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Knowledge absorption capacity's efficacy to enhance innovation performance through big data analytics and digital platform capability

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A B S T R A C T

The 2018 Global Innovation Index ranks Pakistan 118 out of 126 in innovation. One of the main reasons why developing countries, such as Pakistan, fail to innovate is their improvisation of astute and concurrent knowledge. This study explores the contemporary hurdles that lead to manufacturing firms' low agility and innovation performance. Based on the theory of dynamic capability view and the theory of absorptive capacity, we propose that the knowledge absorption capacity of firms can help them organize or utilize dynamic capabilities, such as big data analytics and digital platform capability, to enhance their agility and innovation performance. However, in the presence of a diversified organizational culture (i.e., flexibility orientations and data-driven culture), the desired outcomes may be affected. For this purpose, this study performed a questionnaire survey to collect data for validating the theoretical model. The collected responses from 325 manufacturing firms were analyzed using structural equation modeling, and empirical results reveal a positive relationship between the knowledge absorption capacity, agility, and innovation performance of firms mediated by big data analytics and DP capabilities. Flexibility orientations also showed a significant moderating role, but the role of data-driven culture was not significant. Statistical results reject the hypothesis. This study enriches the scope of the theories mentioned above and comes up with several other interesting theoretical and managerial implications valuable for academicians and policymakers.

Introduction

The 2018 Global Innovation Index names Pakistan as one of the least innovative countries globally; out of 126 countries, Pakistan only ranked 117th in 2017 and 113th in 2018 (Global Innovation Index, 2018). Similarly, the manufacturing industry only contributes 14% to the total GDP of Pakistan (Economic Survey of Pakistan, 2019). Developing countries have to deal with issues in their technologies, human skills, institutional mechanisms, and infrastructures that hinder their innovation efficiency. Innovation is often explained as a radical and incremental innovation (Varis & Littunen, 2010). Similarly, innovation performance may be defined as upgrading the firm's products, services, or processes (Flor, Cooper, & Oltra, 2018).

The manufacturing sector of Pakistan contributed about 13.5% to 13.8% on average to the country's GDP over the past decade. However, this sector only witnessed a 13% growth in the latest fiscal year. Both large-scale manufacturing (LSM) and small-scale manufacturing (SSM) contribute to the manufacturing sector and GDP of Pakistan; LSM contributes about 78% and 10.2% to manufacturing and GDP, whereas SSM contributes about 2.0% in both (Economic Survey of Pakistan, 2019). The inconsistent growth of the manufacturing sector of Pakistan may be ascribed to several reasons, but no previous research has explored this problem in-depth. This empirical work aims to solve this problem by boosting the innovation performance of manufacturing firms.

Specifically, this study proposes that manufacturing firms organize dynamic capabilities that can enhance their agility and innovation performance, such as big data analytics capability (BDAC) and DP capability (DPC). BDA has changed the traditional dynamics of businesses and significantly improved their performance. According to Dubey et al. (2019), big data and predictive analytics can improve the performance of manufacturing firms and enhance both their organizational performance (Purgat & Mrozek, 2018) and competitive advantage (Shan, Luo, Zhou, & Wei, 2019). Previous studies have highlighted the influential role of BDAC. However, no study has explored the mediating role of BDAC in the relationship between the knowledge absorption capacity (KAC) and FA of an organization. Considering the impact of BDAC on both academia and industry, this

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research sheds light on the mediating role of the BDAC of manufacturing firms in enhancing FA and innovation performance.

DPs (DPs) are replacing the traditional ways of interaction between businesses and end-users. For example, IOS and Android platforms provide multiple features and apps with convenience, whereas payment platforms, such as Alipay, WeChat, PayPal, and Apple Pay, offer an unmatchable and valuable contribution to the financial industry. Peer-to-peer DPs, such as Airbnb, Uber, and Task Rabbit, are also gaining popularity. DPs can be used as a dynamic capability for manufacturing firms to enhance their agility and innovation performance. This study distinguishes itself from the extant literature by exploring the mediating role of dynamic capabilities (BDAC and DPC).

Furthermore, this study proposes that the attributes of a firm's dynamic capabilities are established due to this firm's KAC, which may urge the firm to organize dynamic capabilities. KAC can be defined as a firm's ability to acquire, assimilate, transform, and exploit knowledge to bolster its performance. Acquisition and assimilation are associated with a firm's potential absorptive capacity, whereas exploitation and transformation are associated with its realized absorptive capacity. Previous studies have explored the versatile outcomes of AC, such as knowledge utilization (Vasudeva & Anand, 2011), OAC and responsiveness of firms (Liao, Welsch, & Stoica, 2003), KAC and environmental performance (Shahzad et al., 2020), and integration of external knowledge and AC to improve radical innovation (Flor et al., 2018).

Integrating firms' dynamic capabilities to enhance their FA and innovation performance should also be considered under the influential role of organizational culture (OC). OC will either support the flow of knowledge or vice versa, given that culture is unavoidable in any organizational outcome (Smircich, 2017). This research expands the idea of Dubey et al. (2019), who argued that OC facilitates the transformation of BDAC to enhance an organization's performance. This study defines two critical traits of OC, namely, flexibility orientations and data-driven culture (Dubey et al., 2019). An organization's flexible orientations will influence the effectiveness of KAC in building BDAC (i.e., flexible orientations will positively affect manufacturing firms to equip themselves with BDAC). Meanwhile, control orientations, where firms follow the norms and adopt typical decision-making mechanisms from the top management, may not drive firms to equip themselves with any ICT-enabled capabilities, such as BDAC. Therefore, this study further broadens the discussion on the role of DDC as a moderator and mediator in the relationship between BDAC and innovation performance. DDC may be influential in either way to transform the outcomes of BDAC and enhance innovation performance. Given the severity of ongoing issues related to the pace of innovation, this study aims to determine how manufacturing firms' agility and innovation performance can be enhanced. The following research questions are therefore proposed:

- According to the dynamic capability view (DCV), what are the roles of BDAC and DPC in enhancing the agility of firms?
- How does FA enhance the innovation performance of manufacturing firms?
- How does OC (flexibility orientations) moderate the relationship between knowledge absorption capacity and BDAC, and how does DDC moderate the relationship between BDAC and innovation performance?

Theory of absorptive capacity

In 1990, Cohen and Levinthal introduced the AC theory to explore a firm's capacity to recognize and value knowledge from external sources, organize and decode such knowledge, and use it effectively to achieve its goals (Tseng, Pai, & Hung, 2011). In the proposed conceptual model, KAC is derived from the theory of AC.

Dynamic capability view

DCV elaborates on the theme of a resource-based view and posits that "Dynamic capabilities bridge the gap between the firm's resources and changing business environment" (Barney, 1991b). Unlike RBV, DCV emphasizes building and adopting the necessary capabilities in response to external environmental changes. BDAC and DPC are extracted from DCV to represent the dynamic capabilities in this study.

Hypotheses

Knowledge absorption capacity and big data analytics capability

AC is a vital capability of firms to organize several needed capabilities (Shahzad et al., 2020). BDAC has been used in product or service innovation, production and manufacturing, marketing and management, and business growth (Ritala, Olander, Michailova, & Husted, 2015). A firm's performance is highly dependent on its effectiveness in processing and interpreting data (Premkumar, Ramamurthy, & Saunders, 2005). A firm needs a set of tangible and intangible resources in technology, culture, technical and managerial skills, and human resources (Chen & Storey, 2012; Tambe, 2014). Janssen, van der Voort, and Wahyudi (2017) argued that the analytic capability complements big data management. Moreover, the performance of a firm is highly dependent on its effectiveness in processing and interpreting data (Premkumar et al., 2005).

Big data is becoming an integral component of Industry 4.0, a concept that a German industrialist proposes to represent the fourth industrial revolution (Shamim et al., 2019). Developing economies attempt to accomplish business competency through value creation by using big data (George, Haas, & Pentland, 2014). Moreover, the view of DCV underscores the significance of recreating and renewing the strategic capabilities of a firm to keep abreast with the changing technology-driven business environment (Pisano, 2017). Although big data helps policymakers decide based on what they know instead of what they believe (McAfee & Brynjolfsson, 2012), the relevant KAC of a firm facilitates the exploitation of BDAC (Zeng & Glaister, 2018).

Based on these arguments, the following hypothesis is proposed:

H1: *KAC will positively affect the BDAC of manufacturing firms.*

Knowledge absorption capacity and DPs capability

Knowledge absorption is a continuous process; modern firms have developed multiple channels to absorb concurrent knowledge. A firm's capacity to use such knowledge greatly depends on exploiting existing knowledge. Apart from big data, machine learning, artificial intelligence, and the Internet of Things, DPC also prioritizes resource allocation. Most companies competing in a digital ecosystem (Subramaniam, Iyer, & Venkatraman, 2019) are based on AC reflecting their competency to acquire, integrate, transform, and utilize external knowledge and affecting platform capability's adeptness (Ali, Seny Kan, & Sarstedt, 2016; Delmas, Hoffmann, & Kuss, 2011).

With emerging technologies, the chances of achieving an optimal advantage depend on establishing a DP for understanding evolving technologies and on the capacity of a firm to undertake the risk of investing in such a platform to improve its business outcomes (Wang, Liang, ZHONG, XUE, & XIAO, 2012). A well-equipped platform supports firms in standardizing, managing, and allocating unprecedented levels of data (Yoo, Henfridsson, & Lyytinen, 2010). The platform capability of digitization not only has changed the means of building a competitive edge over the past two decades (Parker et al., 2016c) but also plays a vital role in defining the value proposition for all sizes of firms by allowing them to seek and handle data and information (Cenamor, Rönnberg Sjödin, & Parida, 2017). Roberts and

Grover (2012) theorized and discovered that DPC allows firms to sense and answer the demands and needs of customers commendably and thereby depends on the absorptive capacity of these firms. Based on these arguments, the following hypothesis is proposed:

H2: *KAC will positively affect the DPC of manufacturing firms.*

Knowledge absorption capacity and firm's agility

KAC utilizes different learning approaches to enhance a firm's performance, such as exploitative, transformative, and exploratory learning (Lane, Koka, & Pathak, 2006). Assimilation and knowledge acquisition can be linked to potential KAC, whereas a firm's ability to transform and assimilate this knowledge into its operations can be linked to realizing KAC (Ali et al., 2016; FLATTEN, GREVE, & BRETTEL, 2011). Firms that solely focus on exploitations may face difficulties sustaining their competitive performance (Volberda, Foss, & Lyles, 2010). The indirect relationship between KAC and FA has been measured in previous research. For example, Overby, Bharadwaj, and Sambamurthy (2006) found a connection between knowledge reach and richness of agility. Trantopoulos, Von Krogh, Wallin, and Woerter (2017) studied the relationship between IT and knowledge capabilities on the agility of a firm, and they highlighted some salient features of agile businesses, such as meeting customer requirements quickly, managing new products strategically, and completing organizational tasks on time. Therefore, this study assumes that KAC develops a proactive conception to respond to or organize dynamic capabilities, such as FA. The following hypothesis is then put forward:

H3: *KAC will positively affect the FA of manufacturing firms.*

Big data analytics capability and firm's agility

Agility refers to a firm's ability to ascertain new opportunities, utilize its current knowledge, and adapt to abrupt business changes. Several IT-enabled studies argue that these capabilities positively influence firms' outcomes (Weill, Subramani, & Broadbent, 2002). Apart from the conventional agility concepts, a firm should also have the expertise to sense external changes and promptly respond to them (Seo, Paz, & A, 2008). Zhang and Dhaliwal (2009) investigated how the application of IT can enhance firm performance, whereas Bharadwaj (2000) examined the significance of information technology adoption as one of the primary differentiators among firms with varying performance levels. The firm's agility resulting from its IT-enabled skills driven by big data interventions is mainly defined as its analytic expertise in information management (Kiron, Prentice, & Ferguson, 2014; Pavlou & Sawy, 2010). Big data analytics involve successfully processing data with large amounts, high velocity, and diverse types (Wamba et al., 2017), which improves FA. The following hypothesis is then proposed:

H4: *BDAC will positively affect the FA of manufacturing firms.*

DP capability and firm's agility

DPs play essential roles in various fields, ranging from functional technology to strategic management (Yeow, Soh, & Hansen, 2018). Technology platforms provide digital options for firms that enable them to react effectively to business or economic changes. Firms with DPCs enjoy the competitive edge of creating new networks to access their customers, integrating themselves into their supply chain partners in real-time, improving the efficiency of their domestic operations, and offering their customers modern digital services and products (Wheeler, 2002). Agility can be observed among those firms with superior platform capabilities to readily address their business process digitally (Sambamurthy, Bharadwaj, & Grover, 2003). DPs connect firms to various external information sources, allow them to establish ties in an inter-organizational network, and address their structural shortcomings. With the help of DPs, firms tend to evaluate the external market trends and respond to them rapidly by formulating strategies (Chi, Ravichandran, & Andrevski, 2010). Those firms connected to the digital network help other firms receive up-to-date information. DPC allows firms to rapidly develop or improve their products or services in a globally challenging market (Kayworth, Chatterjee, & Sambamurthy, 2001).

The rapid development of DPs is evident in almost every industry. DPs have opened new corridors of thinking beyond the traditional business approaches. These platforms help firms connect to their customers and other businesses simultaneously and improve their products and services (Xiao, Tian, & Mao, 2020). Based on these arguments, the following hypothesis is proposed:

H5: *DPC will positively affect the FA of manufacturing firms.*

Firm's agility and innovation performance

Sambamurthy et al. (2003) defined agility as the capacity of a firm to understand and respond to its customer demands, operational agility as a firm's expertise in structuring operation procedures, and partnering agility as the competency of a firm in forming business relationships. The competitive environment constantly challenges businesses. The literature on FA reveals that agility affects firm performance. Specifically, agility can help firms gain dexterity and speed (Singh et al., 2013), which are vital, especially in a rapidly changing global environment (Heckler, Illinois, & Powell, 2016). A firm's agility also reflects the excellence of a firm in detecting and entering niche markets to redefine its business opportunities. Therefore, agility adds to a firm's innovation performance by addressing and finding solutions to problems and responding to the challenges in the market (Song, 2015). FA also has an imperative impact on a firm (Dove & Palmer, 2004), especially on its performance outcomes than its structural or operational excellence (Yauch, 2011). Côrte-Real, Oliveira, and Ruivo (2017), Wagner, Beimborn, and Weitzel (2014), and Yusuf et al. (2014) explored the influence of agility on business and innovation performance. The following hypothesis is then proposed:

H6: *FA will positively affect the innovation performance of manufacturing firms.*

BDAC and innovation performance

Over the last few years, big data has come to light as an emerging frontier of efficiency and opportunity to transform businesses. The ways of doing business have markedly changed due to BDAC (Barton & Court, 2012). Previous studies show that BDAC can transfigure management and practice (George et al., 2014), which are substantial for innovation and considered the "fourth archetype" in science. According to the theoretical foundation of DCV, BDAC refers to an organization's peculiar capabilities for superlative price setting and improving the quality and contributing to the innovative performance of firms. By using the information technology ecosystem, organizations can transform data into a resource that they can analyze during decision making (Rivera & Shanks, 2015). Data analytics serves as a competitive discriminator (Jeble et al., 2018) that positively affects the firm's innovative performance (Ramakrishnan, Jones, & Sidorova, 2012). Previous research shows that BDAC innovates the entire business system from product to process and from the infrastructural system to the segmental one (Caputo, Marzi, & Pellegrini, 2016). Therefore, in fostering structural innovation, the foundation of data based on BDA plays an influential role (Tempini, 2017), whereas the personalization paradigm facilitates the innovation of services (Ng & Wakenshaw, 2017). Big data extends a company's capabilities and leverages innovation in business models (Vecchio et al., 2018). BDAC shows potential in disrupting the innovative performance. The following hypothesis is then proposed:

H7: *BDAC will positively impact the innovation performance of manufacturing firms.*

DP capability and innovation performance

DCV discusses the higher-order practices of operational capabilities to enlarge the scope and adapt and adjust the existing operational skills of a firm for value creation and value addition (Pavlou & Sawy, 2010). However, as the evolution and amalgamation of technologies in every field complement the performance of firms, the implementation of information and communication technology firmly positions itself on a further higher order of dynamic capability view (Parida & Ortqvist, 2015).

Digital transformation changes the procedures, routines, or processes based on a technological foundation and is driven by information technology. DPs have emerged in response to the technical expansions and development triggered by the rapid spread of multiplexed technologies (Parker et al., 2016c). Therefore, designing and embracing platform capability can help firms witness a radical innovation fueled by digitization. This innovation drive emphasizes the importance of focusing on and exploring opportunities for DPs. The following hypothesis is then proposed:

H8: *DPC will enhance the innovation performance of manufacturing firms.*

Mediation of BDAC between KAC and FA

Previous studies suggest that information technology empowers the agility of firms by accelerating their decision-making process, simplifying their communication, and allowing them to respond to changes swiftly. A unified platform can be established using big data and facilitate the standardization and fusion of these data, which is essential in dexterity. Integrating big data enables firms to gather and distribute information quickly. This capability also allows firms to access real-time, persistent, and comprehensive data, which can help them make quick, efficient, and appropriate decisions (Gupta & George, 2016). The BDAC guarantees extensive data handling and integrates diversified data coming at various speeds, pushing firms to be more agile in responding to this filtered stream of data (Wamba et al., 2017). KAC helps firms organize their smart capabilities, which can improve their performance. BDAC urges firms to make decisions based on factual and accurate information, paving the way for knowledge to come through their KAC. Based on these arguments, the following hypothesis is proposed:

H9: *BDAC will mediate the relationship between KAC and FA.*

Mediation of DPC between KAC and FA

The introduction of warehouse management platforms has scaled the flexible capacity of repositories, yet the internet has channelized the market to a higher order. Although information technology competency leverages firms to be more agile, the degree to which these options can be employed depends on these firms' knowledge absorption and utilization capacity. With the emergence of new technologies, the opportunities for businesses to establish an edge have increased; these firms must possess knowledge management capacity and prevision to understand the significance of emerging technologies. Sambamurthy et al. (2003) explored digitized knowledge capital using platforms to produce knowledge warehouses and share this knowledge throughout an organization to increase its agility. IT-enabled capability refers to developing a DP that reflects the flexibility of technology infrastructures and applications in addressing external business requirements. The risk of long-term stiffness can be overcome using DPs; accordingly, using these platforms has become an important strategic priority for several organizations. Firms discover their agility by utilizing the data and information they collect from DPs (Cenamor, Parida, & Wincent, 2019). Upgrading from legacy systems to internet-based DPs provides these firms with enough flexibility to digitize their processes. Previous studies have proposed diverse definitions of an ecosystem networked by DPs. A DP can be defined as a collection of digital resources, including content and services, that help promote valuable interactions between customers and suppliers (Parker, Van Alstyne, & Choudary, 2016a). DPs do not maintain physical resources, such as infrastructure. They help gain market insights in real-time, support the development of products and services, and allow firms to restructure their processes quickly. DPs are connected directly to consumers, providing firms with a gateway to develop their potential absorptive capacity to acquire, assimilate, and identify knowledge from external sources (Zahra & George, 2002). The following hypothesis is then proposed:

H10: *DPC will mediate the relationship between the KAC and FA of manufacturing firms.*

The moderating role of flexibility orientations

An organization's culture is fundamental in determining its business performance and long-term competitive strength. Meanwhile, its performance is substantially dependent on the philosophy and beliefs of work established by enterprise managers. The efficacy of maintaining strong communication and improving performance outcomes is contingent upon integrating a thriving organizational culture (Idris, Wahab, & Jaapar, 2015). The management and decision-makers typically face many challenges in establishing a flourishing organizational culture, which is integral to improving productivity and performance (Kenny, 2011). However, only a few studies have explored the effects of organizational culture on knowledge absorption and facilitating the adoption of information technology. Although, the previously examined constructs, i.e., knowledge absorption management as the dexterity of valuable information recognition, apprehension and its application to the commercial purpose with the corporate culture, which is a paradigm of ideas and values that frame the performance of an organization, potentially affect the affluent knowledge application. Developing BDAC requires a combination of tangible and intangible resources in line with the decision-making capacity that has fostered a flexible and swift culture that supports factual-based judgments. The following hypothesis is then proposed:

H11: *Flexibility orientations (control orientations) will negatively moderate the relationship between KAC and BDAC, whereas flexible orientations will positively moderate the relationship between KAC and BDAC.*

The moderating role of DDC

Deshpande, Farley, and Webster (1993) argued that organizational culture is vital in deciding how a firm responds to external events and strategies. Organizational culture determines the strategy and the steps taken by a firm in response to technological and business competitions. Technology-oriented firms typically rely on the information and knowledge coming from new resources by engaging in BD analytics. BDAC improves innovation performance based on the decisions made after analyzing massive datasets. Given its value, BD has attracted much attention from service-providing and product-manufacturing firms (Constantiou & Kallinikos, 2015). Nevertheless, extracting real value from BD depends on the DDC of a firm. Several investments in BD projects have failed to draw the desired output due to the lack of an adequate data-driven culture (Lehrer, Wieneke, vom Brocke, Jung, & Seidel, 2018).

Following the logic of DCV, BDAC gives firms a competitive advantage in a high-order construct that is greatly influenced by their strategic resources and data-driven decision-making capability to achieve an excellent performance. A detailed review of the literature on environmental and social sustainability, BDAC, and predictive analytics reveals that core insights are driven by data-encompassing interdepartmental cooperation in the modern economy. Manufacturing and technology-oriented industries depend on consumer data, competitive market orientation, and financial and economic information to identify the traits and hallmarks they can add to their future products. The following hypothesis is then proposed:

H12: *DDC will positively moderate the relationship between BDAC and innovation performance* (Figure 1).

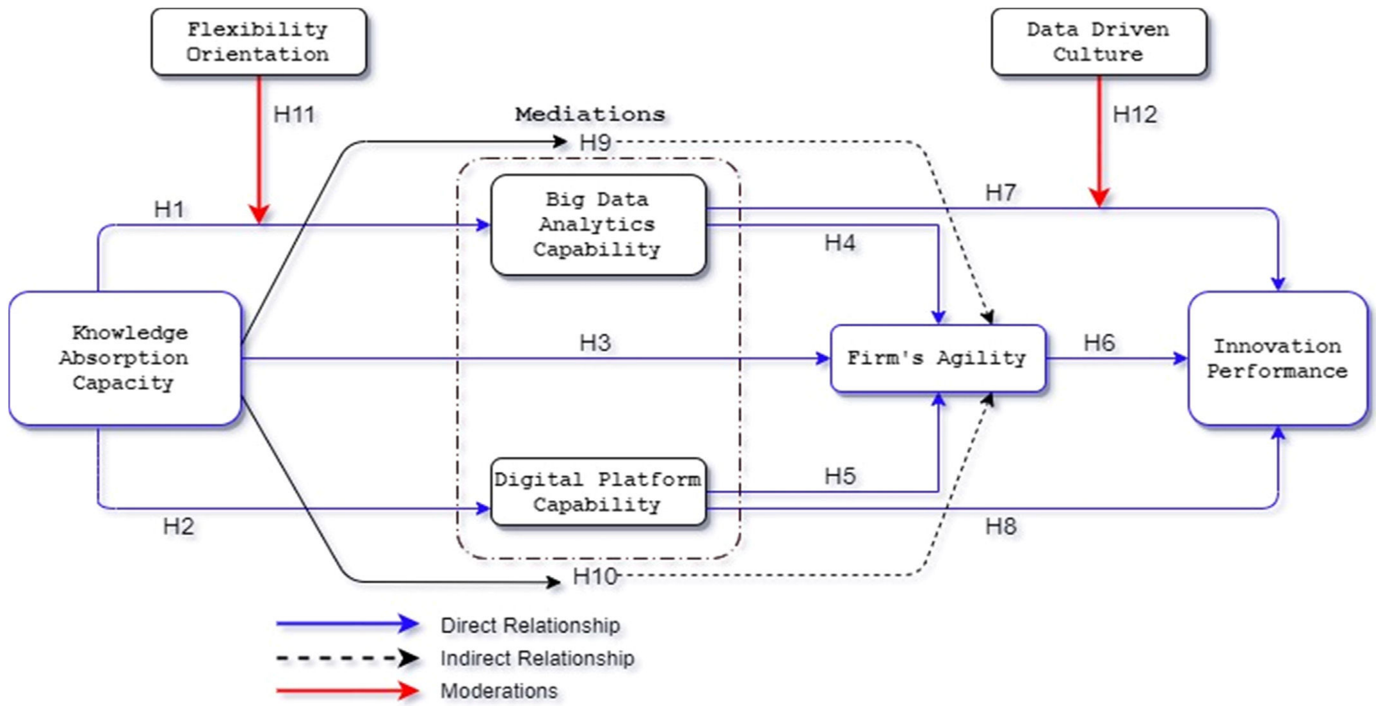

Fig. 1. Research model.

Methods

This research is conducted based on a simple random sampling technique. In the first stage, the manufacturing firms and their relevant statistics were collected from the official websites of the Government of Pakistan, such as the Economic Survey of Pakistan and the Statistics Bureau of Pakistan. An ISO-certified data collection firm was also recruited to collect data from the senior, middle, or frontline managers of manufacturing firms, given their excellent knowledge about their operations. This firm used a self-administered questionnaire designed by the research team to collect data from the target respondents. The recruited managers were contacted by email and other social media platforms. Three hundred forty-seven responses were received, yielding a low response rate of 14%, which was understandable given the COVID-19 pandemic. Among these 347 responses, only 325 were deemed appropriate for the final analysis. Table 1 presents details on Pakistan's manufacturing industry, the research population, and the profiles of the respondents.

Table 1
Demographics.

Details of Demographics (n = 325)			
Attributes	Distribution	N	Percentage
Job Title			
	Senior Manager	27	8%
	Production Manager	40	12%
	Supervisor	56	17%
	Middle Manager	117	36%
	Frontline Manager	85	26%
Education			
	Technical	41	13%
	Graduation	104	32%
	Master	162	50%
	Above Master (MS/MPhil)	18	6%
Gender			
	Male	232	71%
	Female	93	29%
Industry			
	Textile	37	11%
	Coal and Petroleum	20	6%
	Automobiles	36	11%
	Fertilizers	30	9%
	Wood and Papers	31	10%
	Food and Beverages	32	10%
	Pharmaceutical	35	11%
	Surgical Instruments	23	7%
	Engineering Products	21	6%
	Chemical Products	17	5%
	Sports Good	30	9%
	Misc. Manufacturing	13	4%
Ownership			
	Public Firms	97	30%
	Private Firms	228	70%

Measurement items

All constructs used in this study were adapted from the literature and measured on a five-point Likert scale ranging from "strongly disagree" to "strongly agree." KAC was adapted from Jansen, Van Den Bosch, and Volberda (2005) and Shahzad et al. (2020). Sample items included "We have effective routines to identify, value, and import new information and knowledge." BDAC was adapted from Côrte-Real, Ruivo, Oliveira, and Popovič (2019) and Chen, Preston, and Swink (2015). Sample items included "Our enterprise uses BDA purchasing analytics for purchasing." DPC was adapted from Cenamor et al. (2019). Sample items included "We have developed DPs for consumers to share prior experiences, knowledge, and expertise." FA was adapted from Tallon and Pinsonneault (2011) and Ashrafi, Zare Ravasan, Trkman, and Afshari (2019). Sample questions included "Adopt new technologies to produce better, faster, and cheaper products and services." FO was adapted from Dubey, Gunasekaran, and Childe (2019). Sample items included "Our firm follows formal rules and policies which involve less risk." DDC was adapted from Gupta and George (2016) and Dubey et al. (2019), with sample questions including "We base most of the decisions on data rather than instinct." IP was measured with the sample item "In terms of novelty, our firm is always the first one to come up with new ideas about the product", adapted from Maurer, Bartsch, and Ebers (2011) and Prajogo and Ahmed (2006).

Data analysis and results

Measurement model

The reliability and validity of data and instruments were assessed in the measurement model (Barclay, Higgins, & Thompson, 1995). Internal consistency evaluates data reliability based on two measures, namely, Cronbach's alpha and composite reliability. Meanwhile, data validity can be measured via content validity, face validity, convergent validity, and discriminant validity (Chin, 1998; Hair, Ringle, & Sarstedt, 2011).

Cronbach's alpha measures the psychometric reliability of data, the inter-item correlation of each construct, and the average correlation of the actual items. Cronbach's alpha has a minimum threshold of 0.60 (Hair et al., 2011). As shown in Table 2, all Cronbach's alpha values in this study exceed this threshold, thereby suggesting that the average and actual correlations between the items are exact and that the data are reliable and can be used for further analysis.

Composite reliability reveals all indicators of a particular construct (Henseler, Ringle, & Sarstedt, 2015) and can be measured using PLS-SEM. This measure has a minimum threshold of 0.60 (Fornell & Larcker, 1981; Hair et al., 2011). Measures of composite reliability work better when the items are reflective. If these items are formative, then the VIF value is used instead to test the reliability of indicators (Hair et al., 2011; Kutner, Nachtsheim, Neter, & Li, 2005). Composite reliability was employed at the first stage of this study, given that the constructs have reflective items. Table 2 shows that the composite reliability of all items exceeds the 0.60 thresholds.

Convergent validity illustrates the theoretical relationship among the constructs of a model and indicates the degree of correlation between the study variables in the context of the same model. If the variables are not correlated, they do not need to be combined into a single model. Convergent validity is measured based on the average variance extracted, with a minimum acceptable value of 0.50 (Fornell & Larcker, 1981a; Hair et al., 2011). Table 2 shows that all AVE values exceed this threshold, thereby confirming that the constructs are interlinked in the context of the model.

Common method bias (CMB) or variance is related to the adopted measurement method instead of the constructs. CMB arises when the data for the dependent and independent variables are collected from the same set of respondents (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). CMB is a severe problem that can jeopardize the results of any study. Accordingly, researchers have used several methods to address CMB, including Harman's single factor test (Maxwell & Harman, 1968), Liang's method (Liang, Wang, Xue, & Ge, 2017), Bagozzi's approach (Bagozzi, Yi, & Phillips, 1991), and Kock's inner VIF method (Kock, 2015). Bagozzi's method was employed in this study to test CMB. According to this method, if the correlation among the variables is less than 0.90, the data are free from CMB and can be further analyzed.

The inner VIF proposed by Kock (2015) was also employed to test CMB by performing a full collinearity test. The inner VIF was calculated while considering each variable dependent once. As shown in Table 2, all inner VIF values are less than the 5 thresholds (Kock, 2015), proving that CMB is not a severe concern in this study.

Discriminant validity (Fornell–Larcker criterion)

One way to measure the discriminant validity is using the Fornell–Larcker criterion, which compares the square root of AVE with the inter-construct correlation. Specifically, the square root of AVE should be greater than the inter-variable correlation to confirm discriminant validity (Fornell & Larcker, 1981a). The shared variance of the model was less than the square root of AVE. Table 3 reports that the square roots of AVE are greater than the inter-construct correlations reported in the same column.

Heterotrait-Monotrait (HTMT) ratio

In a contemporary research context, a higher factor loading can contaminate the results of the Fornell–Larcker criterion and subsequently affect the discriminant validity of the constructs. The HTMT ratio can be used as an alternate measure of discriminant validity (Henseler et al., 2015). HTMT ratio is a breakthrough in the context of PLS-SEM. Results of Monte Carlo simulations even show that the HTMT ratio outperforms the other measures of discriminant validity in terms of accuracy. Table 4 reports that all HTMT ratios are below the minimum threshold of 0.90 (Henseler et al., 2015), confirming discriminant validity.

Assessment of the structural equation model

Coefficient of determination (R2)

R^2 assesses the variance in the independent variable due to the independent variables. R^2 has no minimum threshold; depending on their study context and discipline, researchers should decide whether their obtained R^2 can explain enough variance (Henseler, Ringle, & Sinkovics, 2009; Hulland, 1999). R^2 measures the overall predictive efficiency of the model that illustrates the combined variance of all independent variables. BDAC obtained an R^2 value of 0.578, suggesting that KAC explains 57.8% of BDAC variance.

Similarly, KAC explains 29.7% of the variance in DPC, KAC, DPC, and BDAC collectively explain 64.5% of the variance in FA, and FA, DPC, and BDAC collectively explain 56% of the variance in IP.

Determining effect size (f2)

The effect size measures the influence of individual variables by omitting the independent variable from the model and subsequently observing the change in this variable. PLS-SEM uses the parameter f^2 to capture the effect of individual variables on the dependent variables. In previous studies, f^2 values of 0.02, 0.13, and 0.26 are categorized as a low, medium, and high, respectively (Cohen, 1988). According to the standard, all the values are small, medium, and high, except one with no DPC effect on IP.

Predictive relevance (Q2)

To analyze the predictive relevance of the model, Q^2 is calculated in Smart-PLS via a blindfold procedure. In previous studies, Q^2 values of 0.02, 0.13, and 0.26 are categorized as low, medium, and high. All variables in this study have a sufficiently high Q^2, thereby indicating the high predictive relevance of the model.

Direct path analysis

Bootstrapping uses a replacement procedure to enhance the sample size. Each observation was selected from the population each time and replaced with other elements; in this way, all elements have an equal chance of being chosen as samples. An observation may be selected more than once or may not be included in the sample. The minimum sample size for bootstrapping should equal the actual sample size (Wetzels, Odekerken-Schröder, & Van Oppen, 2009). However, a subsample of 5000 observations has been recommended in the literature (Hair, Risher, Sarstedt, & Ringle, 2019). Following this suggestion, this study applied bootstrapping with 5000 subsamples to obtain more accurate estimates. Bootstrapping returns all the relationships specified in the model and their significance and strength. Table 5 presents the path coefficients of the direct, indirect, and moderating effects as specified in the model.

The direct relationships proposed in H1 to H8 were all supported by the results in Table 5. H1 proposed a direct and positive effect of KAC on BDAC (β=0.360, T-value= 5.226 p<0.001), H2 proposed a positive and direct impact of KAC on DPC (β=0.545, T-value= 6.389 p<0.001), H3 proposed a positive effect of KAC on FA (β=0.298, T-value= 3.808

Table 2
Convergent validity.

Constructs	Items-loading	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)	VIF
Big Data Analytics Capability					
BDAC1	0.708	0.849	0.885	0.525	2.743
BDAC2	0.721				3.608
BDAC3	0.741				3.558
BDAC4	0.699				2.173
BDAC5	0.756				2.421
BDAC6	0.761				2.617
BDAC7	0.682				1.454
Data-Driven Culture					
DDC1	0.854	0.920	0.927	0.720	2.199
DDC2	0.796				3.046
DDC3	0.91				3.132
DDC4	0.795				3.3
DDC5	0.88				2.943
Digital Platform Capability					
Connect to Businesses					
CTB1	0.884	0.907	0.942	0.844	0.907
CTB2	0.943				4.959
CTB3	0.927				4.419
Connect to Customers					
CTC1	0.88	0.770	0.868	0.688	2.343
CTC2	0.846				2.217
CTC3	0.757				1.269
Firms Agility					
FA1	0.679	0.883	0.907	0.550	1.832
FA2	0.776				2.486
FA3	0.725				2.277
FA4	0.768				2.186
FA5	0.721				1.993
FA6	0.769				2.173
FA7	0.748				1.984
FA8	0.741				1.865
Flexibility Orientation					
FO1	0.858	0.827	0.887	0.666	2.19
FO2	0.893				2.675
FO3	0.871				2.363
FO4	0.612				1.256
Innovation Performance					
Process Innovation					
PIN1	0.762	0.713	0.836	0.629	1.143
PIN2	0.815				2.068
PIN3	0.802				2.036
Product Innovation					
PRIN1	0.749	0.823	0.883	0.654	1.633
PRIN2	0.798				1.765
PRIN3	0.838				2.122
PRIN4	0.845				2.150
Knowledge Absorptive Capacity					
Acquisition					
AQC1	0.88	0.825	0.896	0.741	2.011
AQC2	0.859				1.959
AQC3	0.842				1.713
Assimilation					
ASM1	0.864	0.821	0.894	0.737	1.826
ASM2	0.856				1.831
ASM3	0.855				1.864
Transformation					
TRNS1	0.888	0.864	0.917	0.786	2.399
TRNS2	0.886				2.132
TRNS3	0.885				2.178
Exploitation					
EXP1	0.905	0.876	0.924	0.802	2.447
EXP2	0.885				2.304
EXP3	0.897				2.408

$p<0.001$), H4 proposed a positive effect of BDAC on FA (β=0.422, T-value= 5.213 $p<0.001$), H5 proposed a positive effect of DPC on FA (β=0.213, T-value= 3.681 $p<0.001$), H6 proposed a positive effect of FA on IP (β=0.264, T-value= 3.115 $p<0.001$), H7 proposed a positive impact of BDAC on IP (β=0.367, T-value= 4.699 $p<0.001$), and H8 proposed a positive impact of DPC (β=0.193, T-value= 2.273 $p<0.05$).

Mediation and moderation analysis

Using PLS-SEM to test mediation has been debated by researchers for several decades. The mediation analysis procedure proposed by Baron and Kenny (1986) has been widely adopted in recent studies. However, contemporary research on methodologies (e.g., Hayes &

Table 3
Fornell Larker criterion.

Fornell-Larker Criterion												
Constructs	AQC	ASM	TRAN	EXP	BDAC	CTB	CTC	DDC	FA	FO	PIN	PRIN
AQC	0.86											
ASM	0.61	0.86										
TRAN	0.41	0.5	0.89									
EXP	0.59	0.75	0.41	0.9								
BDAC	0.51	0.49	0.55	0.43	0.73							
CTB	0.31	0.33	0.41	0.35	0.48	0.92						
CTC	0.45	0.44	0.49	0.46	0.63	0.75	0.83					
DDC	−0.01	−0.03	0.01	−0.09	−0.01	−0.03	−0.04	0.85				
FA	0.51	0.53	0.59	0.55	0.74	0.49	0.67	−0.004	0.74			
FO	0.39	0.28	0.33	0.33	0.64	0.42	0.49	−0.04	0.51	0.82		
PIN	0.38	0.36	0.34	0.42	0.47	0.35	0.44	−0.07	0.5	0.39	0.79	
PRIN	0.46	0.49	0.57	0.46	0.67	0.45	0.58	0.02	0.62	0.5	0.43	0.81

Table 4
HTMT ratio.

HTMT Ratio												
Constructs	AQC	ASM	TRAN	EXP	BDAC	CTB	CTC	DDC	FA	FO	PIN	PRIN
AQC												
ASM	0.74											
TRAN	0.48	0.60										
EXP	0.70	0.88	0.47									
BDAC	0.61	0.57	0.63	0.50								
CTB	0.36	0.38	0.46	0.39	0.55							
CTC	0.55	0.55	0.60	0.55	0.77	0.90						
DDC	0.05	0.05	0.05	0.08	0.04	0.05	0.06					
FA	0.60	0.62	0.67	0.61	0.84	0.55	0.80	0.05				
FO	0.47	0.35	0.39	0.40	0.77	0.48	0.60	0.04	0.59			
PIN	0.49	0.45	0.40	0.50	0.58	0.42	0.58	0.08	0.60	0.52		
PRIN	0.56	0.60	0.68	0.54	0.78	0.52	0.72	0.05	0.72	0.61	0.54	

Table 5
Path coefficients and significance.

Path Coefficients and Significance				
Hypothesis	Coefficient	Standard Deviation	T Statistics	P-Values
Direct Relationships				
H1: KAC -> BDAC	0.360	0.069	5.226	0.000***
H2: KAC -> DPC	0.545	0.085	6.389	0.000***
H3: KAC -> FA	0.298	0.078	3.808	0.000***
H4: BDAC -> FA	0.422	0.081	5.213	0.000***
H5: DPC -> FA	0.213	0.058	3.681	0.000***
H6: FA -> IP	0.264	0.085	3.115	0.002***
H7: BDAC -> IP	0.367	0.078	4.699	0.000***
H8: DPC -> IP	0.193	0.085	2.273	0.023**
Mediating Relationships				
H9: KAC -> BDAC -> FA	0.152	0.034	4.511	0.000***
H10: KAC -> DPC -> FA	0.116	0.037	3.119	0.002***
Moderating Effects				
H11: KAC*FO -> BDAC	−0.069	0.042	1.651	0.099*
H12: BDAC*DDC -> IP	0.090	0.078	1.147	0.251

Note: ****, **, * represent the significance level at 1%, 5% and 10% respectively.*

Scharkow, 2013) reported some theoretical and methodological deficiencies in this procedure.

Results of this procedure pointed toward both direct and indirect effects. The direct effects were significant and positive, whereas the indirect or mediating effects were significant and pointed in the same direction as the direct effects. Therefore, a partial mediation was observed between the KAC and FA. These results support H9, which proposed that BDAC mediates the relationship between KAC and FA (β=0.152, T-value= 4.511 p<0.001), and H10, which proposed that DPC mediates the relationship between KAC and FA (β=0.116, T-value= 3.119 p<0.001).

Two moderating effects were also tested. First, the moderating effect of FO on the direct relationship between KAC and BDAC was significant, thereby supporting H11 (β=−0.069, T-value= 1.651, p<0.10. The interaction graph in Fig. 2 shows that negative values of FO weaken the relationship between KAC and BDAC, whereas its positive values strengthen such a relationship. Therefore, flexible orientation increases the positive effect of KAC on BDAC and vice versa. Second, control orientation weakened the positive effect of KAC on BDAC. Specifically, control orientation was insignificant with a negative coefficient, suggesting that a weak data-driven culture weakens the relationship between BDAC and IP, thereby rejecting H12 (β=−0.090, T-value= 1.147 p>0.10). Data-driven culture also produced an insignificant moderating effect.

Fig. 3 shows the moderating effect of DDC on the relationship between BDAC and IP.

Fig. 4 presents the path coefficients along with their values.

Overall model fit

The outer model calculates the reliability and validity, whereas the inner model evaluates the predictive efficiency. The standardized root means square residual (SRMR) has a minimum acceptable value of 0.08 (Henseler et al., 2015). The other value, normed fit index (NFI), is associated with the chi-square index and preferably has higher values. An NFI value of near 1 is considered acceptable. In this study, the SRMR and NFI values were calculated to assess the model fit. Under the saturated model, the obtained SRMR value was 0.07, below the 0.08 threshold.

Meanwhile, the NFI value was 0.70, near 1, suggesting a good model fit. The goodness-of-fit (GOF) index considers the performance of both the measurement and structural models. This index also provides operational solutions to the problems faced by previously developed models in measuring the GOF of PLS path models. Accordingly, the GOF index has been widely employed (Chin, 2010). Studies using PLS-SEM also adopt this index for global validation of models (e.g., Duarte & Raposo, 2010; Rigdon, Ringle, & Sarstedt, 2010). In this study, the GOF index was calculated as follows;

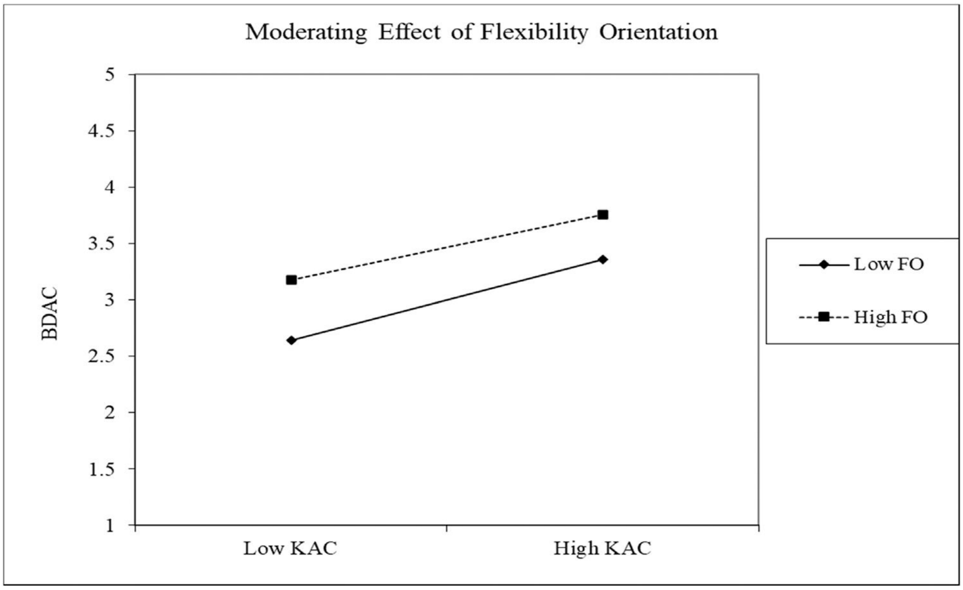

Fig. 2. Moderating effect of FO.

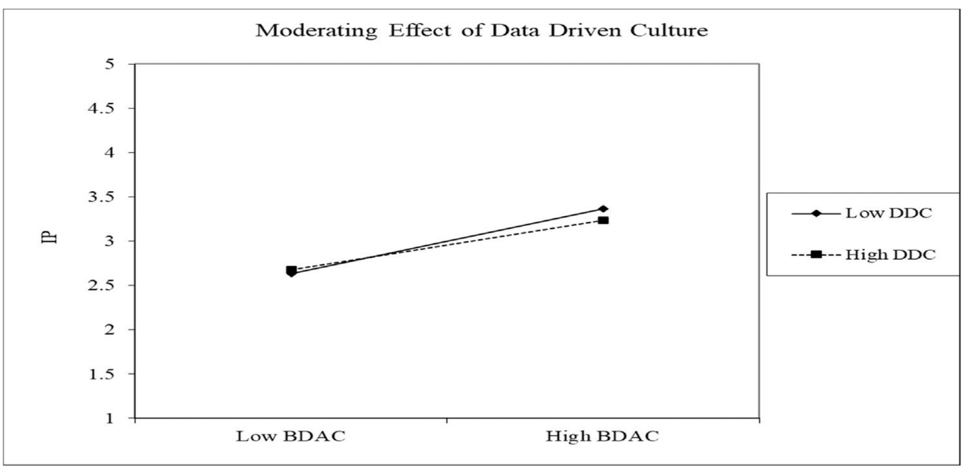

Fig. 3. Moderating effect of DDC.

$$GOF = \sqrt{AVE * \overline{R}}$$

Where AVE represents the average commonalities, the GOF index may range from 0 to 1, where 0.10 is small enough to validate a model, 0.25 is considered moderate, and 0.36 is significant enough to approve the global validation of the model and indicates that this model is both parsimonious and reasonable (Henseler et al., 2015). As shown in Table 6, the computed GOF index is 0.586, confirming the research model's global fitness.

Table 6
The goodness of Fit Index.

The goodness of Fit Index			
Constructs	**AVE**	**R^2**	**GOF**
BDAC	0.526	0.578	
DPC	0.872	0.297	
FA	0.550	0.645	
IP	0.711	0.560	0.586
FO	0.666		
KAC	0.661		
DDC	0.631		
Average	0.660	0.520	

Discussion

The above results support the direct relationships proposed in H1 to H10. Each variable in the conceptual model was individually investigated, and the computed empirical values exceeded the threshold. These results prove that KAC can help firms equip themselves with dynamic capabilities to meet their requirements and satisfy their external environment's needs.

Dynamic capabilities (BDAC and DPC) are vital in bolstering a firm's performance and agility. Studies have also demonstrated the critical role of BDAC as a mediator of the relationship between organizational capabilities and performance (Hsinchun et al., 2018; Wang, Yeoh, Richards, Wong, & Chang, 2019). The statistical results of this work also underscore the positive and significant roles of BDAC and DPC as mediators of the relationship between KAC and FA.

Similarly, both variables' moderating roles are part of cultural traits and flexibility orientations (flexible and control orientations). This study proposed that flexibility orientations will moderate the relationship between KAC and BDAC. The flexible orientations of firms encourage change. FO and CO produce different outcomes related to the acceptance of change in a firm. The concept of flexibility orientations was adapted from Dubey et al. (2019), where both

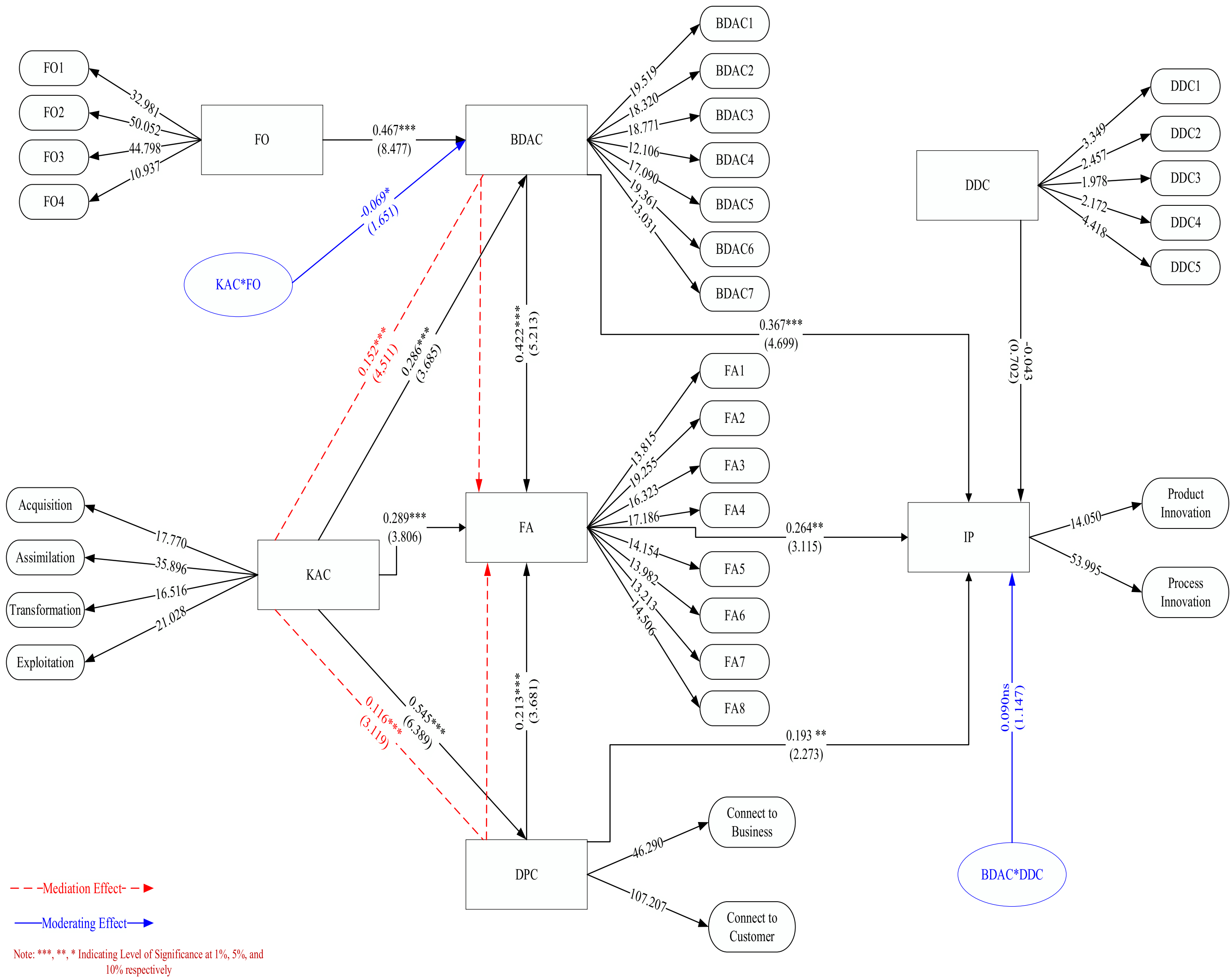

Fig. 4. Path coefficient.

flexible and control orientations were checked individually. Unlike H1 to H11, H12 was not empirically supported for two reasons. First, most manufacturing firms in Pakistan are privately owned. Second, even government-owned manufacturing firms follow a traditional hierarchical management system where the top management makes all the decisions and thereby controls the orientations of these firms. This research followed the flexibility control orientations philosophy of Dubey, Gunasekaran, Childe, Blome, and Papadopoulos (2019), who proposed that control orientations will negatively impact the outcomes. In line with this philosophy, the statistical results proved that CO negatively moderates the relationship between KAC and BDAC. Empirical evidence also suggested that CO negatively moderates the relationship between the KAC of firms and the formation of BDAC. Previous studies suggest that firms from a data-driven culture highly focus on their decision-making and that DDC helps these firms decide based on data than on instincts (Gupta & George, 2016).

Conclusion

This research proposed that the manufacturing firms in Pakistan can enhance their innovation performance by introducing several dynamic capabilities. Before deciding which dynamic capabilities are critical, this research stresses KAC as a fundamental capability of firms (Spithoven, Clarysse, & Knockaert, 2010) that allows them to integrate dynamic capability. KAC was adapted from absorptive capacity theory as an independent variable. Other studies also proposed that KAC can help manufacturing firms formulate their BDAC (Mikalef et al., 2018) and DPC, which can be extensions of DCV. Both of these dynamic capabilities transform KAC to enhance the collective agility of manufacturing firms. In this case, agility is the outcome of the dynamic capability of firms (Teece, Peteratd, & Leih, 2016). This investigation also proposed that a firm's agility needs a theory to describe the phenomenon's comprehensiveness.

DPs may also need a different theory to encompass the multifunctional and complex nature of various DPs. DPC and BDAC mediate the relationship between KAC and agility, and collective agility enhances the innovation performance of manufacturing firms. Positive individual relationships were reported between the independent variable (KAC) and mediators (BDAC and DPC). As a trait of organizational culture, CO was reported to moderate the relationship between KAC and BDAC negatively. In this case, DDC cannot transform BDAC to enhance the innovation performance of manufacturing firms. DDC was a significant moderating variable that negatively moderates the relationship between BDAC and IP.

Theoretical contribution

First, this research broadens the scope of two well-known theories, DCV and absorptive capacity theory, by integrating them into a single framework and highlighting their importance. Second, this research highlights KAC as an enabler for firms to form or utilize BDAC and DPC, thereby enriching the literature on absorptive capacity and dynamic capabilities. Previous studies have mainly explored KAC as a dynamic capability of firms instead of a basis that helps firms equip themselves and organize their dynamic capabilities. Third, this study contributes to the literature on BDAC and DPC by combining these capabilities into a single dynamic capability that boosts the agility of manufacturing firms. Fourth, the outcomes of this research explain the diversified role of dynamic capabilities as a mediator of the relationship between the knowledge absorption and agility of a firm. Fifth, as one of its most significant contributions to the literature, this study examines the role of FA as an outcome of dynamic capabilities, uncovers the heterogenic role of agility, and explains that agility cannot always be treated as a dynamic capability of a firm. Another key finding of this work is that, in many cases, the agility of a firm may be an outcome of its immutable resources and capabilities. This research primarily contributes to the literature on organizational culture. In any firm-level research, the role of organizational culture should be considered, given its potential to disrupt the relationships among desirable outcomes.

Managerial contribution

This research benefits the stakeholders of manufacturing firms, who should focus on seeking alternative media for gathering and transforming knowledge (KAC), which can help them utilize their dynamic capabilities (BDAC and DPCs) at their maximum potential. Moreover, full utilization of BDA and DP can help manufacturing firms enhance their agility and performance. Managers of manufacturing firms should consider the importance of KAC and arrange specific dynamic capabilities, such as BDAC and DPC, to enhance their agility. Following the outcomes of this research, managers of manufacturing firms should adapt and transform a flexible organizational culture that may help change the outcomes of their dynamic capabilities as well as improve their agility and innovation performance, given that control orientations and a less-developed data-driven culture can stop firms from absorbing knowledge and nurturing their dynamic capabilities.

Limitations

Due to the COVID-19 pandemic, the data were only collected using online media, which may introduce ambiguities in the collected survey responses. Future studies may use secondary data to produce diversified outcomes, such as proxies for innovation and data analytics. Performance comparisons across neighboring developing countries may also be conducted using the same variables, (Fig. 1).

Appendices

Tables 1−6

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