innovation in the healthcare supply chain sector (Bag et al., 2023). Scholars have linked BDA to service innovation (Shamim et al., 2021), explorative and exploitative innovation (Sivarajah et al., 2024), and supply chain innovation (Bhatti et al., 2024). However, this study emphasizes the establishment of related management capabilities and presents unique insights into the relationship between BDAMC and overall innovation performance. Consistent with this, it is argued that the latest big data technologies enable firms to acquire large amounts of data from various databases and rapidly convert them into valuable information. For instance, Hadoop, Storm, and SQL streams rapidly store and process large amounts of data. However, firms cannot achieve their business objectives simply through access to big data. They must establish related management capabilities (Johnson et al., 2017; McAfee et al., 2012; Shamim et al., 2020b). The literature acknowledges that BDA enhances business performance, competitiveness, and decision-making quality (Akter et al., 2020; Awan et al., 2021d; Elia et al., 2022; Suoniemi et al., 2020). In contrast, little is known about whether big data influence a firm's transformation capacity (Gao & Sarwar, 2024; Ghasemaghaei & Calic, 2019b). We advance this research stream by empirically proving that BDAMC enables firms to swiftly acquire valuable information resources and efficiently deploy them to generate inimitable outcomes in terms of new concepts, unique ideas, products, and services, thereby facilitating innovation performance. Our study makes a significant theoretical contribution by showing that BDAMC enhances a firm's innovation performance.

Third, this study deepens the contemporary understanding by finding that BDAMC yields innovation performance through strategic agility and strategic alignment. In line with scholars such as Shams et al. (2021), Zahoor et al. (2022), we argue that strategic agility enables organizations to anticipate changes in the external business environment, thus elevating their potential to enhance innovation performance. These anticipations are primarily supported by BDAMC. Establishing BDAMC enhances an organization's ability to rapidly adapt to changes by monitoring the external market environment for prospective opportunities and threats (strategic agility) (Shams et al., 2021), subsequently fostering the firm's innovation performance. TBDAMC, through swift acquisition and data processing, serves flexibility, proactiveness, and dynamism (strategic agility), facilitating innovation performance. Furthermore, organizations are investing in BDA because of its exceptional advantages. However, research indicates that only a few firms have fully exploited big data (Ghasemaghaei & Calic, 2019a; Ross et al., 2013), and a considerable number of organizations have failed to achieve performance gains through BDA (Mikalef et al., 2019). We assert that this is because the organization's business strategies and strategies of information systems are not harmonized or unidirectional. Prior research also reports that technology-based capabilities require other organizational-level competencies to generate the desired outcomes (Ravichandran, 2018). In this regard, we affirm that organizations can leverage big data to achieve the intended outcomes of innovation performance through strategic alignment. BDAMC provides authentic information in a timely manner during the strategic management process, helping firms devise strategically aligned and complementary business and information systems that foster their transformation capabilities. More precisely, fortifying BDAMC enables firms to devise strategically aligned strategies that subsequently improve their innovation performance. Our study extends this stream of research (Elia et al., 2022; Gao & Sarwar, 2024; Suoniemi et al., 2020), which suggests that the association between big data and outcomes could be mediated by other variables. Prior studies have examined the connection between big data and criterion constructs via knowledge creation (Shamim et al., 2021), analytics capability (Shamim et al., 2020b), mechanisms of value creation (Elia et al., 2022), decision-making efficiency (Awan et al., 2021d), data-driven culture (Akhtar et al., 2019), and market-directed competencies (Suoniemi et al., 2020). However, little is known about the mediating roles of strategic agility and strategic alignment. Thus, this study's findings contribute significantly to the current understanding by showing that strategic agility and strategic alignment mediate the connection between BDAMC and innovation performance.

Lastly, this study offers valuable contextual novelty. Unlike previous studies that examined the relationship between big data and various criterion constructs in China, Norway, Italy, the United States, European countries, New Zealand, and the Czech Republic (Akhtar et al., 2019; Awan et al., 2021d; Dong & Yang, 2020; Elia et al., 2022; Ghasemaghaei & Calic, 2020; Mikalef et al., 2020; Shamim et al., 2019), this study validates the BDAMC model in the Pakistani manufacturing sector. The model hypothesizes a direct connection between BDAMC and innovation performance. It also hypothesizes a connection between strategic agility and strategic alignment. This study extends the body of knowledge on big data by investigating the associations between BDAMC, strategic agility, strategic alignment, and innovation performance in the Pakistani context.

Managerial implications

In today's complex business environment, organizational survival and success rely heavily on how swiftly and efficiently they adapt to the changes that occur in the market. A business's success depends heavily on its innovation capabilities. Therefore, top management are looking for different prospects that serve dynamism and enable them to successfully create and implement new ideas. This study is of great value to practitioners, as it sheds light on how to improve organizational

innovation performance. Moreover, after realizing the potential of big data and their related applications, a significant number of organizations have started investing in BDA. However, in real-time scenarios, they cannot capitalize on big data to achieve performance gains, raising a critical question: What pathways do big data create value in? The BDAMC model of the research offers substantial managerial implications by answering this question.

Operationalizing big data-based technological systems at the ground level is a complex process. Failure to do so results in significant financial and human resource losses. To efficiently use big data and implement their related systems in the organizational context, this study's outcomes clarify to top management that establishing BDAMC is an approach to consider. It elevates the organizational capacity to generate new ideas and concepts, thereby enhancing a firm's innovation performance. Furthermore, it provides strategic agility by strengthening a firm's potential to swiftly adapt to change, which improves its innovation performance. We derived these practical implications from the outcomes of Hypotheses 1, 2, and 3. Finally, our study provides empirical evidence that BDA provides information to facilitate strategic management processes that increase the alignment between organizations' goals, objectives, vision, mission, and strategies with information system strategies, which subsequently fosters the organization's innovation performance. This managerial implication is suggested, because strategic alignment significantly and positively mediates the connection between BDAMC and innovation performance.

Limitation and research directions

Despite its substantial theoretical and practical implications, this study had some limitations. The limitations of this study provide avenues for future research. First, BDA is a function of different factors such as technology-related, management-related, environment-related, and structure-related factors. Owing to time and resource limitations, this study focused only on BDAMC's role in enhancing innovation performance. Future research should consider other BDA functions and explore them on a broader scale. Second, we empirically examined the proposed conceptual model based on feedback obtained from manufacturing firms. Prospective inquiries can also be used to explore big data-related research models in other sectors. Third, we carefully designed this study and took all recommended measures to guard against common method bias. However, survey-based methods are prone to such biases. Future studies could apply other methods to explore the associations among the constructs under investigation. Fourth, the study was conducted in a single country and a single sector. Therefore, cross-sectoral and cross-country comparative studies can inspire future research. Finally, this study reviewed the literature on the latent constructs investigated in the English language and assessed their associations. However, globally, only 20 % of the population speaks and understands English (Sarwar et al., 2024). Prospective inquiries could

consider literature in other languages to devise a more detailed and broadly applicable research model.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon request. The authors collected the primary data from potential respondents to test the higher-level model of the study. The data will be made available upon request from the corresponding author. Thanks

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CRediT authorship contribution statement

Zahid Sarwar: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Zhi-hong Song:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization, Resources. **Syed Tauseef Ali:** Writing – review & editing, Validation, Software, Methodology, Data curation. **Muhammad Asif Khan:** Visualization, Software, Methodology, Investigation, Formal analysis. **Farman Ali:** Writing – review & editing, Software, Resources, Methodology, Formal analysis.

Declaration of competing interest

The authors declare that they have no conflict of interest, financial, personal, or otherwise.

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Appendix A

Constructs' statements.

Code	Constructs and Statements	Source
	BDA management capabilities (BDAMC)	Gao and Sarwar (2024), Wamba et al. (2017)
	BDA Planning capability (PLNC)	
PLNC1	We continuously examine innovative opportunities for the strategic use of business analytics.	
PLNC2	We enforce adequate plans for the utilization of business analytics.	
PLNC3	We perform business analytics planning processes in systematic ways.	
PLNC4	We frequently adjust business analytics plans to better adapt to changing conditions	
	BDA Investment capability (INVC)	

(continued on next page)

(continued)

Code	Constructs and Statements	Source
INVC1	When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work.	
INVC2	When we make business analytics investment decisions, we project how much these options will help end users make quicker decisions.	
INVC3	When we make business analytics investment decisions, we estimate whether they will consolidate or eliminate jobs.	
INVC4	When we make business analytics investment decisions, we estimate the cost of training that end users will need	
INVC5	When we make business analytics investment decisions, we estimate the time managers will need to spend overseeing the change	
	BDA Coordination capability (COOC)	
COOC1	In our organization, business analysts and line people meet regularly to discuss important issues.	
COOC2	In our organization, business analysts and line people from various departments regularly attend cross-functional meetings.	
COOC3	In our organization, business analysts and line people coordinate their efforts harmoniously.	
COOC4	In our organization, information is widely shared between business analysts and line people so that those who make decisions or perform jobs have access to all available know-how.	
	BDA Control capability (CONCA)	
CONC1	In our organization, the responsibility for analytics development is clear.	
CONC2	We are confident that analytics project proposals are properly appraised.	
CONC3	We constantly monitor the performance of the analytics function.	
CONC4	Our analytics department is clear about its performance criteria.	
CONC5	Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process.	
CONC6	Our company is better than competitors in reducing cost within a business process.	
CONC7	Our company is better than competitors in bringing complex analytical methods to bear on a business process.	
CONC8	Our company is better than competitors in bringing detailed information into a business process.	
	Strategic agility (SAG)	Demir et al. (2021), Tallon and Pinsonneault (2011)
SAG1	How easily and quickly your firm respond to changes in aggregate consumer demand.	
SAG2	How easily and quickly your firm customize a product or service to suit an individual customer	
SAG3	How easily and quickly your firm react to new product or service launches by competitors.	
SAG4	How easily and quickly your firm introduce new pricing schedules in response to changes in competitors' prices.	
SAG5	How easily and quickly your firm adopt new technologies to produce better, faster and cheaper products and services.	
	Strategic alignment (SA)	Sarwar et al. (2024)
SA1	The information system strategy is congruent with the corporate business strategy in our organization	
SA2	Decisions in information system planning are tightly linked to the organization's strategic plan	
SA3	Our business strategy and information system strategy are closely aligned	
	Innovation performance (IP)	Gunday et al. (2011), Sarwar et al. (2024)
IP1	Our firm is good at renewing the administrative system and the mind set in line with firm's environment	
IP2	Different types of Innovations are introduced for work processes and methods in our firm	
IP3	Our firm is good at improving the quality of new products and services introduced	
IP4	Our firm introduces number of new product and service projects.	
IP5	A good percentage of new products in the existing product portfolio are introduced in our firm	
IP6	A good number of innovations under intellectual property protection are observed in our firm	

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Dr. Zahid Sarwar: Dr. Sarwar is a known author in the fields of innovation, strategy, and management. The author is a Postdoc researcher at Shanxi University, a prestigious first-class university China. He has published original articles in well-known SSCI journals such as Asia Pacific Journal of Management, Information Technology and Management, Asia Pacific Journal of Innovation and Entrepreneurship, Sage open, and more. His research areas are strategic management, technology management, business ethics, and innovation. His research articles on big data management and sustainable strategic orientation are “under-review” in top ranked journals such as Journal of Strategic Information Systems and more. He also serves as a reviewer in the Asia Pacific Journal of Management, Information Processing & Management, Chinese Management Studies, Sage open, Heliyon, and Economic Research.

Professor (Dr) Song, Zhi-hong: Professor Song is currently serving as a “Professor” at Shanxi University in School of Economics and Management. Professor Song has completed Masters and PhD in Management from distinguished University of International Business and Trade. His research interests include data mining, innovation management, and platform governance. His research has appeared in a variety of journals, such as Chinese Management Studies, Asia Pacific Journal of Tourism Research, and Studies in Science of Science.

Dr. Syed Tauseef Ali: Dr. Ali is a postdoctoral research fellow at the School of Accounting and Finance, Hong Kong Polytechnic University (PolyU). His writing research agenda involves an on-going and substantial line of inquiry in the fields of corporate governance, corporate innovation, corporate finance, and behavioral finance.

Dr. Muhammad Asif Khan: Dr. Khan is a research Scholar in the Department of Business and Economic Studies at the University of Naples Parthenope, Italy. He has published research articles in SSCI and SCOPUS index journals such as Asia Pacific Journal of Innovation and Entrepreneurship, Asian Journal of Accounting Research, Sage Open, and Asian journal of Economics and Banking. He also serves as a reviewer in various journals.

Dr. Farman Ali: Dr. Ali is serving as an assistant professor at King Faisal University Saudi Arabia. He has published original articles in various SSCI journals. His research articles published in Journal of Knowledge Economy and Economic Letters.