

**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**

Awan Usama, Bhatti Sabeen Hussain, Shamim Saqib, Khan Zaheer, Akhter
Pervaiz, Balta Maria

This is a Final draft version of a publication
published by Wiley
in British Journal of Management

DOI: 10.1111/1467-8551.12549

Copyright of the original publication:

© 2021 British Academy of Management and Wiley Periodicals LLC

Please cite the publication as follows:

Awan, U., Bhatti, S.H., Shamim, S., Khan, Z., Akhter, P., Balta, M. (2021). 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. *British Journal of Management*. DOI: 10.1111/1467-8551.12549

**This is a parallel published version of an original publication.
This version can differ from the original published article.**

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

4

5 **Abstract:**

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

21

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

24

1 **1. Introduction**

2 Faced with intensified competition, manufacturing firms utilize advanced and
3 emerging technologies to reduce delivery times and meet their customers' expectations by
4 providing customized products (Swafford *et al.* 2006). The business-to-business (B2B)
5 literature has recently paid much attention to the role played by the involvement of customers
6 as data analysts (Zhang & Xiao, 2020). The concept of customers as data analysts is defined
7 as “*customers (actively) participating in big data analytics (BDA), such as acquisition and*
8 *analysis of big data, and implementation of findings from big data analytics*” (Zhang & Xiao,
9 2020: p.100). In a B2B context, for instance, customers could include business partners, such
10 as suppliers and distributors. Their involvement in big data analytics yields opportunities for
11 data-driven organizations (Kunz *et al.*, 2017; Akhtar *et al.*, 2018). Menguc, Auh, and
12 Yannopoulos (2014) provided a comprehensive review of customer involvement in the design
13 stage as a source of information-processing effects on innovation outcomes. Despite this
14 progress, many B2B firms are still ignoring the importance of customer involvement in BDA
15 (Zhang & Xiao, 2020). Côte-Real, Oliveira, and Ruivo (2017) discussed the relationship
16 between BDA capabilities (BDACs), value chain, and firm performance, and suggested that
17 it requires further investigations.

18 Previous studies have argued that BDACs enable manufacturing firms to gain data
19 insights into and respond to any recurrent changes in the marketplace and production
20 processes (Dubey *et al.* 2018). Empirical studies have also demonstrated the positive
21 moderating impact of dynamic capabilities (DCs) on the relationship between BDACs and
22 firm performance (Wamba *et al.*, 2017). Recently, Mandal (2019) has investigated the
23 relationship between BDACs and firm agility, and scholars have observed that such
24 relationship is equivocal (Yasmin *et al.*, 2020), whereas most previous studies have found a
25 positive association between BDACs and firm performance (Akter *et al.* 2016; Rialti *et al.*
26 2019). Furthermore, most of the literature has acknowledged that BDACs are an important
27 resource for performance improvement (Khanra *et al.*, 2020), particularly in manufacturing
28 environments (Papadopoulos *et al.*, 2021; Aydiner *et al.*, 2019). These mixed results highlight
29 the need to explore and identify the organizational characteristics necessary to improve
30 manufacturing performance (Dubey *et al.*, 2019b). Specifically, Awan, Sroufe, and Shahbaz

1 (2021) have suggested the need to clarify how and when BDACs lead to increased
2 performance.

3 The prevalence of making big data more manageable through novel visualization,
4 filtering, and the use of machine learning models has enabled researchers to expand their
5 understanding of big data and creativity (Dahlstedt 2019). BDA is a way whereby
6 management insights that require sophisticated analytics and processing techniques can be
7 extracted through structured and unstructured data (Gupta & George 2016). In regard to
8 exploring the real meaning of data, creativity is becoming a key factor in developing the new
9 skills and abilities needed to uncover unexpected patterns of information in the data and to
10 explore novel representations of them (Dahlstedt, 2019). Despite the crucial role played by
11 organizational creativity in the generation of novel and useful ideas suited to respond to
12 rapidly changing business situations (Anderson *et al.*, 2014; Darvishmotevali *et al.*, 2020),
13 organization creativity still makes an essential contribution to agility, but its impact may be
14 somewhat indirect (Darvishmotevali *et al.* 2020). The current literature has not explicitly
15 explained what facilitates the relationship between agility and manufacturing performance
16 (Iqbal *et al.* 2018). Recent studies have highlighted the significant role played by creativity in
17 improving organizational agility (Darvishmotevali *et al.*, 2020). According to Dahlstedt
18 (2019), it is not yet clear how manufacturing agility and performance depend on
19 organizational creativity. The previous literature has investigated the significance of BDACs
20 for firm performance and organizational or operational agility (Akhtar *et al.*, 2018; Yasmin *et al.*,
21 2020), where agility was based on internal manufacturing processes and external
22 dimensions (e.g., supply chain processes). However, relatively little research has examined
23 the contextual factors affecting the relationship between BDACs and agility and,
24 consequently, their impact on manufacturing performance. To address this gap, the purpose
25 of our study was to explain what might affect such relationship. In doing so, we explored why
26 organizational creativity and the participation of customers as data analysts (in B2B contexts,
27 industrial customers; i.e., lead firms for suppliers) are important for the achievement of higher
28 levels of manufacturing agility and, consequently, manufacturing performance.

29 We drew key insights from the Resource-Based View (RBV), linking it with the RBV
30 of big data (Akhtar *et al.*, 2019), and dynamic capabilities (DCs) theories and contribute to
31 the existing literature by explaining why enhancing BDACs and organizational creativity can

1 improve agility and manufacturing performance. We also explored an important additional
2 factor by articulating that organizational agility and manufacturing performance are also
3 dependent upon the customers' involvement as data analysts. Against the backdrop of the
4 above discussion, we explored the following research question: what are the distinct and joint
5 effects of BDA, the involvement of customers as data analysts, and organizational creativity
6 on manufacturing agility and performance? The contextual motivation of this study stemmed
7 from the institution-based view, which is the third leg of the strategy tripod (Peng, Sun,
8 Pinkham, & Chen, 2009). The institution-based view suggests that, when formal institutions
9 are ineffective, informal sources of value creation—e.g., knowledge creation and
10 innovation—become more important (Su *et al.*, 2016) and firms can gain significant value by
11 utilizing both tangible and intangible resources as per the RBV, where big data can represent
12 an important resource for value creation (Akhtar *et al.*, 2019). Our study leveraged the unique
13 context of Pakistani engineering manufacturers, which are facing the challenge of institutional
14 voids, and thereby rely on external sources of knowledge creation and innovation (Khan *et*
15 *al.*, 2018).

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

25

26 **2. Theoretical background**

27 *2.1. Resource based view and dynamic capabilities view*

28 The RBV has made significant contributions to the rapidly growing area of research on
29 BDACs. Still, little is known about how firms build their capabilities through BDA (Gupta &
30 George, 2016). The term big data is often used to describe huge, composite, and real-time
31 volumes of data that require complicated management, analysis, and processing mechanisms

1 to extract information (Laney, 2012). The term BDACs refers to the “...*tangible resources*
2 *(that) include data, technology, and other basic resources (e.g., time and investments), while*
3 *human resources (that) consist of managerial and technical big data skills*” (Gupta & George,
4 2016: p.1051). Here, we suggest that intangible organizational resources enable the
5 development of BDACs. We describe an intangible resource that enables an organization to
6 identify several human and technological resources suited to facilitate several processes aimed
7 at creating organizational capabilities.

8 As per the RBV, firm resources (both tangible and intangible) contribute to creating
9 sustained competitive advantages that cannot be imitated by competitors (Barney, 2001). The
10 RBV of big data, which includes “*all assets and capabilities that can provide a basis for big*
11 *data collection, storage and analytics*”, especially provides a basis for competitive
12 advantages and creates value by unpacking insights drawn from the complex bundles of big
13 data and related skills (Akhtar *et al.*, 2019: p. 266). Thus, most manufacturing firms rely on
14 possessing intangible, unique, and creative resources (Shen *et al.*, 2019), including
15 servitization for value creation (cf. Neely, 2008; Gomes *et al.*, 2019). Barney (2001)
16 suggested that firms can utilize organizational assets, processes, unique capabilities, and
17 knowledge to improve their performance and develop sustainable competitive advantages.
18 Researchers have established that organizational BDA is a strong predictor of DCs (Mikalef
19 *et al.*, 2020) and that organizational BDA depends on an organization’s resource base. This
20 argument is consistent with the RBV. For instance Mikalef *et al.* (2020) combined the RBV
21 with DCs to explain the tangible and intangible resources that affect a firm’s ability to
22 integrate, build, and reconfigure the competencies needed to address any disruptive changes
23 in the marketplace. The RBV of the firm is characterized by the integration of technological
24 and human resources to create value for the company (Barney, 1991). Most studies have
25 examined the effect of BDACs on firm performance using only the RBV as a theoretical lens
26 (Akter *et al.*, 2016; Wamba *et al.*, 2017). However, scholars have also indicated that resources,
27 on their own, might not create value for firms as the latter need to possess the capabilities to
28 effectively deploy and leverage resources for value creation (Teece *et al.*, 1997; Lin & Wu,
29 2014). Recent literature also emphasizes on IT-embeddedness in DCs (Steininger *et al.*, 2021).
30 Steininger *et al.* (2021) argues that DCs encompass sensing, seizing, and transforming
31 capabilities. In this scenario, we discuss the role of customer as data analyst and

1 organizational creativity in the transformation of organizational competencies for value
2 creation though big data.

3 DCs are an extension of the RBV and refer to the ability of firms to create new competencies
4 and reconfigure existing ones (Teece *et al.*, 1997; Teece, 2007). DCs pertain to the use and
5 deployment of resources to leverage sensing, seizing, and reconfiguration capabilities in order
6 to gain a competitive advantage (Teece, 2007). In other words, in modern settings, DCs are
7 defined as the “*ability to promptly adopt changes and process data and information for*
8 *actionable knowledge or analytics that enable the effective tackling of changes in the market*”
9 (Akhtar *et al.*, 2018: p. 308). Although the RBV and DCs have evolved from two different
10 perspectives, they are complementary to each other because capabilities are attained through
11 the utilization of resources (Barney *et al.*, 2001), and organizations develop sustainable
12 competitive advantages on the basis of hard to imitate resources and capabilities. However,
13 despite their importance, little research has examined both perspectives on the utilization of
14 BDACs in a manufacturing environment. Following Wamba, Dubey, Gunasekaran, and Akter
15 (2020), we conceptualized agility as a DC. Agility has also been suggested as a meta-
16 capability (Doz & Kosonen, 2010), and through this organizations can effectively respond to
17 external changes for value creation (Weber & Tarba, 2014). According to Teece (2012, p.
18 1395) DCs are defined as the organizational “*ability to integrate, build, and reconfigure*
19 *internal and external resources/competencies to address, and possibly shape, rapidly*
20 *changing business environments*”. According to Augier and Teece (2007, p.412), “*if a firm*
21 *possesses resources/competencies but lacks DC, it has a chance to make a competitive return*
22 *for a short period, but superior returns cannot be sustained*”. The DC perspective focuses on
23 the ability of a company to renew its resources in response to environmental changes (Teece,
24 2014). Agility, consisting of multiple internal and external parameters, could be interlocked
25 with DCs, which are built over time (Akhtar *et al.*, 2018).

26 2.2. Componential theory of organizational creativity

27 Organizational creativity, which is multidimensional, has been most frequently used to
28 produce novel and applicable ideas (Oldham & Cummings, 1996). According to Sawyer and
29 Griffin (1993), “*creativity for organizations – doing something for the first time anywhere or*
30 *creating new knowledge – represents a dramatic aspect of organizational change that may*
31 *provide the key to understanding change phenomena and, ultimately, organizational*

1 *effectiveness and survival*” (p. 293). Similarly, Darvishmotevali *et al.* (2020) suggested that
2 researchers should consider organizational creativity to explain the effects of agility on
3 performance outcomes. Amabile (1997) proposed the componential theory of organizational
4 creativity (CTOC), which has been adequately addressed in the extant literature (Rennick &
5 McKay, 2018). Amabile (1997) suggested a framework of CTOC measures that includes three
6 elements: expertise (a cognitive pathway that includes memory for knowledge and technical
7 proficiency), creative-thinking (taking a new perspective on problems), and intrinsic task
8 motivation, with organizational capabilities emerging from the combination of these elements
9 (de Vasconcellos *et al.*, 2019). The intrinsic task motivation component include two elements,
10 intrinsic motivation (driven by profound interest and participation) and extrinsic motivation
11 (the desire to achieve a certain objective) (Amabile, 1997). Previous studies on the different
12 aspects of organizational agility have also focused on organizational creativity. However,
13 there is lack of understanding of the process through which manufacturing firms increase their
14 agility (Lee, Wang, & Grover, 2020). Following Amabile's (1997) CTOC, we proposed that
15 organizational creativity has the potential for adapting and embracing the changes needed to
16 respond proactively in order to remove uncertain barriers. Therefore, organizational agility is
17 determined by an organization's ability to create the internal structures and processes suited
18 to enable its members to build the skills needed to deal with environmental changes. Figure 1
19 presents the framework of this study.

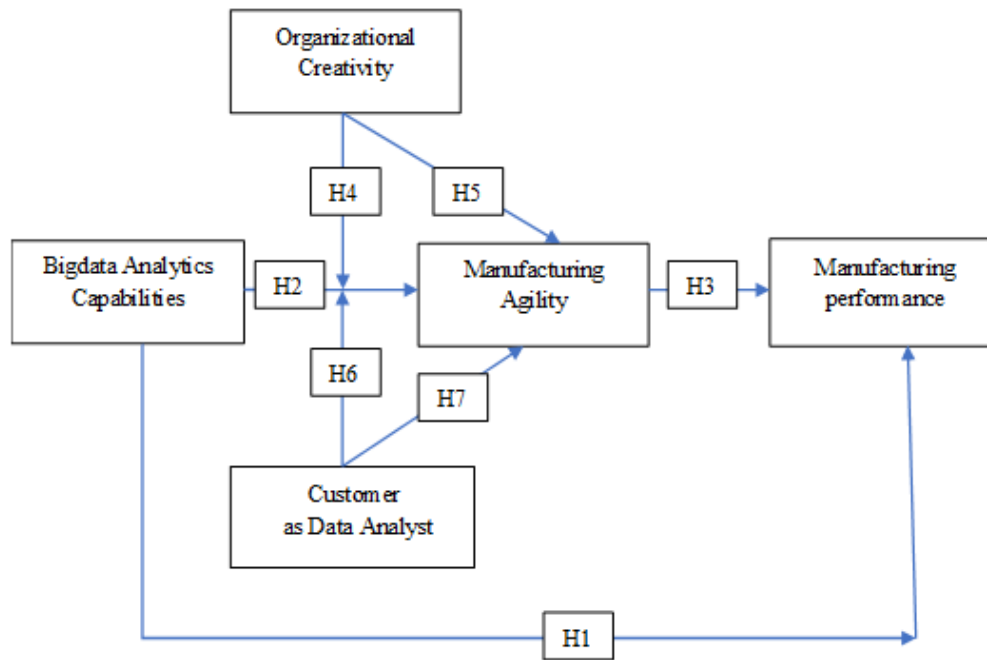


Figure1. Hypothesized model

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).

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

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

17

18 3.2. *Big data analytics capabilities and manufacturing agility*

19 Yasmin *et al.* (2020) argued that BDACs are significantly related to firm operational
20 performance, while Wamba *et al.* (2020) argued that BDACs enable firms to handle disruption
21 and to better identify any emerging opportunities. Shamim *et al.* (2021) also heightened the
22 importance of BDAC at operational and strategic levels to create new knowledge and business
23 value. Agility is an important component of operational strategy, as it enables firms to respond
24 to market changes in a timely fashion (Tallon & Pinsonneault, 2011). According to
25 Braunscheidel and Suresh (2009), manufacturing agility is defined as “*the ability to efficiently*
26 *change operating states in response to uncertain and changing market conditions*”(p.120).
27 According to Shokouhyar *et al.* (2020), firms can identify opportunities and ultimately make
28 better decisions through manufacturing agility. Following Wamba *et al.* (2020a), we
29 conceptualized agility as a DC that refers to an organization’s ability to create new and
30 reconfigure its existing competencies to respond to a changing environment (Teece, 2007,
31 2012) Specifically, prior research has noted that BDA may affect an organization's ability to
32 recognize the need to react and make quick decisions (Wamba & Mishra, 2017).

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

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

14 3.3. *Manufacturing agility and manufacturing performance*

15 Manufacturing agility emphasizes the importance of adapting, responding to changing market
16 conditions, and rapidly improving manufacturing lead-time. Manufacturing agility is an
17 advanced stage of lean production. Previous research examined the relationship between
18 agility and manufacturing performance and found a positive relationship (Eckstein *et al.*,
19 2015; Roberts & Grover, 2012). In relation to performance outcomes, it may be assumed that
20 a firm with agile capability is more likely to improve them (Weber & Tarba, 2014; Christofi
21 *et al.*, 2021). Recently, Rialti *et al.* (2019) found a positive and significant association between
22 agility and performance. At the conceptual level, manufacturing agility promotes flexibility
23 and enhanced responsiveness (Zhang, 2011). Agile manufacturing consequently creates an
24 environment conducive to rapid customer response, thus meeting product and market
25 demands (Braunscheidel & Suresh, 2009). Manufacturing agility enables firms to adapt to
26 changing market demand, reduce order to delivery time, and improve manufacturing lead
27 times. Hallgren and Olhager (2009) argued that manufacturing agility focuses on delivery
28 reliability and quality improvements. Similarly, Iqbal *et al.*, (2018) validated a positive
29 relationship between manufacturing agility and performance outcomes. In the big data
30 environment, previous researchers have established that manufacturing firms with greater

1 agility can render their internal operations more efficient and streamlined. Accordingly, we
2 hypothesized:

3 *H3. Manufacturing agility is positively associated with manufacturing performance.*

4 *3.4. The moderating role of organizational creativity*

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

17 Organizational creativity is multidimensional and has been most frequently used to
18 produce novel and applicable ideas (Oldham & Cummings 1996). Darvishmotevali *et al.*
19 (2020) suggested that researchers should consider organizational creativity to explain the
20 effects of agility on performance outcomes. From this perspective, taking advantage of a given
21 organizational capability stems from its suitability to respond to external changes in adapting,
22 integrating, and reconfiguring internal and external managerial skills and resources (Teece *et*
23 *al.*, 1997). Firms' capabilities enable them to complete tasks efficiently and transform their
24 resources in order to better understand and respond to market changes (Day, 2011). The
25 findings of past studies show that organizational creativity plays an important role in many
26 forms of organizational agility. More recently, studies on agility have begun to shift their
27 focus to the process through which agility occurs (Lee *et al.*, 2020). For example, de
28 Vasconcellos *et al.* (2019) explored how business competencies emerge through creativity. In
29 contrast, Darvishmotevali *et al.* (2020) explored the impact of organizational agility on
30 creativity using contingency theory. We argued that organizational creativity requires
31 individuals to come up with novel ideas according to business needs and priorities. In our

1 study, organizational creativity can be regarded as a potential pathway leading to new ideas
2 and solutions suitable to grow and respond quickly in complex environments.

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

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

21 Recently Wamba *et al.* (2020) have examined agility as a mediating variable between
22 BDACs and firm operational performance. Rialti *et al.* (2019) also highlighted BDACs as an
23 organization's key resource, which is highly dependent upon external resources to enhance
24 agility. BDACs represent effective ways of obtaining insights from structured and
25 unstructured data. The development of BDACs requires technological resources and involves
26 a complex process that may benefit from customer input. According to Wamba *et al.* (2017),
27 BDACs are a crucial part of a firm's operations because they enable the generation of insights
28 from data. Previous studies support the notion that BDAC can trigger agility (Côrte-Real *et*
29 *al.*, 2017). Wamba *et al.* (2020) highlighted the need for further studies investigating how
30 BDACs could enhance organizational performance. Conceptually, manufacturing agility, as
31 a mediating mechanism, implies that a manufacturer can manage its BDACs to extract

1 information for strategic use: to predict customer and market demands and plan and adapt to
2 changing conditions, thus enhancing its performance outcomes. Alhawari *et al.* (2021)
3 suggested that the integration of creative activities helps to translate customer demand.
4 Researchers have argued that a firm's ability to re-arrange information resources and utilize
5 them to address uncertain changing conditions by utilizing innovative ideas can better identify
6 both customer and market demand, consequently enhancing performance (Rialti *et al.*, 2019).
7 Thus, we proposed that manufacturer performance is dependent on organizational creativity
8 to affect the BDACs-manufacturing agility link. Likewise, manufacturing agility cannot be
9 leveraged effectively if an organization's creativity fails to develop BDACs. Based on the
10 preceding discussion, we proposed that:

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

14 3.5. *The moderating role played by the involvement of customers as data analysts*

15 Customer involvement can also promote firm performance (Anning-Dorson 2018), with
16 several previous studies having demonstrated that customer involvement is an important
17 mechanism for firm innovation (Awan *et al.*, 2019; Menguc *et al.*, 2014; Song & Thieme,
18 2009). In addition, the involvement of customers as data analysts enables firms to completely
19 grasp any knowledge and useful information stemming from data analytics and is likely to
20 enhance innovation. External actors, such as customers (industrial customers; e.g., lead firms
21 for suppliers), become more important when firms face the challenges posed by institutional
22 voids such as those observed across emerging markets (Khan *et al.*, 2018; Adomako *et al.*,
23 2020). The institution-based view also suggests that firms rely on informal sources and
24 external actors to create value (Peng *et al.*, 2009). In the context of our study, we argued that
25 the involvement of industrial customers in BDA facilitates engineering manufacturers in
26 creating value from big data, which leads to manufacturing agility. In the relationship of
27 BDACs and organizational agility, the DC approach posits that a firm can create new
28 understandings from available resources, which enables the transformation and renewal of
29 information (Eckstein *et al.*, 2015; Eisenhardt, 1989).

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

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

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

23

24 **4. Methodology**

25 *4.1. Research design*

26 The data for our study were collected from engineering manufacturers based in Pakistan. Our
27 respondents possessed a wide range of experiences, which ensured the diversity of our sample.
28 We identified our sample firms from a list maintained by the Pakistan Engineering Council
29 (PEC). A total of 1,175 engineering manufacturers were identified, and a questionnaire was
30 sent to the 810 firms that met our study's criteria. Pakistani engineering manufacturers were
31 chosen because, in order to maintain and improve its quality management practices, the

1 manufacturing sector is actively pursuing the improvement of their agile manufacturing
2 practices by developing lean ones (Iqbal *et al.*, 2018).

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

24 *4.2.Measures*

25 The prior literature offered three indicators that we could use to measure BDACs. We selected
26 the one proposed by Akter *et al.* (2016). We measured all the scales on a seven-point Likert
27 scale. We conceptualized BDACs as a first-order reflective construct from analytics planning,
28 coordination, technical knowledge and management, and business knowledge, which we
29 selected based on feedback received from experts. We first conducted an exploratory factor
30 analysis performing a principal component analysis and varimax rotation of all the selected

1 items and deleted items that had factor loadings below the recommended threshold values. In
2 line with Akter *et al.*'s (2016) study, we used six indicators that provided a comprehensive
3 view of the construct.

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

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

24 In our study, we controlled for several firm-related variables. To assess common
25 method bias (CMB), we utilized different strategies recommended by various scholars
26 (Nederhof, 1985; Podsakoff *et al.*, 2012). First, we used different scales for endogenous and
27 exogenous variables (Podsakoff *et al.*, 2012). Second, we used Harman's single factor
28 procedure to examine CMB. Exploratory factor analysis confirmed that the first factor
29 explained 31.4% of the variance, thus showing that CMB was not a significant concern in our
30 study. We assessed non-response bias by comparing early and late respondents by means of

1 non-parametric tests in terms of industry distribution. Further, we also performed a t-test in
 2 terms of size and performance outcomes at the 0.05 level of significance. The t-test results
 3 showed no significant differences, thus confirming that CMB did not adversely affect the
 4 findings of our study.

5. Results

5.1. The results of measurement model

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

14

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

1

2

3

4

5

6

7

8

9

10

11

12

13

14

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). Table 2 shows that all the endogenous constructs meet the criteria (Hair *et al.*, 2020).

15

5.2. The results of the structural model

16

17

18

19

20

21

22

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 (<i>H1</i>)	0.36	0.03	5.01
BDAC → Manufacturing agility (<i>H2</i>)	0.44	0.03	9.62
Manufacturing agility → Manufacturing performance (<i>H3</i>)	0.26	0.02	4.20
Organizational creativity*BDAC → Manufacturing agility (<i>H4</i>)	0.29	0.03	4.35
Organizational creativity*BDAC → (Manufacturing agility → Manufacturing performance) (<i>H5</i>)	0.09	0.00	2.04
Customers as data analysts*BDAC → Manufacturing agility (<i>H6</i>)	0.41	0.03	3.02
Customers as data analysts*BDAC → (Manufacturing agility → Manufacturing performance) (<i>H7</i>)	0.12	0.02	3.55

1 5.3.Result analysis

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

7 To assess the proposed moderation effect in the structural model, we performed a
 8 hierarchical moderation regression analysis in the macro process (Hayes, 2013) in line with
 9 the recommendations provided by Preacher and Hayes (2008) and MacKinnon *et al.* (2007).
 10 A significant relationship was found to exist between BDACs and organizational creativity
 11 ($\beta=0.14$; $p<0.01$) and BDACs and the involvement of customers as data analysts ($\beta=0.29$,
 12 $p<0.01$). For H4, our results revealed that the interaction terms contributed to bringing change
 13 in the variance explained ($\text{adj-R}^2=0.29$; $P=0.002$). The interaction-term was found to be
 14 positive and significant ($\beta=0.10$, $p<0.05$). To provide a better illustration of our results, we
 15 calculated a significant slope at both higher (1 standard deviation above the mean) and lower
 16 (1 standard deviation below the mean) levels, after accounting for the main effects of BDACs
 17 and organizational creativity. The results revealed that organizational creativity had a positive
 18 effect on the relationship between BDACs and manufacturing agility ($\beta=0.29$; $p<0.05$). The
 19 nature of this interaction thus suggested that BDACs are most impactful on manufacturing
 20 agility in the presence of high levels of organizational creativity (see Figure2).

Table 4. Moderated Mediation simple effects			21
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 ₂₃
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 ₂₄

25

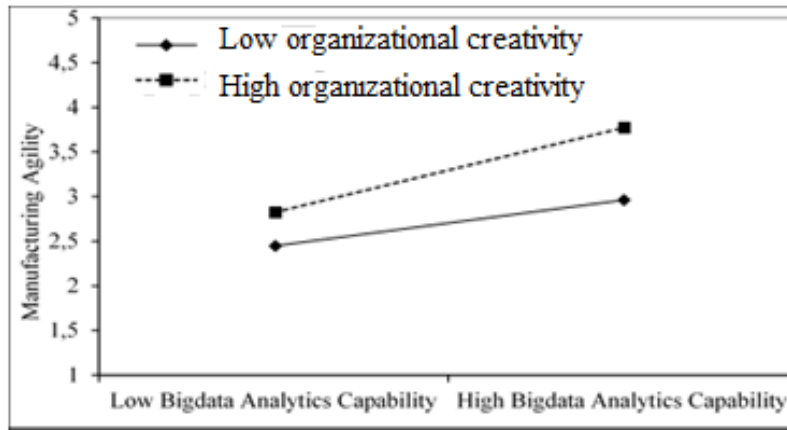


Figure 2. The moderating role of organizational creativity

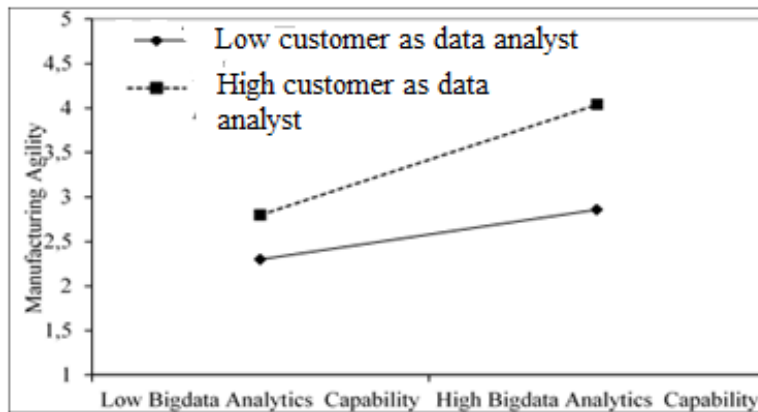


Figure 3. The moderating role of customers as data analysts (H6)

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

1 results suggested that the value of adjusted- R^2 was slightly changed (adj- $R^2=0.335$; $P=0.025$),
2 and the interaction terms were found to be significant ($\beta=0.09$; $p<0.05$).

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

17 **6. Discussion and conclusion**

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

24 Dahlstedt (2019) claimed that creative organizations attain higher data analytics
25 insights. Despite the importance of BDAC for agility (Rialti *et al.* 2019), no prior study has
26 examined the moderating impact of organizational creativity on the relationship between
27 BDAC and agility. Our findings extend this line of research by investigating the impact of
28 organizational creativity on BDAC and manufacturing agility. Hence, those engineering firms
29 that encourage innovative ideas and their employees' creative mindsets are better positioned
30 to take advantage of BDACs and adapt more effectively to changing conditions. This suggests

1 that engineering manufacturers with high creativity and BDACs can enhance their
2 manufacturing agility (to forecast market demand effectively, reduce order to delivery cycle
3 times, and perform customization). Our findings on the moderation-mediation effects
4 reinforce the notion that managers' technical proficiency, particular target work, taking a new
5 perspective on problems, and intrinsic motivation bring a new perspective in utilizing data
6 analytics.

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

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

28 29 *6.1.Theoretical Contributions*

30 This study makes important contributions to the extant literature. First, it embeds the RBV
31 and DCs to examine the relationship between BDACs and manufacturing agility. Although

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

30 Third, to the best of our knowledge, this study is among the few to consider the
31 involvement of customers as data analysts and examine its effects on manufacturing agility.
32 The novelty of our study consists in its examination of whether or not customers, as data

1 analysts, significantly moderate the relationship between BDACs and manufacturing agility.
2 Specifically, the previous literature has so far neglected the important relationship between
3 BDACs and manufacturing agility in the presence of the involvement of customers as data
4 analysts, arguing that the advantage of manufacturing agility often lies in operational and
5 relationship flexibility (Lee et al., 2020). Some studies have also exclusively focused on how
6 customers, as a source of data analysis, impact new product performance (Zhang & Xiao,
7 2020), and on how customer involvement, as a source of processing information, affects firm
8 outcomes (Anning-Dorson, 2018; Cui & Wu, 2017). Little attention has been paid to
9 exploring the impact of the involvement of customers as data analysts on various performance
10 outcomes. This study provides new insights into the achievement of manufacturing agility,
11 which has been largely ignored by extant scholarship. We extend the existing literature by
12 proposing that, in a B2B context, the involvement of customers as data analysts can enhance
13 the positive effect of BDACs on manufacturing agility. Our study further underpins the
14 argument that organizational creativity leads to a stronger relationship between BDACs and
15 manufacturing agility. In doing so, it provides meaningful theoretical evidence and advances
16 the existing literature by demonstrating how the involvement of customers as data analysts is
17 a key organizational external knowledge mechanism suited to understanding how
18 organizations may balance their capabilities to develop manufacturing agility. Our study
19 extends the research conducted in this area by providing evidence that customer involvement
20 effectively increases the positive effect of BDACs on manufacturing agility.

21 *6.2. Practical Implications*

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

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

22

23 *6.3.Limitations and Future Research*

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

1 among partners, such as focal firms and suppliers. Future research could extend this
2 discussion by incorporating the role played by social capital in the proposed framework,
3 particularly when discussing the moderating role of customers as data analysts.
4

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)		
<p>“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’.</p> <p>Our customers’ involvement:</p>		
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		
<p>“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’.</p>		
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)		

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

1

1 **Reference list:**

- 2 Adebanjo, D., Teh, P. L. and Ahmed, P. K. (2016). 'The impact of external pressure and
3 sustainable management practices on manufacturing performance and environmental
4 outcomes'. *International Journal of Operations and Production Management*. 36 (9):
5 995–1013.
- 6 Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R. and Childe, S. J. (2016). 'How to
7 improve firm performance using big data analytics capability and business strategy
8 alignment?' *International Journal of Production Economics*. 182: 113–31.
9 <http://dx.doi.org/10.1016/j.ijpe.2016.08.018>.
- 10 Amabile, T. M. (1997). 'Motivating creativity in organizations: On doing what you love and
11 loving what you do'. *California Management Review*. 1 (1): 39–58.
- 12 ———, Conti, R., Coon, H., Lazenby, J. and Herron, M. (1996). 'Assessing the work
13 environment for creativity'. *Academy of management journal*. 39 (5): 1154–84.
- 14 Anderson, N., Potočnik, K. and Zhou, J. (2014). 'Innovation and Creativity in
15 Organizations: A State-of-the-Science Review, Prospective Commentary, and Guiding
16 Framework'. *Journal of Management*. 40 (5): 1297–333.
- 17 Anning-Dorson, T. (2018). 'Customer involvement capability and service firm performance:
18 The mediating role of innovation'. *Journal of Business Research*. 86 (September
19 2016): 269–80.
- 20 Ashrafi, A., Zare Ravasan, A., Trkman, P. and Afshari, S. (2019). 'The role of business
21 analytics capabilities in bolstering firms' agility and performance'. *International
22 Journal of Information Management*. 47 (July 2018): 1–15.
23 <https://doi.org/10.1016/j.ijinfomgt.2018.12.005>.
- 24 Augier, M. and Teece, D. J. (2007). 'Dynamic capabilities and multinational enterprise:
25 Penrosean insights and omissions'. *Management international review*. 47 (2): 175–92.
- 26 Awan, U., Nauman, S., & Sroufe, R. (2020). 'Exploring the effect of buyer engagement on
27 green product innovation: Empirical evidence from manufacturers'. *Business Strategy
28 and the Environment*. <https://onlinelibrary.wiley.com/doi/abs/10.1002/bse.2631>.

- 1 Awan, U., S. Shamim, Z. Khan, N. U. Zia, S. M. Shariq and M. N. Khan (2021). 'Big data
2 analytics capability and decision-making: The role of data-driven insight on circular
3 economy performance', *Technological Forecasting and Social Change*, 168, pp.
4 120766.
- 5 Awan, U., Sroufe, R. and Kraslawski, A. (2019). 'Creativity enables sustainable
6 development: Supplier engagement as a boundary condition for the positive effect on
7 green innovation'. *Journal of Cleaner Production*. 226: 172–85.
8 <https://doi.org/10.1016/j.jclepro.2019.03.308>.
- 9 ———, ——— and Shahbaz, M. (2021). 'Industry 4.0 and Circular Economy: A Literature
10 Review and Recommendations for Future Research'. *Business Strategy and the
11 Environment*. <https://doi.org/10.1002/bse.2731>
- 12 Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S. and Delen, D. (2019). 'Business
13 analytics and firm performance: The mediating role of business process performance'.
14 *Journal of Business Research*. 96 (October 2018): 228–37.
15 <https://doi.org/10.1016/j.jbusres.2018.11.028>.
- 16 Bag, S., Wood, L. C., Xu, L., Dhamija, P. and Kayikci, Y. (2020). 'Big data analytics as an
17 operational excellence approach to enhance sustainable supply chain performance'.
18 *Resources, Conservation and Recycling*. 153 (November 2019): 104559.
19 <https://doi.org/10.1016/j.resconrec.2019.104559>.
- 20 Barlette, Y. and Baillette, P. (2020). 'Big data analytics in turbulent contexts: towards
21 organizational change for enhanced agility'. *Production Planning & Control*. 1–18.
22 <https://doi.org/10.1080/09537287.2020.1810755>
- 23 Barney, J. B. (2001). 'Resource-based theories of competitive advantage : A ten- year
24 retrospective on the resource-based view'. *Journal of Management*. 27: 643–50.
- 25 Barney, J., Wright, M. and Ketchen, D. J. (2001). 'Journal of Management_2001_Barney,
26 Wright, Ketchen_The resource-based view of the firm Ten years after 1991.pdf'.
27 *Journal of Management*. 27: 625–41.
- 28 Braunscheidel, M. J. and Suresh, N. C. (2009). 'The organizational antecedents of a firm's
29 supply chain agility for risk mitigation and response'. *Journal of Operations*

- 1 *Management*. 27 (2): 119–40.
- 2 Chen, Y. S. and Chang, C. H. (2013). ‘The Determinants of Green Product Development
3 Performance: Green Dynamic Capabilities, Green Transformational Leadership, and
4 Green Creativity’. *Journal of Business Ethics*. 116 (1): 107–19.
- 5 Côte-Real, N., Oliveira, T. and Ruivo, P. (2017). ‘Assessing business value of Big Data
6 Analytics in European firms’. *Journal of Business Research*. 70: 379–90.
7 <http://dx.doi.org/10.1016/j.jbusres.2016.08.011>.
- 8 Cua, K. O., McKone, K. E. and Schroeder, R. G. (2001). ‘Relationships between
9 implementation of TQM, JIT, and TPM and manufacturing performance’. *Journal of*
10 *Operations Management*. 19 (6): 675–94.
- 11 Cui, A. S. and Wu, F. (2016). ‘Utilizing customer knowledge in innovation: antecedents and
12 impact of customer involvement on new product performance’. *Journal of the academy*
13 *of marketing science*. 44 (4): 516–38.
- 14 Cui, A. S. and Wu, F. (2017). ‘The impact of customer involvement on new product
15 development: Contingent and substitutive effects’. *Journal of Product Innovation*
16 *Management*. 34 (1): 60–80.
- 17 Dahlstedt, P. (2019). ‘Big Data and Creativity’. *European Review*. 27 (3): 411–39.
- 18 Darvishmotevali, M., Altinay, L. and Köseoglu, M. A. (2020). ‘The link between
19 environmental uncertainty, organizational agility, and organizational creativity in the
20 hotel industry’. *International Journal of Hospitality Management*. 87 (August 2019):
21 102499. <https://doi.org/10.1016/j.ijhm.2020.102499>.
- 22 Davenport, T. (2014). *Big data at work: dispelling the myths, uncovering the opportunities*.
23 Harvard Business Review Press.
- 24 Day, G. S. (2011). ‘Closing the marketing capabilities gap’. *Journal of marketing*. 75 (4):
25 183–95.
- 26 de Vasconcellos, S. L., Garrido, I. L. and Parente, R. C. (2019). ‘Organizational creativity as
27 a crucial resource for building international business competence’. *International*
28 *Business Review*. 28 (3): 438–49. <https://doi.org/10.1016/j.ibusrev.2018.11.003>.

- 1 Doz, Y. L. and M. Kosonen (2010). 'Embedding strategic agility: A leadership agenda for
2 accelerating business model renewal', *Long range planning*, 43, pp. 370-382
- 3 Dubey, R., Gunasekaran, A. and Childe, S. J. (2019a). 'Big data analytics capability in
4 supply chain agility'. *Management Decision*.57(8): 2092-2112.
5 <https://doi.org/10.1108/MD-01-2018-0119>
- 6 ———, ———, ———, Blome, C. and Papadopoulos, T. (2019b). 'Big data and predictive
7 analytics and manufacturing performance: integrating institutional theory, resource-
8 based view and big data culture'. *British Journal of Management*. 30 (2): 341–61.
- 9 ———, Luo, Z., Gunasekaran, A., Akter, M. S. and Hazen, B. (2018). 'Big data and
10 predictive analytics in humanitarian supply chains: Enabling visibility and coordination
11 in the presence of swift trust'. *The International Journal of Logistics Management*. 29
12 (2): 485–512.
- 13 Eckstein, D., Goellner, M., Blome, C. and Henke, M. (2015). 'The performance impact of
14 supply chain agility and supply chain adaptability: The moderating effect of product
15 complexity'. *International Journal of Production Research*. 53 (10): 3028–46.
16 <http://dx.doi.org/10.1080/00207543.2014.970707>.
- 17 Eisenhardt, K. M. (1989). 'Building theories from case study research'. *Academy of
18 management review*. 14 (4): 532–50.
- 19 Ferdows, K. and De Meyer, A. (1990). 'Lasting improvements in manufacturing
20 performance: In search of a new theory'. *Journal of Operations Management*. 9 (2):
21 168–84.
- 22 Ferraris, A., Mazzoleni, A., Devalle, A. and Couturier, J. (2019). 'Big data analytics
23 capabilities and knowledge management: impact on firm performance'. *Management
24 Decision*.57(8):1923-1936. <https://doi.org/10.1108/MD-07-2018-0825>
- 25 Ferreira, J., Coelho, A. and Moutinho, L. (2020). 'Dynamic capabilities, creativity and
26 innovation capability and their impact on competitive advantage and firm performance:
27 The moderating role of entrepreneurial orientation'. *Technovation*. 92–93 (February
28 2017): 102061. <https://doi.org/10.1016/j.technovation.2018.11.004>.

- 1 Gupta, M. and George, J. F. (2016). 'Toward the development of a big data analytics
2 capability'. *Information and Management*. 53 (8): 1049–64.
3 <http://dx.doi.org/10.1016/j.im.2016.07.004>.
- 4 Hair, J. F., Howard, M. C. and Nitzl, C. (2020). 'Assessing measurement model quality in
5 PLS-SEM using confirmatory composite analysis'. *Journal of Business Research*. 109
6 (November 2019): 101–10.
- 7 Hajli, N., Tajvidi, M., Gbadamosi, A. and Nadeem, W. (2020). 'Understanding market
8 agility for new product success with big data analytics'. *Industrial Marketing
9 Management*. 86: 135–43.
- 10 Hallgren, M. and Olhager, J. (2009). 'Lean and agile manufacturing: External and internal
11 drivers and performance outcomes'. *International Journal of Operations and
12 Production Management*. 29 (10): 976–99.
- 13 Hayes, A. (2013). *Integrating Mediation and Moderation Analysis: fundamentals using
14 PROCESS*. Guilford publications, New York, USA.
- 15 Hayes, A. F. and Preacher, K. J. (2013). *Conditional process modeling: Using structural
16 equation modeling to examine contingent causal processes*. In: pp. 217–264). In G. R.
17 Hancock & R. O. Mueller (Eds.), *Structural equation modelling: A second course* (2
18 ed. (ed.). Greenwich, CT: Information Age.
- 19 Iqbal, T., Huq, F. and Bhutta, M. K. S. (2018). 'Agile manufacturing relationship building
20 with TQM, JIT, and firm performance: An exploratory study in apparel export industry
21 of Pakistan'. *International Journal of Production Economics*. 203 (August 2017): 24–
22 37. <https://doi.org/10.1016/j.ijpe.2018.05.033>.
- 23 Khanra, S., A. Dhir and M. Mäntymäki (2020). 'Big data analytics and enterprises: a
24 bibliometric synthesis of the literature', *Enterprise Information Systems*, 14, pp. 737-
25 768.
- 26 Kunz, W., Aksoy, L., Bart, Y., Heinonen, K., Kabadayi, S., Ordenes, F. V., Sigala, M.,
27 Diaz, D. and Theodoulidis, B. (2017). 'Customer engagement in a Big Data world'.
28 *Journal of Services Marketing*. 31 (2): 161–71.

- 1 Laney, D. (2012). 'The importance of "big data": A definition'. *Gartner. Retrieved*. 21:
2 2014–8.
- 3 Lee, H. and Choi, B. (2003). 'Knowledge management enablers, processes, and
4 organizational performance: An integrative view and empirical examination'. *Journal*
5 *of Management Information Systems*. 20 (1): 179–228.
- 6 Lee, N. C. A., Wang, E. T. G. and Grover, V. (2020). 'IOS drivers of manufacturer-supplier
7 flexibility and manufacturer agility'. *Journal of Strategic Information Systems*. 29 (1):
8 101594. <https://doi.org/10.1016/j.jsis.2020.101594>.
- 9 Li, W., Bhutto, T. A., Xuhui, W., Maitlo, Q., Zafar, A. U. and Ahmed Bhutto, N. (2020).
10 'Unlocking employees' green creativity: The effects of green transformational
11 leadership, green intrinsic, and extrinsic motivation'. *Journal of Cleaner Production*.
12 255: 120229. <https://doi.org/10.1016/j.jclepro.2020.120229>.
- 13 Lin, Y. and Wu, L.Y. (2014). Exploring the role of dynamic capabilities in firm
14 performance under the resource-based view framework. *Journal of Business Research*,
15 67(3), pp.407-413.
- 16 MacKinnon, D. P., Fairchild, A. J. and Fritz, M. S. (2007). 'Mediation analysis'. *Annu. Rev.*
17 *Psychol.* 58: 593–614.
- 18 Mandal, S. (2019). 'The influence of big data analytics management capabilities on supply
19 chain preparedness, alertness and agility: An empirical investigation'. *Information*
20 *Technology and People*. 32 (2): 297–318.
- 21 Menguc, B., Auh, S. and Yannopoulos, P. (2014). 'Customer and supplier involvement in
22 design: The moderating role of incremental and radical innovation capability'. *Journal*
23 *of Product Innovation Management*. 31 (2): 313–28.
- 24 Mikalef, P., Krogstie, J., Pappas, I. O. and Pavlou, P. (2020). 'Exploring the relationship
25 between big data analytics capability and competitive performance: The mediating
26 roles of dynamic and operational capabilities'. *Information and Management*. 57 (2):
27 103169. <https://doi.org/10.1016/j.im.2019.05.004>.
- 28 Najafi-Tavani, Z., Mousavi, S., Zaefarian, G. and Naudé, P. (2020). 'Relationship learning

- 1 and international customer involvement in new product design: The moderating roles
2 of customer dependence and cultural distance'. *Journal of Business Research*. 120
3 (August 2019): 42–58. <https://doi.org/10.1016/j.jbusres.2020.07.020>.
- 4 Nederhof, A. J. (1985). 'Methods of Coping With Social Desirability Bias: A Review'.
5 *European Journal of Social Psychology*. 15: 263–80.
- 6 Oldham, G. R. and Cummings, A. (1996). 'Employee Creativity: Personal and Contextual
7 Factors at Work'. *Academy of Management Journal*. 39 (3): 607–34.
- 8 Omar Alhawari, Usama Awan, Bhutta, M. K. S. and Ülkü, M. A. (2021). *Insights from*
9 *Circular Economy Literature : A Review of Extant Definitions and Unravelling Paths*
10 *to Future Research*. 13: 1–22.
- 11 Pagell, M. and Gobeli, D. (2009). 'How plant managers' experiences and attitudes toward
12 sustainability relate to operational performance'. *Production and Operations*
13 *Management*. 18 (3): 278–99.
- 14 Pakistan Economic Forum (2016). *Engineering Goods Industry ENGINEERING GOODS*
15 *INDUSTRY*. 2016. [https://www.pbc.org.pk/wp-content/uploads/Presentation-](https://www.pbc.org.pk/wp-content/uploads/Presentation-Engineering-Industry-of-Pakistan.pdf)
16 [Engineering-Industry-of-Pakistan.pdf](https://www.pbc.org.pk/wp-content/uploads/Presentation-Engineering-Industry-of-Pakistan.pdf) (accessed 10 April 2021).
- 17 Podsakoff, P. M., MacKenzie, S. B. and Podsakoff, N. P. (2012). 'Sources of Method Bias
18 in Social Science Research and Recommendations on How to Control It'. *Annual*
19 *Review of Psychology*. 63 (1): 539–69.
- 20 Preacher, K. J. and Hayes, A. F. (2008). 'Asymptotic and resampling strategies for assessing
21 and comparing indirect effects in multiple mediator models'. *Behavior research*
22 *methods*. 40 (3): 879–91.
- 23 Rennick, C. and McKay, K. (2018). 'Componential Theories of Creativity: A Case Study of
24 Teaching Creative Problem Solving'. In: *Proceedings of the Canadian Engineering*
25 *Education Association (CEEAA)*. 2018.
26 <https://ojs.library.queensu.ca/index.php/PCEEAA/article/view/12991>.
- 27 Rialti, R., Zollo, L., Ferraris, A. and Alon, I. (2019). 'Big data analytics capabilities and
28 performance: Evidence from a moderated multi-mediation model'. *Technological*

- 1 *Forecasting and Social Change*. 149 (October): 119781.
2 <https://doi.org/10.1016/j.techfore.2019.119781>.
- 3 Roberts, N. and Grover, V. (2012). 'Investigating firm's customer agility and firm
4 performance: The importance of aligning sense and respond capabilities'. *Journal of*
5 *Business Research*. 65 (5): 579–85. <http://dx.doi.org/10.1016/j.jbusres.2011.02.009>.
- 6 Shamim, S., Y. Yang, N. U. Zia and M. H. Shah (2021). 'Big data management capabilities
7 in the hospitality sector: Service innovation and customer generated online quality
8 ratings', *Computers in Human Behavior*, pp. 106777.
- 9 Shamim, S., J. Zeng, Z. Khan and N. U. Zia (2020). 'Big data analytics capability and
10 decision making performance in emerging market firms: The role of Contractual and
11 Relational Governance Mechanisms', *Technological Forecasting and Social Change*,
12 161, pp. 120315.
- 13 Shamim, S., J. Zeng, S. M. Shariq and Z. Khan (2019). 'Role of big data management in
14 enhancing big data decision-making capability and quality among Chinese firms: A
15 dynamic capabilities view', *Information & Management*, 56, pp. 103135.
- 16 Shen, H., Mei, N. and Gao, Y. (2019). 'Improving radical innovation in China's
17 manufacturing firms: A resource management-based interpretation of social ties and
18 firm capabilities'. *Journal of Manufacturing Technology Management*. 30 (7): 1034–
19 54.
- 20 Shokouhyar, S., Seddigh, M. R. and Panahifar, F. (2020). 'Impact of big data analytics
21 capabilities on supply chain sustainability'. *World Journal of Science, Technology and*
22 *Sustainable Development*. 17 (1): 33–57.
- 23 Song, M. and Thieme, J. (2009). 'The role of suppliers in market intelligence gathering for
24 radical and incremental innovation'. *Journal of Product Innovation Management*. 26
25 (1): 43–57.
- 26 Steininger, D. M., P. Mikalef, A. Pateli, A. O. de Guinea and A. Ortiz-De. (2021). 'Dynamic
27 Capabilities in Information Systems Research: A Critical Review, Synthesis of Current
28 Knowledge, and Recommendations for Future Research',

- 1 Swafford, P. M., Ghosh, S. and Murthy, N. (2006). 'The antecedents of supply chain agility
2 of a firm: Scale development and model testing'. *Journal of Operations Management*.
3 24 (2): 170–88.
- 4 Tallon, P. P. and Pinsonneault, A. (2011). 'Competing perspectives on the link between
5 strategic information technology alignment and organizational agility: insights from a
6 mediation model'. *Mis Quarterly*.35(2) 463–86. <https://doi.org/10.2307/23044052>
- 7 Teece, D. J. (2012). 'Dynamic capabilities: Routines versus entrepreneurial action'. *Journal*
8 *of management studies*. 49 (8): 1395–401.
- 9 Teece, D.J. (2014). 'A dynamic capabilities-based entrepreneurial theory of the
10 multinational enterprise'. *Journal of International Business Studies*. 45 (1): 8–37.
- 11 Teece, D.J. (2007). Explicating dynamic capabilities: the nature and microfoundations of
12 (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), 1319-
13 1350.
- 14 Teece, D.J., Pisano, G. and Shuen, A. (1997). 'Dynamic capabilities and strategic
15 management'. *Strategic Management Journal*..509-533.
- 16 Tortorella, G. L., Giglio, R. and van Dun, D. H. (2019). 'Industry 4.0 adoption as a
17 moderator of the impact of lean production practices on operational performance
18 improvement'. *International journal of operations & production*
19 *management*.39(6/7/8):860-886. <https://doi.org/10.1108/IJOPM-01-2019-0005>
- 20 Tu, Z. and Liu, X. (2010). 'RETRACTED ARTICLE: A new integrated VMI-based model
21 for single vendor and multiple buyers with ordering cost reduction'. *ICAMS 2010 -*
22 *Proceedings of 2010 IEEE International Conference on Advanced Management*
23 *Science*. 3: 303–8.
- 24 Vachon, S. and Klassen, R. D. (2008). 'Environmental management and manufacturing
25 performance: The role of collaboration in the supply chain'. *International Journal of*
26 *Production Economics*. 111 (2): 299–315.
- 27 Wamba, S. F., Dubey, R., Gunasekaran, A. and Akter, S. (2020a). 'The performance effects
28 of big data analytics and supply chain ambidexterity: The moderating effect of

1 environmental dynamism'. *International Journal of Production Economics*. 222
2 (September 2019): 107498. <https://doi.org/10.1016/j.ijpe.2019.09.019>.

3 ———, ———, ——— and ——— (2020b). 'The performance effects of big data
4 analytics and supply chain ambidexterity: The moderating effect of environmental
5 dynamism'. *International Journal of Production Economics*. 222: 107498.

6 ———, Gunasekaran, A., Akter, S., Ren, S. J., Dubey, R. and Childe, S. J. (2017a). 'Big
7 data analytics and firm performance: Effects of dynamic capabilities'. *Journal of*
8 *Business Research*. 70: 356–65.

9 ———, ———, ———, Ren, S. J. fan, Dubey, R. and Childe, S. J. (2017b). 'Big data
10 analytics and firm performance: Effects of dynamic capabilities'. *Journal of Business*
11 *Research*. 70: 356–65. <http://dx.doi.org/10.1016/j.jbusres.2016.08.009>.

12 ——— and Mishra, D. (2017). 'Big data integration with business processes: a literature
13 review'. *Business Process Management Journal*. 23(3):477-492.
14 <https://doi.org/10.1108/BPMJ-02-2017-0047>

15 Weber, Y. and S. Y. Tarba (2014). 'Strategic agility: A state of the art introduction to the
16 special section on strategic agility', *California management review*, 56, pp. 5-12.

17 Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S. and Delen, D. (2020). 'Big data analytics
18 capabilities and firm performance: An integrated MCDM approach'. *Journal of*
19 *Business Research*. 114 (April): 1–15. <https://doi.org/10.1016/j.jbusres.2020.03.028>.

20 Zhang, D. Z. (2011). 'Towards theory building in agile manufacturing strategies - Case
21 studies of an agility taxonomy'. *International Journal of Production Economics*. 131
22 (1): 303–12. <http://dx.doi.org/10.1016/j.ijpe.2010.08.010>.

23 Zhang, H. and Xiao, Y. (2020). 'Customer involvement in big data analytics and its impact
24 on B2B innovation'. *Industrial Marketing Management*. 86 (March 2019): 99–108.
25 <https://doi.org/10.1016/j.indmarman.2019.02.020>.

26

27

1

2