The role of big data analytics in manufacturing agility and performance: moderation-mediation analysis of organizational creativity and of the involvement of customers as data analysts

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Abstract:

The involvement of customers as data analysts enables firms to gain valuable insights and create value from big data. We provide a theoretical explanation, drawn from the resource-based view, for the influence of the involvement of customers as data analysts and of the development of big data analytics capabilities in business to business contexts as routes to manufacturing agility and performance. Our study empirically tested a framework in which organizational creativity and the involvement of customers as data analysts may differentially influence the relationship between big data analytics capabilities and manufacturing agility. We further tested whether the relative impact of manufacturing agility depends on organizational creativity and the involvement of customers as data analysts. To test our proposed framework, we took a partial least square structural modeling approach using data collected through a survey involving 179 engineering manufacturers operating across different industrial sectors in Pakistan. We provide evidence for organizational creativity and customer involvement presenting a promising opportunity for manufacturers to gain better insights from resources, and for the deployment of big data analytics capabilities leading to better manufacturing agility and performance.

Keywords. Organizational creativity; big data analytics capability; customer involvement as a data analyst; manufacturing agility; manufacturing performance; emerging markets

1. Introduction

Faced with intensified competition, manufacturing firms utilize advanced and emerging technologies to reduce delivery times and meet their customers' expectations by providing customized products (Swafford *et al.* 2006). The business-to-business (B2B) literature has recently paid much attention to the role played by the involvement of customers as data analysts (Zhang & Xiao, 2020). The concept of customers as data analysts is defined as "*customers (actively) participating in big data analytics (BDA), such as acquisition and analysis of big data, and implementation of findings from big data analytics*" (Zhang & Xiao, 2020: p.100). In a B2B context, for instance, customers could include business partners, such as suppliers and distributors. Their involvement in big data analytics yields opportunities for data-driven organizations (Kunz et al., 2017; Akhtar et al., 2018). Menguc, Auh, and Yannopoulos (2014) provided a comprehensive review of customer involvement in the design stage as a source of information-processing effects on innovation outcomes. Despite this progress, many B2B firms are still ignoring the importance of customer involvement in BDA (Zhang & Xiao, 2020). Côrte-Real, Oliveira, and Ruivo (2017) discussed the relationship between BDA capabilities (BDACs), value chain, and firm performance, and suggested that it requires further investigations.

Previous studies have argued that BDACs enable manufacturing firms to gain data insights into and respond to any recurrent changes in the marketplace and production processes (Dubey *et al.* 2018). Empirical studies have also demonstrated the positive moderating impact of dynamic capabilities (DCs) on the relationship between BDACs and firm performance (Wamba *et al.*, 2017). Recently, Mandal (2019) has investigated the relationship between BDACs and firm agility, and scholars have observed that such relationship is equivocal (Yasmin *et al.*, 2020), whereas most previous studies have found a positive association between BDACs and firm performance (Akter *et al.* 2016; Rialti *et al.* 2019). Furthermore, most of the literature has acknowledged that BDACs are an important resource for performance improvement (Khanra et al., 2020), particularly in manufacturing environments (Papadopoulos et al., 2021; Aydiner et al., 2019). These mixed results highlight the need to explore and identify the organizational characteristics necessary to improve manufacturing performance (Dubey *et al.*, 2019b). Specifically, Awan, Sroufe, and Shahbaz

(2021) have suggested the need to clarify how and when BDACs lead to increased performance.

The prevalence of making big data more manageable through novel visualization, filtering, and the use of machine learning models has enabled researchers to expand their understanding of big data and creativity (Dahlstedt 2019). BDA is a way whereby management insights that require sophisticated analytics and processing techniques can be extracted through structured and unstructured data (Gupta & George 2016). In regard to exploring the real meaning of data, creativity is becoming a key factor in developing the new skills and abilities needed to uncover unexpected patterns of information in the data and to explore novel representations of them (Dahlstedt, 2019). Despite the crucial role played by organizational creativity in the generation of novel and useful ideas suited to respond to rapidly changing business situations (Anderson *et al.*, 2014; Darvishmotevali *et al.*, 2020), organization creativity still makes an essential contribution to agility, but its impact may be somewhat indirect (Darvishmotevali *et al.* 2020). The current literature has not explicitly explained what facilitates the relationship between agility and manufacturing performance (Iqbal *et al.* 2018). Recent studies have highlighted the significant role played by creativity in improving organizational agility (Darvishmotevali *et al.*, 2020). According to Dahlstedt (2019), it is not yet clear how manufacturing agility and performance depend on organizational creativity. The previous literature has investigated the significance of BDACs for firm performance and organizational or operational agility (Akhtar et al., 2018; Yasmin et al., 2020), where agility was based on internal manufacturing processes and external dimensions (e.g., supply chain processes). However, relatively little research has examined the contextual factors affecting the relationship between BDACs and agility and, consequently, their impact on manufacturing performance. To address this gap, the purpose of our study was to explain what might affect such relationship. In doing so, we explored why organizational creativity and the participation of customers as data analysts (in B2B contexts, industrial customers; i.e., lead firms for suppliers) are important for the achievement of higher levels of manufacturing agility and, consequently, manufacturing performance.

We drew key insights from the Resource-Based View (RBV), linking it with the RBV of big data (Akhtar *et al.*, 2019), and dynamic capabilities (DCs) theories and contribute to the existing literature by explaining why enhancing BDACs and organizational creativity can improve agility and manufacturing performance. We also explored an important additional factor by articulating that organizational agility and manufacturing performance are also dependent upon the customers' involvement as data analysts. Against the backdrop of the above discussion, we explored the following research question: what are the distinct and joint effects of BDA, the involvement of customers as data analysts, and organizational creativity on manufacturing agility and performance? The contextual motivation of this study stemmed from the institution-based view, which is the third leg of the strategy tripod (Peng, Sun, Pinkham, & Chen, 2009). The institution-based view suggests that, when formal institutions are ineffective, informal sources of value creation—e.g., knowledge creation and innovation—become more important (Su *et al.*, 2016) and firms can gain significant value by utilizing both tangible and intangible resources as per the RBV, where big data can represent an important resource for value creation (Akhtar et al., 2019). Our study leveraged the unique context of Pakistani engineering manufacturers, which are facing the challenge of institutional voids, and thereby rely on external sources of knowledge creation and innovation (Khan *et al.*, 2018).

Our study makes important contributions to the extant literature, triggering the scholarly debate on the involvement of customers as data analysts and examining its effects on manufacturing agility. Drawing key insights from the RBV, we identified the important role played by the involvement of customers as data analysts as a unique information technology resource that firms can deploy to attain agility. Our study also contributes to the literature by highlighting BDA as one of the key factors influencing manufacturing agility and performance. To date, little is known about how this relationship can be improved. Our research addresses this gap and provides a possible explanation by highlighting the vital role played by creativity and customer involvement in data analytics.

2. Theoretical background

2.1. Resource based view and dynamic capabilities view

The RBV has made significant contributions to the rapidly growing area of research on BDACs. Still, little is known about how firms build their capabilities through BDA (Gupta & George, 2016). The term big data is often used to describe huge, composite, and real-time volumes of data that require complicated management, analysis, and processing mechanisms to extract information (Laney, 2012). The term BDACs refers to the "*...tangible resources (that) include data, technology, and other basic resources (e.g., time and investments), while human resources (that) consist of managerial and technical big data skills*" (Gupta & George, 2016: p.1051). Here, we suggest that intangible organizational resources enable the development of BDACs. We describe an intangible resource that enables an organization to identify several human and technological resources suited to facilitate several processes aimed at creating organizational capabilities.

As per the RBV, firm resources (both tangible and intangible) contribute to creating sustained competitive advantages that cannot be imitated by competitors (Barney, 2001). The RBV of big data, which includes *"all assets and capabilities that can provide a basis for big data collection, storage and analytics",* especially provides a basis for competitive advantages and creates value by unpacking insights drawn from the complex bundles of big data and related skills (Akhtar *et al.*, 2019: p. 266). Thus, most manufacturing firms rely on possessing intangible, unique, and creative resources (Shen *et al.,* 2019), including servitization for value creation (cf. Neely, 2008; Gomes *et al.*, 2019). Barney (2001) suggested that firms can utilize organizational assets, processes, unique capabilities, and knowledge to improve their performance and develop sustainable competitive advantages. Researchers have established that organizational BDA is a strong predictor of DCs (Mikalef *et al.*, 2020) and that organizational BDA depends on an organization's resource base. This argument is consistent with the RBV. For instance Mikalef *et al.* (2020) combined the RBV with DCs to explain the tangible and intangible resources that affect a firm's ability to integrate, build, and reconfigure the competencies needed to address any disruptive changes in the marketplace. The RBV of the firm is characterized by the integration of technological and human resources to create value for the company (Barney, 1991). Most studies have examined the effect of BDACs on firm performance using only the RBV as a theoretical lens (Akter *et al.*, 2016; Wamba *et al.*, 2017). However, scholars have also indicated that resources, on their own, might not create value for firms as the latter need to possess the capabilities to effectively deploy and leverage resources for value creation (Teece *et al.*, 1997; Lin & Wu, 2014). Recent literature also emphasizes on IT-embeddedness in DCs (Steininger et al., 2021). Steininger et al. (2021) argues that DCs encompass sensing, seizing, and transforming capabilities. In this scenario, we discuss the role of customer as data analyst and organizational creativity in the transformation of organizational competencies for value creation though big data.

DCs are an extension of the RBV and refer to the ability of firms to create new competencies and reconfigure existing ones (Teece *et al.*, 1997; Teece, 2007). DCs pertain to the use and deployment of resources to leverage sensing, seizing, and reconfiguration capabilities in order to gain a competitive advantage (Teece, 2007). In other words, in modern settings, DCs are defined as the "*ability to promptly adopt changes and process data and information for actionable knowledge or analytics that enable the effective tackling of changes in the market*" (Akhtar *et al.*, 2018: p. 308). Although the RBV and DCs have evolved from two different perspectives, they are complementary to each other because capabilities are attained through the utilization of resources (Barney *et al.*, 2001), and organizations develop sustainable competitive advantages on the basis of hard to imitate resources and capabilities. However, despite their importance, little research has examined both perspectives on the utilization of BDACs in a manufacturing environment. Following Wamba, Dubey, Gunasekaran, and Akter (2020), we conceptualized agility as a DC. Agility has also been suggested as a meta-capability (Doz & Kosonen, 2010), and through this organizations can effectively respond to external changes for value creation (Weber & Tarba, 2014). According to Teece (2012, p. 1395) DCs are defined as the organizational "*ability to integrate, build, and reconfigure internal and external resources/competencies to address, and possibly shape, rapidly changing business environments*". According to Augier and Teece (2007, p.412), "*if a firm possesses resources/competencies but lacks DC, it has a chance to make a competitive return for a short period, but superior returns cannot be sustained*". The DC perspective focuses on the ability of a company to renew its resources in response to environmental changes (Teece, 2014). Agility, consisting of multiple internal and external parameters, could be interlocked with DCs, which are built over time (Akhtar *et al.*, 2018).

2.2. Componential theory of organizational creativity

Organizational creativity, which is multidimensional, has been most frequently used to produce novel and applicable ideas (Oldham & Cummings, 1996). According to Sawyer and Griffin (1993), "*creativity for organizations – doing something for the first time anywhere or creating new knowledge – represents a dramatic aspect of organizational change that may provide the key to understanding change phenomena and, ultimately, organizational* *effectiveness and survival*" (p. 293). Similarly, Darvishmotevali *et al.* (2020) suggested that researchers should consider organizational creativity to explain the effects of agility on performance outcomes. Amabile (1997) proposed the componential theory of organizational creativity (CTOC), which has been adequately addressed in the extant literature (Rennick & McKay, 2018). Amabile (1997) suggested a framework of CTOC measures that includes three elements: expertise (a cognitive pathway that includes memory for knowledge and technical proficiency), creative-thinking (taking a new perspective on problems), and intrinsic task motivation, with organizational capabilities emerging from the combination of these elements (de Vasconcellos *et al.*, 2019). The intrinsic task motivation component include two elements, intrinsic motivation (driven by profound interest and participation) and extrinsic motivation (the desire to achieve a certain objective) (Amabile, 1997). Previous studies on the different aspects of organizational agility have also focused on organizational creativity. However, there is lack of understanding of the process through which manufacturing firms increase their agility (Lee, Wang, & Grover, 2020). Following Amabile's (1997) CTOC, we proposed that organizational creativity has the potential for adapting and embracing the changes needed to respond proactively in order to remove uncertain barriers. Therefore, organizational agility is determined by an organization's ability to create the internal structures and processes suited to enable its members to build the skills needed to deal with environmental changes. Figure1 presents the framework of this study.

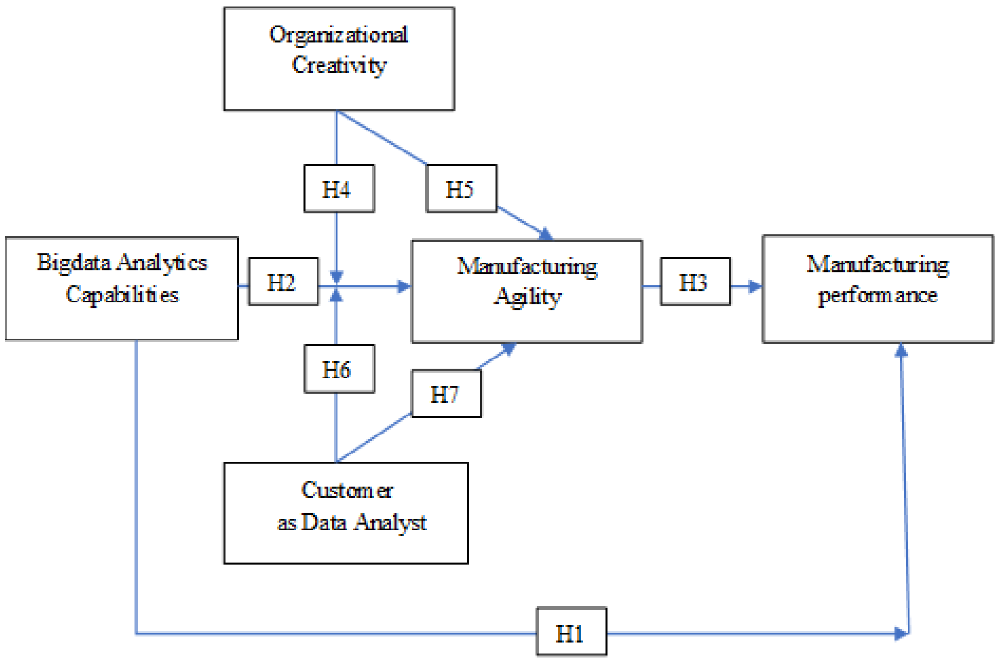

Figure1. Hypothesized model

3. Literature review and hypotheses development

3.1.Big data analytics capability and manufacturing performance

Over the last two decades, research conducted into performance of manufacturing firms has augmented our understanding of the related operations. Still, such studies have focused only on the positive effects of external pressure (Adebanjo *et al.*, 2016), environmental collaboration (Vachon & Klassen, 2008), and the adoption of industry 4.0 technologies (Tortorella *et al.*, 2019). Manufacturing performance refers to the capability of a manufacturer to improve unit cost, lead time, flexibility, on-time delivery, and cost-efficiency (Cua *et al.*, 2001). Manufacturing performance is a critical outcome of operational strategy because, if the available information resources are not properly utilized, the within-firm data analytics resources remain underutilized (Dubey *et al.*, 2019b). BDACs play a salient role in the utilization of the information resources of a firm with the aim of improving its performance (Akter *et al.*, 2016; Wamba *et al.*, 2017). According to Akter *et al.* (2016), BDACs refer to a "*holistic process that involves the collection, analysis, use, and interpretation of data for various functional divisions to gain actionable insights, create business value, and establishing competitive advantage*"(p.86).

BDACs are critically important for the implementation of flexible and cost-effective operational strategies. Some prior studies have examined the relationship between BDACs, firm performance (Rialti *et al.*, 2019; Wamba *et al.*, 2017), and innovation capability (Bag *et al.*, 2020). We argue that BDACs will more likely steer data analytics toward seeking a winning solution to implementing flexibility, cost efficiency, lead-time improvement, and on-time delivery. BDACs can lead firms to move away from the traditional way of using data and enable them to extract from them some meaningful insights for effective decision-making (Shamim et al., 2020; Awan et al., 2021). The theoretical evidence of the RBV for BDACs is consistent with those studies that have considered the RBV as one of the firmest theories referenced by many academicians to explain the relationship between organizational resources and agility (Gupta & George, 2016). Thus, in light of the above argumentation and as per the RBV, we proposed that BDACs enable firms to extract information useful for their strategic planning processes and help them to better adapt to changing environmental conditions. Accordingly, we formulated the following hypothesis.

H1. Big data analytics capabilities are positively associated with manufacturing performance.

3.2.Big data analytics capabilities and manufacturing agility

Yasmin *et al.* (2020) argued that BDACs are significantly related to firm operational performance, while Wamba *et al.* (2020) argued that BDACs enable firms to handle disruption and to better identify any emerging opportunities. Shamim et al. (2021) also heighted the importance of BDAC at operational and strategic levels to create new knowledge and business value. Agility is an important component of operational strategy, as it enables firms to respond to market changes in a timely fashion (Tallon & Pinsonneault, 2011). According to Braunscheidel and Suresh (2009), manufacturing agility is defined as "*the ability to efficiently change operating states in response to uncertain and changing market conditions*"(p.120). According to Shokouhyar *et al.* (2020), firms can identify opportunities and ultimately make better decisions through manufacturing agility. Following Wamba *et al.* (2020a), we conceptualized agility as a DC that refers to an organization's ability to create new and reconfigure its existing competencies to respond to a changing environment (Teece, 2007, 2012) Specifically, prior research has noted that BDA may affect an organization's ability to recognize the need to react and make quick decisions (Wamba & Mishra, 2017).

BDACs can enable a firm to develop more visibility and to be more agile (Dubey *et al.*, 2019a) and transparent (Hajli *et al.*, 2020). Barlette and Baillette (2020) further argued that BDACs are a prerequisite for building organizational change in order to enhance manufacturing agility, which is a capability that enables firms to respond quickly to market changes (Braunscheidel & Suresh, 2009). Nevertheless, high levels of BDACs can assist firms in adapting to improve the information they use in their decision-making processes (Ashrafi *et al.*, 2019). Following the previously established theoretical framework—whereby researchers have established that organizational BDACs are a strong predictor of DCs (Mikalef *et al.*, 2020)—BDACs trigger the development of the capability to accurately forecast market demand, plan for contingency action in response to changing market conditions, rapidly reduce order to delivery cycle times, and thus reduce manufacturing lead times. Thus, we suggest that.

H2. Big data analytics capabilities are positively associated with manufacturing agility.

3.3. Manufacturing agility and manufacturing performance

Manufacturing agility emphasizes the importance of adapting, responding to changing market conditions, and rapidly improving manufacturing lead-time. Manufacturing agility is an advanced stage of lean production. Previous research examined the relationship between agility and manufacturing performance and found a positive relationship (Eckstein *et al.*, 2015; Roberts & Grover, 2012). In relation to performance outcomes, it may be assumed that a firm with agile capability is more likely to improve them (Weber & Tarba, 2014; Christofi *et al.*, 2021). Recently, Rialti et al. (2019) found a positive and significant association between agility and performance. At the conceptual level, manufacturing agility promotes flexibility and enhanced responsiveness (Zhang, 2011). Agile manufacturing consequently creates an environment conducive to rapid customer response, thus meeting product and market demands (Braunscheidel & Suresh, 2009). Manufacturing agility enables firms to adapt to changing market demand, reduce order to delivery time, and improve manufacturing lead times. Hallgren and Olhager (2009) argued that manufacturing agility focuses on delivery reliability and quality improvements. Similarly, Iqbal *et al.*, (2018) validated a positive relationship between manufacturing agility and performance outcomes. In the big data environment, previous researchers have established that manufacturing firms with greater agility can render their internal operations more efficient and streamlined. Accordingly, we hypothesized:

H3. Manufacturing agility is positively associated with manufacturing performance.

3.4.The moderating role of organizational creativity

Researchers have investigated how creativity can influence innovation performance. Organizational creativity can promote the capabilities needed to explore and adopt new ways of working (Anderson *et al.*, 2014). Creativity refers to the generation of new and valuable ideas, while innovation has generally been argued to refer to both the production and implementation of creative ideas (Amabile *et al.*, 1996). Amabile (1997) proposed the componential theory of organizational creativity (CTOC), which has been adequately addressed in the extant literature (Rennick & McKay, 2018). Previous research has also acknowledged that organizational creativity may strongly impact the DCs of developing firms (de Vasconcellos *et al.* 2019), and that customer engagement enables an organization to solve problems in novel ways (Alhawari *et al.*, 2021). There is overwhelming evidence in the literature that creativity is an important mechanism that enables a firm to develop its innovation capabilities and, consequently, improve its performance (Ferreira *et al.*, 2020).

Organizational creativity is multidimensional and has been most frequently used to produce novel and applicable ideas (Oldham & Cummings 1996). Darvishmotevali *et al.* (2020) suggested that researchers should consider organizational creativity to explain the effects of agility on performance outcomes. From this perspective, taking advantage of a given organizational capability stems from its suitability to respond to external changes in adapting, integrating, and reconfiguring internal and external managerial skills and resources (Teece *et al.*, 1997). Firms' capabilities enable them to complete tasks efficiently and transform their resources in order to better understand and respond to market changes (Day, 2011). The findings of past studies show that organizational creativity plays an important role in many forms of organizational agility. More recently, studies on agility have begun to shift their focus to the process through which agility occurs (Lee *et al.*, 2020). For example, de Vasconcellos *et al*. (2019) explored how business competencies emerge through creativity. In contrast, Darvishmotevali *et al.* (2020) explored the impact of organizational agility on creativity using contingency theory. We argued that organizational creativity requires individuals to come up with novel ideas according to business needs and priorities. In our study, organizational creativity can be regarded as a potential pathway leading to new ideas and solutions suitable to grow and respond quickly in complex environments.

Some studies have shown that creativity is particularly important for organizational agility (Darvishmotevali *et al.*, 2020). Ferreira *et al.* (2020) analyzed the determinants of firm performance—including innovation capability and creativity—and found a positive relationship between them. Furthermore, Awan et al. (2019) stressed the importance of examining the direct and indirect influence of creativity on firm performance. The literature on manufacturing performance is substantial, and many studies have investigated the impact of different organizational factors on it. Previous research has acknowledged that creativity wields substantial influence on firm performance when it is coupled with firm capabilities. As previously suggested, creativity can affect firm performance, either directly or indirectly, by enhancing innovation capabilities. However, previous research studies have overlooked the influence creativity wields on agility by enhancing BDACs. Following Dahlstedt (2019), we assumed that creativity is likely to exert a strong influence on the relationship between BDACs and manufacturing agility. Following Amabile's (1997) CTOC, we proposed that organizational creativity has the potential for adapting and embracing changes in order to respond proactively. Based on the preceding discussion, we suggested:

H4. Manufacturing firms that are characterized by a high level of organizational creativity gain high manufacturing agility from BDAC, as compared to firms with low levels of creativity.

Recently Wamba *et al.* (2020) have examined agility as a mediating variable between BDACs and firm operational performance. Rialti et al. (2019) also highlighted BDACs as an organization's key resource, which is highly dependent upon external resources to enhance agility. BDACs represent effective ways of obtaining insights from structured and unstructured data. The development of BDACs requires technological resources and involves a complex process that may benefit from customer input. According to Wamba *et al.* (2017), BDACs are a crucial part of a firm's operations because they enable the generation of insights from data. Previous studies support the notion that BDAC can trigger agility (Côrte-Real *et al.,* 2017).Wamba *et al.* (2020) highlighted the need for further studies investigating how BDACs could enhance organizational performance. Conceptually, manufacturing agility, as a mediating mechanism, implies that a manufacturer can manage its BDACs to extract information for strategic use: to predict customer and market demands and plan and adapt to changing conditions, thus enhancing its performance outcomes. Alhawari *et al.* (2021) suggested that the integration of creative activities helps to translate customer demand. Researchers have argued that a firm's ability to re-arrange information resources and utilize them to address uncertain changing conditions by utilizing innovative ideas can better identify both customer and market demand, consequently enhancing performance (Rialti *et al.*, 2019). Thus, we proposed that manufacturer performance is dependent on organizational creativity to affect the BDACs-manufacturing agility link. Likewise, manufacturing agility cannot be leveraged effectively if an organization's creativity fails to develop BDACs. Based on the preceding discussion, we proposed that:

H5. Organizational creativity moderates the indirect relationship between BDACs and manufacturing performance through manufacturing agility; when organizational creativity is high, this indirect relationship will become more positive.

3.5. The moderating role played by the involvement of customers as data analysts

Customer involvement can also promote firm performance (Anning-Dorson 2018), with several previous studies having demonstrated that customer involvement is an important mechanism for firm innovation (Awan *et al.*, 2019; Menguc *et al.*, 2014; Song & Thieme, 2009). In addition, the involvement of customers as data analysts enables firms to completely grasp any knowledge and useful information stemming from data analytics and is likely to enhance innovation. External actors, such as customers (industrial customers; e.g., lead firms for suppliers), become more important when firms face the challenges posed by institutional voids such as those observed across emerging markets (Khan *et al.*, 2018; Adomako *et al.*, 2020). The institution-based view also suggests that firms rely on informal sources and external actors to create value (Peng *et al.*, 2009). In the context of our study, we argued that the involvement of industrial customers in BDA facilitates engineering manufacturers in creating value from big data, which leads to manufacturing agility. In the relationship of BDACs and organizational agility, the DC approach posits that a firm can create new understandings from available resources, which enables the transformation and renewal of information (Eckstein *et al.*, 2015; Eisenhardt, 1989).

Najafi-Tavani et al. (2020) found that supplier performance is moderated by learning through better customer relationships. On the other hand, Cui and Wu (2017) highlighted the importance of customer involvement, which may contribute to the development of new products. However, little or no research has been conducted on how the participation of customers as data analysts could enhance manufacturing agility through BDACs. The extant literature identifies customer involvement as a source of firm innovation performance (Cui & Wu, 2016). Recent studies also offer support for customer involvement as a source of data collection and analysis (Zhang & Xiao, 2020). Najafi-Tavani et al. (2020) found that customer involvement enhances the relationship of firm performance and its antecedents. However, the existing research provides little evidence of whether there are external organizational resources in the presence of which manufacturing agility mediates the relationship between BDACs and manufacturing performance. We argued that the involvement of customers as data analysts enables firms to utilize new resources and information, so that any novel insights generated by BDACs are more likely to be utilized to enhance manufacturing agility and, consequently, performance. Based on these arguments and consistent with the institution-based view, we proposed the following set of hypotheses.

H6. Manufacturing firms characterized by high levels of customer involvement as data analysts gain higher manufacturing agility from BDACs compared to firms with low levels of customer involvement.

H7. The involvement of customers as data analysts moderates the indirect relationship between BDACs and manufacturing performance through manufacturing agility; when customer involvement is high, this indirect relationship will become more positive.

4. Methodology

4.1.Research design

The data for our study were collected from engineering manufacturers based in Pakistan. Our respondents possessed a wide range of experiences, which ensured the diversity of our sample. We identified our sample firms from a list maintained by the Pakistan Engineering Council (PEC). A total of 1,175 engineering manufacturers were identified, and a questionnaire was sent to the 810 firms that met our study's criteria. Pakistani engineering manufacturers were chosen because, in order to maintain and improve its quality management practices, the manufacturing sector is actively pursuing the improvement of their agile manufacturing practices by developing lean ones (Iqbal *et al.*, 2018).

We developed an online survey questionnaire to test our hypotheses. Before conducting the actual survey and following discussions on the proposed questionnaire, we pre-tested the latter on 11 academics and business professionals to ensure that the questions were understandable, easy to answer, and in the industry's domain.. The online link to the final questionnaire was emailed to randomly selected manufacturers along with a cover letter explaining the purpose of the survey. We targeted senior managers who participated and assessed BDA-related issues and were responsible for the decision-making in their respective production units. We chose these managers because they were knowledgeable about business analytics and operational management and how it could be applied to other aspects of the business. Eventually, 179 of the 810 firms returned questionnaires suitable for further analysis. Finally, we removed those survey questionnaires that stated that they had been involved in other business activities because their physical movements and production were not entirely known, yielding a 22% response rate. Our data collection methodology was consistent with those of prior studies that had collected data from various industrial sectors in Pakistan (Iqbal *et al.*, 2018). The main sub-sectors of the engineering firms that participated in the survey were as follows: metal- and wood-working machinery, agricultural machinery, aluminum utensils, copper and brass utensils, domestic refrigerators and deep freezers, automotive, instruments and related products, and plumbing and sanitary fittings. Our respondents were production and R&D managers, operations and information technology directors, presidents and vice presidents of analytics, and executives in charge of activities such as purchasing, production, operations and planning, and warehousing.

4.2.Measures

The prior literature offered three indicators that we could use to measure BDACs. We selected the one proposed by Akter *et al.* (2016). We measured all the scales on a seven-point Likert scale. We conceptualized BDACs as a first-order reflective construct from analytics planning, coordination, technical knowledge and management, and business knowledge, which we selected based on feedback received from experts. We first conducted an exploratory factor analysis performing a principal component analysis and varimax rotation of all the selected items and deleted items that had factor loadings below the recommended threshold values. In line with Akter *et al.*'s (2016) study, we used six indicators that provided a comprehensive view of the construct.

This study adapted Lee and Choi's (2003) organizational creativity construct and used the measures that related to the organizational level creativity concept. This organizational creativity construct had been previously validated by Darvishmotevali *et al.* (2020). This scale measure organizational creativity by assessing organization’s ability to generate novel ideas and fostering an environment that supports generation of novel ideas. Five items are used to measure organizational creativity.

In line with the previous research on the involvement of customers as data analysts (Zhang & Xiao, 2020), we also developed a scale suited to measure the construct of the customer as a data analyst. We developed the involvement of customers as data analysts on the basis of the insights gained by Cui and Wu (2017). From the literature review, these items were framed in the context of the involvement of customers as creative data sources and analysts. After the factor loading analysis, we dropped two items—namely, ‘data on sales and marketing’ and ‘research and development data’. A confirmatory factor analysis (CFA) performed on the five remaining items indicated an acceptable factor loading. The three facets of manufacturing agility were measured at the firm level as the product, customer, and market demands. Manufacturing agility was measured using six items adapted from Lee *et al.* (2020). The scale of manufacturing performance developed by Adebanjo *et al.* (2016) was also used in the study, taking into account unit manufacturing, cost, manufacturing lead time, and procurement time (Ferdows & De Meyer, 1990; Pagell & Gobeli, 2009; Tu & Liu, 2010). We measured customer involvement as data analysis using five items on seven-point Likert scale.

In our study, we controlled for several firm-related variables. To assess common method bias (CMB), we utilized different strategies recommended by various scholars (Nederhof, 1985; Podsakoff *et al.*, 2012). First, we used different scales for endogenous and exogenous variables (Podsakoff *et al.*, 2012). Second, we used Harman’s single factor procedure to examine CMB. Exploratory factor analysis confirmed that the first factor explained 31.4% of the variance, thus showing that CMB was not a significant concern in our study. We assessed non-response bias by comparing early and late respondents by means of non-parametric tests in terms of industry distribution. Further, we also performed a t-test in terms of size and performance outcomes at the 0.05 level of significance. The t-test results showed no significant differences, thus confirming that CMB did not adversely affect the findings of our study.

5. Results

5.1.The results of measurement model

We analyzed firm-level data by means of (variance-based) partial least squares structural equation modeling (PLS-SEM). We did so for the following reasons: (1) it enables to predict endogenous constructs and minimize unexplained variance; (2) it can handle small data and complex models; and (3) it provides predictive relevance using Q^2, effect size using f^2, and model fit using R^2 (Li *et al.*, 2020). To perform moderation analysis, we mean-centered our moderating variables. In our approach to moderation analysis, we followed Hayes (2013). Table1 indicates the means, standard revisions, and correlation values of the constructs.

Table 1. Correlation matrix

	Construct	Mean	Std. Dev.	1	2	3	4	5	6	7	8
1	BDAC	4.86	0.83	**0.66**							
2	Manufacturing agility	5.75	0.74	0.56**	**0.59**						
3	Customer as data analyst	5.74	0.68	0.410**	0.13*	**0.75**					
4	Organizational creativity	4.42	0.71	0.43**	0.10*	-0.04	**0.71**				
5	Manufacturing performance	4.49	0.35	0.40**	0.41**	0.07	0.11*	**0.67**			
6	Firm Age	2.26	1.25	0.10*	0.06	-0.03	0.004	0.00	1		
7	Firm Size	2.88	1.02	-0.001	0.03	0.00	0.07	0.00	0.001	1	
8	Type of industry	1.94	0.98	0.002	0.03	0.07	0.03	0.04	0.02	0.03	1

.*p<0.05, **p<0.01

The AVE of constructs is on the diagonal

Table 2. Cronbach's Alpha, Composite Reliability, AVE, Factor Loading, VIF, and HTMT Values						
Construct	**CA**	**CR**	**AVE**	**Factor Loading**	**VIF**	**HTMT < 0.85**
BDAC	0.92	0.92	0.66			0.68
BDAC1				0.83	2.04	
BDAC2				0.80	2.55	
BDAC3				0.86	2.09	
BDAC4				0.78	3.06	
BDAC5				0.83	2.10	
BDAC6				0.77	2.97	
Organizational creativity	0.9	0.92	0.71			0.59
OCR 1				0.84	2.19	
OCR 2				0.85	2.31	
OCR 3				0.85	2.60	
OCR 4				0.84	2.41	
OCR 5				0.82	2.12	
Customer as data analyst	0.92	0.93	0.75			0.72
CADA1				0.89	3.12	
CADA2				0.85	3.00	
CADA3				0.85	2.28	
CADA4				0.85	3.29	
CADA5				0.88	3.02	
Manufacturing agility	0.86	0.89	0.59			0.63
MFAG1				0.77	2.49	
MFAG2				0.82	2.86	
MFAG3				0.73	1.7	
MFAG4				0.67	1.47	
MFAG5				0.82	2.49	
MFAG6				0.80	2.38	
Manufacturing performance	0.90	0.92	0.67			0.52
MFGP1				0.74	1.86	
MFGP2				0.81	2.16	
MFGP3				0.83	2.31	
MFGP4				0.84	2.50	
MFGP5				0.84	2.62	
MFGP6				0.83	2.63	

CA: Cronbach's alpha, CR: Composite Reliability, AVE: Average Variance extracted, VIF: Variance inflation factor, HTMT: Heterotrait-Monotrait

Moreover, the factor loading values for all the items were found to be significant and higher than 0.65, thus indicating convergent validity. Convergent validity is also an important part of a measurement model (Hair *et al.,* 2020). The factor loadings of all constructs were found to exceed the recommended value. Thus, higher loadings show a higher quality of a measurement model (Chen & Chang, 2013). Lastly, we employed the Heterotrait-Monotrait ratio (HTMT) approach to establish discriminant validity. Discriminant validity is used to establish that constructs are different and unique, and they measure what they are meant to. As a rule of thumb, scholars suggest that the HTMT value should be lower than 0.85. In our study, the HTMT values were found to be below 0.6. Our results thus indicate that the measurement model fits well with the data (Hair *et al.,* 2020). The Cronbach's alpha and composite reliability (CR) values were found to be higher than the recommended threshold of 0.70 (Hair *et al.,* 2020). Table2 shows that all the endogenous constructs meet the criteria (Hair *et al.,* 2020).

5.2.The results of the structural model

The fit indices of the structural model suggested that the model had an adequate fit with the data. First, the results obtained using the variance inflation factor (VIF) approach confirmed that there were no multicollinearity issues in the model (Hair *et al.,* 2020), with all VIF values being <5. Thus, we established that there was no multicollinearity in the model. Our final model (3) revealed an R^2 value higher than 0.26, which suggested a better in-sample prediction of the model. Next, we checked for the effect size. Effect size (f^2) values in the ranges of 0.02, 0.15 and 0.35 are considered as small, medium, and large respectively (Hair *et al.,* 2020).

Table 3 Structural Model Analysis

Path Relationships	Path Value	P-value	T-value
BDAC→ Manufacturing performance ***(H1)***	0.36	0.03	5.01
BDAC→ Manufacturing agility ***(H2)***	0.44	0.03	9.62
Manufacturing agility → Manufacturing performance ***(H3)***	0.26	0.02	4.20
Organizational creativity*BDAC → Manufacturing agility ***(H4)***	0.29	0.03	4.35
Organizational creativity*BDAC → (Manufacturing agility → Manufacturing performance) ***(H5)***	0.09	0.00	2.04
Customers as data analysts*BDAC → Manufacturing agility ***(H6)***	0.41	0.03	3.02
Customers as data analysts*BDAC → (Manufacturing agility → Manufacturing performance) ***(H7)***	0.12	0.02	3.55

5.3.Result analysis

The findings support H1 and H2, showing that BDACs are positively and significantly associated with manufacturing agility (β=0.44; $p<0.05$) and manufacturing performance (β=0.36; $p<0.05$). In H3, we posited that manufacturing agility significantly affects manufacturing performance (β=0.26; $p<0.05$). Results support H3. Table3 presents the structural model analysis.

To assess the proposed moderation effect in the structural model, we performed a hierarchical moderation regression analysis in the macro process (Hayes, 2013) in line with the recommendations provided by Preacher and Hayes (2008) and MacKinnon *et al.* (2007). A significant relationship was found to exist between BDACs and organizational creativity (β=0.14; $p<0.01$) and BDACs and the involvement of customers as data analysts (β=0.29, $p<0.01$). For H4, our results revealed that the interaction terms contributed to bringing change in the variance explained (adj-R^2=0.29; P=0.002). The interaction-term was found to be positive and significant (β=0.10, $p<0.05$). To provide a better illustration of our results, we calculated a significant slope at both higher (1 standard deviation above the mean) and lower (1 standard deviation below the mean) levels, after accounting for the main effects of BDACs and organizational creativity. The results revealed that organizational creativity had a positive effect on the relationship between BDACs and manufacturing agility (β=0.29; $p<0.05$). The nature of this interaction thus suggested that BDACs are most impactful on manufacturing agility in the presence of high levels of organizational creativity (see Figure2).

Table 4. Moderated Mediation simple effects

Moderator Variable	Direct Effect	Indirect Effect	Total Effect
Organizational creativity	B=0.27, t=7.02, SE=0.03	0.092, SE=0.045	0.36,t=7.89 Se=0.04
Involvement of customers as data analysts	0.238, t=5.74 SE=0.04	0.128, SE=0.036	0.36,t=7.89 Se=0.04

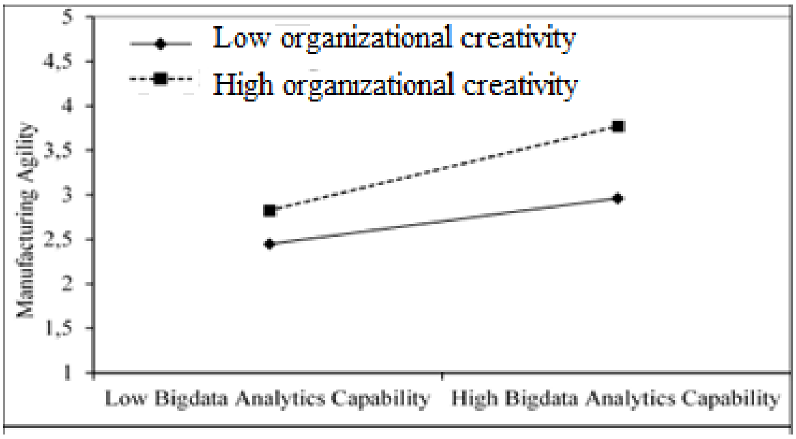

Figure 2. The moderating role of organizational creativity

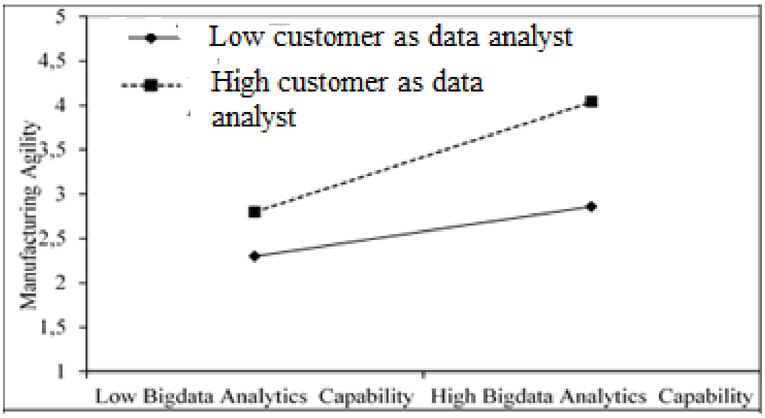

Figure 3. The moderating role of customers as data analysts (H6)

The finding suggests that BDACs are most beneficial when organizational creativity is high. In hypothesis H5, we proposed that the relationship between BDACs and manufacturing performance via manufacturing agility would be more positive when organizational creativity was higher. The moderation-mediation results are shown in Table 4. We examined the conditional indirect effect using the method recommended by Preacher and Hayes (2008) in SPSS, using process macro with bias-corrected 95% confidence intervals (CI). The indirect effect was found to be significant and positive in the presence of high organizational creativity, b=0.09, $p<0.05$, CI (0.03, 0.02). The values of CI do not contain zero, indicating that the indirect effects of BDAC on manufacturing performance via manufacturing agility are stronger when organizational creativity is high. For our H6, the results suggested that the value of adjusted-R^2 was slightly changed (adj-R^2=0.335; P=0.025), and the interaction terms were found to be significant (β=0.09; p<0.05).

After accounting for the main effects of BDACs and customers as data analysts, customer involvement increased the relationship between BDACs and manufacturing agility (β=0.41; p<0.05). The results suggest that the involvement of customers as data analysts significantly moderates the effect of BDACs. The findings thus suggest that BDACs are most beneficial for manufacturing agility in the presence of a high involvement of customers as data analysts. The nature of this interaction suggests that BDACs are most impactful for manufacturing agility in the presence of high levels of customer involvement (see Figure 3). In H7, we proposed that the relationship between BDACs and manufacturing performance via manufacturing agility would be more positive when the involvement of customers as data analysts was higher. We examined the conditional indirect effect using the method recommended by Hayes and Preacher (2013). The indirect effect was found to be significant—b=0.12, SE=0.03, (0.12, 0.14). We found evidence that the indirect effects of BDACs on manufacturing performance via manufacturing agility is stronger when the involvement of customers as data analysts is higher.

6. Discussion and conclusion

In line with the findings of previous research (Eckstein *et al.*, 2015; Iqbal *et al.*, 2018), ours also suggest that manufacturing agility significantly mediates the relationship between BDACs and manufacturing performance. We interpret these results in relation to the engineering industry being increasingly focused on using BDACs to improve firm agility and improve its performance outcomes in the face of the rapid changes taking place through emerging technologies and greater levels of digitization.

Dahlstedt (2019) claimed that creative organizations attain higher data analytics insights. Despite the importance of BDAC for agility (Rialti *et al.* 2019), no prior study has examined the moderating impact of organizational creativity on the relationship between BDAC and agility. Our findings extend this line of research by investigating the impact of organizational creativity on BDAC and manufacturing agility. Hence, those engineering firms that encourage innovative ideas and their employees' creative mindsets are better positioned to take advantage of BDACs and adapt more effectively to changing conditions. This suggests that engineering manufacturers with high creativity and BDACs can enhance their manufacturing agility (to forecast market demand effectively, reduce order to delivery cycle times, and perform customization). Our findings on the moderation-mediation effects reinforce the notion that managers' technical proficiency, particular target work, taking a new perspective on problems, and intrinsic motivation bring a new perspective in utilizing data analytics.

Further, our findings support BDA as one of the key factors influencing manufacturing performance (Dubey *et al.,* 2019b). We provide empirical evidence that a firm's intangible resources help it to develop resources to use data analytics, plan to better adapt to changing technological resources, and make quicker decisions; deviating from the dominating view that organizations can only achieve performance and competitive advantage by creating tangible resources or capabilities (Dubey *et al.*, 2019b). Previous research has shown that BDACs positively influences agility (Dubey *et al.s* 2019a; Rialti *et al.,* 2019). Nonetheless, few research studies have thoroughly and empirically investigated how the involvement of customers as data analysts and organizational creativity influence manufacturing agility and firm performance. This study extends the research of Zhang & Xiao (2020) by suggesting that the involvement of customers as data analysts is critically important to enhance manufacturing performance in data-centric environments. Consistent with Menguc et al. (2014), our findings also provide evidence that the involvement of customers as data analysts helps to generate insights into market conditions.

We found that in the engineering industry, the impact of customer involvement as data analysts tends to capitalize on the firm performance through manufacturing agility. We interpret these results as the engineering industry is increasingly focused on using BDAC to improve firm agility and improve performance outcomes in the face of rapid change of digitization. Our findings suggest that engineering manufacturers from developing countries are tempted to take advantage of the involvement of customers as data analysts to increase their manufacturing agility, consequently affecting firm performance.

6.1.Theoretical Contributions

This study makes important contributions to the extant literature. First, it embeds the RBV and DCs to examine the relationship between BDACs and manufacturing agility. Although the extant literature has highlighted the importance of both the RBV and DCs for BDACs and agility (Wamba, Dubey, Gunasekaran, & Akter, 2020), they ways in which different firm resources affect the development of such capabilities has not been systematically explained. To date, most research on BDACs has relied on the RBV to describe their effect on manufacturing agility. Our conceptual model contributes new insights into how firms' intangible resources help them develop the capabilities they need to improve their manufacturing agility. We extend this research by articulating the organizational creativity resource conditions that make the development of such capabilities beneficial for manufacturing agility. Second, although the extant literature has highlighted the importance of BDACs for firm performance (Akhtar et al., 2019; Akter et al., 2016; Rialti et al., 2019; Wamba et al., 2017), the ways in which a firm's various resources affect the development of such performance have not been explained. Darvishmotevali et al. (2020) suggested that researchers should consider organizational creativity to explain the effects of agility on performance outcomes. Our study contributes to the literature on the conceptualization of organizational creativity (Amabile, 1997). As the prior literature provides little understanding of how organizations develop manufacturing agility (Lee et al., 2020), our study—following Amabile (1997) contributes to this line of inquiry by illustrating how organizational creativity and BDACs contribute to manufacturing agility. Also, to date, little is known about how this impact can be improved. Our study is the first to provide empirical evidence that the distinct effect of BDACs on manufacturing agility is stronger in the presence of higher organizational creativity. Amabile (1997) proposed CTOC which has been adequately addressed in the extant literature (Rennick & McKay, 2018). Our findings on the moderation-mediation effects reinforce the role played by organizational creativity in enhancing the effect of BDACs on manufacturing performance through manufacturing agility, such that the relationship is more positive for those manufacturing firms with a high level of creativity. We demonstrate that organizational creativity—involving the use of expertise, task motivation, and knowledge—helps to cope with uncertain changes and to thrive in a competitive environment. Hence, CTOC can help to develop and seize novel ideas as to how to mobilize the resources needed to capture business value and reconfigure any existing set of resources for value creation.

Third, to the best of our knowledge, this study is among the few to consider the involvement of customers as data analysts and examine its effects on manufacturing agility. The novelty of our study consists in its examination of whether or not customers, as data analysts, significantly moderate the relationship between BDACs and manufacturing agility. Specifically, the previous literature has so far neglected the important relationship between BDACs and manufacturing agility in the presence of the involvement of customers as data analysts, arguing that the advantage of manufacturing agility often lies in operational and relationship flexibility (Lee et al., 2020). Some studies have also exclusively focused on how customers, as a source of data analysis, impact new product performance (Zhang & Xiao, 2020), and on how customer involvement, as a source of processing information, affects firm outcomes (Anning-Dorson, 2018; Cui & Wu, 2017). Little attention has been paid to exploring the impact of the involvement of customers as data analysts on various performance outcomes. This study provides new insights into the achievement of manufacturing agility, which has been largely ignored by extant scholarship. We extend the existing literature by proposing that, in a B2B context, the involvement of customers as data analysts can enhance the positive effect of BDACs on manufacturing agility. Our study further underpins the argument that organizational creativity leads to a stronger relationship between BDACs and manufacturing agility. In doing so, it provides meaningful theoretical evidence and advances the existing literature by demonstrating how the involvement of customers as data analysts is a key organizational external knowledge mechanism suited to understanding how organizations may balance their capabilities to develop manufacturing agility. Our study extends the research conducted in this area by providing evidence that customer involvement effectively increases the positive effect of BDACs on manufacturing agility.

6.2.Practical Implications

This study benefits manufacturing firms and their managers in several ways. First, the findings show that manufacturing performance may depend on organizational creativity. The central implication for managers is that creative behaviors can guarantee that their firm will manage to convert unique ideas into resources suited to enhance BDACs in order to improve manufacturing lead times, inventory turnover, and procurement lead times. In this context, we suggest that manufacturing firms should not only promote creativity but also invest in BDAC training in order to enable all stakeholders to contribute to generating future insights into market demand, understand customer expectations, and rapidly devise production plans aimed at reducing manufacturing lead times.

Second, our findings motivate the engagement of production managers in BDA management practices and in improving creativity in their organizations to gain agility. Our findings may also assist managers in recognizing how customer involvement can enable their firms to achieve superior manufacturing-centric agility. A lack of data visualization capabilities may endanger the decision-making processes of manufacturing organizations. Some previous studies have also highlighted how the incorporation of knowledge from external actors is a challenging and important aspect of digital change transformation. Our findings show managers that the involvement of customers as data analysts may help identify changes in market conditions in order to devise new digital transformation strategies suited to reduce order to delivery cycle times. Thus, firms that focus on manufacturing agility should consider customer involvement in order to deliver value. A data analyst can help bring useful information on customer feedback and provide inputs in product design and data analytics plans. Finally, given the increasing concerns regarding manufacturing agility and its management, our proposed theoretical model can serve as a practical means by which engineering firms may increase their performance outcomes. Our findings also guide managers to achieve superiority in manufacturing performance; managers should involve customers in data analysis. Customer involvement is beneficial to support firm agility as they are able to transfer a wide range of operational information suited to detect market trends, generate future insights into market demand, and understand customer requirements on product customization and order to delivery cycle times. It also helps firms in forecasting future events.

6.3.Limitations and Future Research

Our data collection was limited to Pakistani engineering firms, which limits the generalizability of this study. Future research could extend the investigation of these issues and validate our model in other regions. The involvement of customers as data analysts may unleash new insights useful to forecast market demands and increase access to the available information, which could then be shared with other departments to better adapt to digital transformation changes. Future studies could also investigate how BDACs affect existing organizational structures and impact radical and incremental innovation capabilities. Furthermore, when involving customers as data analysts, it would be important to consider the role played by social capital—i.e., trust, support, information, and knowledge sharing among partners, such as focal firms and suppliers. Future research could extend this discussion by incorporating the role played by social capital in the proposed framework, particularly when discussing the moderating role of customers as data analysts.

Appendix A. Measurement Items		Source
Big data Analytics Capabilities (BDAC). “Please identify the relative use of the following BDA applications in your firm.” Likert scale ranging from 1 = ‘never’ to 7 = ‘always’		
BDAC1	“We continuously examine innovative opportunities for the strategic use of big data analytics.”	Akter et al. (2016)
BDAC2	“We enforce plans for the introduction and utilization of big data analytics adequately.”	
BDAC3	“We perform big data analytics planning processes in systematic ways.”	
BDAC4	“We frequently adjust big data analytics plans to better adapt to changing conditions.”	
BDAC5	“When we make big data analytics investment decisions, we project how much these options will help end-users make quicker decisions.”	
BDAC6	“In our organization, business analysts and line personnel frequently meet to discuss important issues both formally and informally.”	
Organizational creativity (ORGC) “Please indicate the level of your agreement to the following statements that are related to the effects of organization creativity on your firm's business performance.” Likert scale ranging from 1 = ‘strongly disagree’ to 7 = ‘strongly agree’		
OCR 1	“Has produced many novel ideas (services/products).”	Lee and Choi (2003)
OCR 2	“Fosters an environment that is conducive to our own ability to produce novel ideas (services/products).”	
OCR 3	“Spends much time in producing novel ideas (services/products).”	
OCR 4	“Considers producing novel ideas (services/products) as important activities.”	
OCR 5	“Actively produces novel ideas (services/products).”	

Customer involvement as a data analyst (CADA) “Please indicate the level of your agreement to the following statements that are related to the effects of customer involvement as a data analyst in establishing the overall direction of data management” Likert scale ranging from 1 = ‘strongly disagree’ to 7 = ‘strongly agree’. Our customers’ involvement:		
CADA1	“Provides significant data support to generate future insights.”	Zhang and Xiao (2020)
CADA2	“Transfers a wide range of technologies suited to forecast events.”	
CADA3	“Provides data on customer feedback”	
CADA4	“Articulates a vision to support the use of data.”	
CADA5	“Provides support in interpreting data analytics.”	
Manufacturing Agility “The extent to which the manufacturing firm could rapidly respond to changes in the market and reconfigure production lines.” “Likert scale ranging from 1 = ‘not at all’ to 7 = ‘to a great extent’.		
MFAG1	“We are capable of forecasting market demand effectively.”	Lee et al. (2020)
MFAG2	“We are capable of rapidly responding to real market demand.”	
MFAG3	“We are capable of rapidly reducing order-to-delivery cycle times.”	
MFAG4	“We are capable of rapidly performing product customization.”	
MFAG5	“We are capable of rapidly reducing manufacturing lead times and development cycle times.”	
MFAG6	“We are capable of rapidly increasing the frequency of new product introductions.”	
Manufacturing performance (MFGP)		

<table>
<tr><td colspan="2">“Indicate the extent to which manufacturing performance has changed during the last three years.”
“Likert scale ranging from 1 = ‘not at all’ to 7 = ‘to a great extent’.</td><td></td></tr>
<tr><td>MFGP1</td><td>“Unit manufacturing cost.”</td><td rowspan="6">Adebanjo et al. (2016)</td></tr>
<tr><td>MFGP2</td><td>“Flexibility to change the volume.”</td></tr>
<tr><td>MFGP3</td><td>“Manufacturing lead time.”</td></tr>
<tr><td>MFGP4</td><td>“Inventory turnover.”</td></tr>
<tr><td>MFGP5</td><td>“Procurement lead times.”</td></tr>
<tr><td>MFGP6</td><td>“On-time delivery.”</td></tr>
</table>

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