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# Big data analytics capabilities and firm performance: An integrated MCDM approach

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ABSTRACT

This study explores the interdependence of big data analytics (BDA) capabilities and the impact of these capabilities on firm performance using an integrated multicriteria decision-making (MCDM) methodology. Drawing on a rich data set obtained from selected case study firms in Pakistan, three MCDM tools, namely, intuitionistic fuzzy decision-making trial and evolution laboratory (IF-DEMATEL), analytic network process (ANP), and simple additive weighting (SAW), are employed to assess the relative importance of BDA capabilities and the relationship of these capabilities with the firm performance. The results show that BDA capabilities are interdependent, and infrastructure capabilities are the highest-ranked among all, followed by management and human resource capabilities, respectively. The SAW results indicate an association between BDA capabilities and firm performance. Moreover, BDA capabilities are more strongly related to operational performance than to market performance.

## 1. Introduction and motivation

Big data has become a popular buzzword; its popularity fueled by technological advancements in both software and hardware (Sena, Bhaumik, Sengupta, & Demirbag, 2019). Big data has attracted massive attention from both academics and practitioners as the next big thing in management and has even been proposed by some scholars as the next management revolution (Brynjolfsson & McAfee, 2012; Ren, Wamba, Akter, Dubey, & Childe, 2017). Big data analytics (BDA) is an emerging hot topic among scholars and business communities since it has superseded traditional statistical tools and brought value to firms in both financial and non-financial terms (Aydiner et al. 2019a; Chen, Roger, & Chiang, 2012; Sena et al., 2019).

Numerous articles and white papers have explored the current and potential applications of BDA. The Business Intelligence and Data Analytics Survey 2018 reports that all businesses plan to increase spending on business intelligence and analytics tools and further plan to grow their human resource (HR) capabilities in the coming years (Phillips et al., 2018). In a survey by Gartner (2016), the talent gap is envisaged as the biggest obstacle standing in the way of chief information officers achieving their digitization aims. In their jointly undertaken survey, this view is shared by Accenture and GE (2015), who report that 63 percent of executives believe that hiring talent with the requisite expertise is essential to fix the challenge of the talent gap.

A contradictory view is that modern data analysis techniques have replaced the jobs performed by humans, but the truth is that the purpose of technological advancement is to facilitate jobs performed by humans, not to replace or eradicate them. Modern technologies are meant to augment technology-human interaction, not to replace the human contribution (Duan, Edwards, & Dwivedi, 2019). In fact, BDA simplifies the job and reduces human error. Around the globe, there is a propensity to apply BDA instead of relying on intuition and experience for effective decision-making. Researchers are providing strategic and practical guidelines to benefit from big data. However, the application perspective of big data through rigorous academic investigation and theorization is still developing. Moreover, the internal mechanisms to

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devise strategies based on BDA are not fully explored. To date, numerous researchers have studied the advantages of BDA in connection with firm performance. The most interesting and baffling questions in BDA research are what capabilities to acquire to get ahead in big data efforts and whether to acquire technical or non-technical capabilities.

This study contributes to BDA research in a number of ways. Firstly, the study explores the relationship between BDA capabilities and firm performance using the resource-based view (RBV) and dynamic capabilities view (DCV) as theoretical lenses. The key rationale for adopting these two views is that the technological capability of exploiting BDA needs to be accompanied by several additional firm-specific resources that can eventually lead to improved performance.

Secondly, a hybrid multi-criteria decision-making (MCDM) method is designed to quantify the effect of BDA capabilities on firm performance. This methodology aims at exploring the hierarchical relationships and interdependence of BDA capabilities. The prioritization of BDA capabilities categorized under infrastructure, HR, and management, and measuring their linkages with firm performance, provides a useful contribution to BDA research, as the literature is lacking in studies applying MCDM methods.

Another notable novelty of this study is that it is conducted in a key emerging market, Pakistan, which is indisputably a fast-growing market that displays similar traits to the other emerging large country-markets such as Mexico, Brazil, Turkey, and Thailand. While BDA research and practice have focused mainly on industrialized countries, there seems to be a shortage of empirical research in other country contexts, primarily in emerging markets. Pakistan offers a substantial context for enlarging this stream of research since it has become crucial for firms operating in all sectors to develop BDA capabilities along with other competing economies. Although most emerging markets tend to suffer from institutional voids with respect to economic, legal, and financial infrastructure, BDA scholars in emerging markets have revealed that BDA might help both public and private firms to deal with the imperatives of global competition. The application of a hybrid MCDM methodology to a BDA field in an emerging market setting like Pakistan is a valuable addition to the extant body of literature.

## 2. Theoretical background and conceptual framework

Although conceptual research in big data has been gaining momentum for the past decade, empirical research is at a rudimentary stage. The paucity of empirical studies leaves professionals in uncharted waters when it comes to implementation and capacity-building. A fallacy that big data is data of huge size or volume prevails; nonetheless, the literature explains big data in terms of five dimensions, known as 5Vs: volume, velocity, variety, veracity, and value (Ferraris, Mazzoleni, Devalle, & Couturier, 2018: 3). Wamba, Akter, Edwards, Chopin, and Gnanzou (2015: 6) define big data as "a holistic approach to manage, process and analyze 5Vs (volume, variety, velocity, veracity, and value) to create actionable insights for sustained value delivery, measuring performance and competitive advantages."

The link between BDA capabilities and firm performance has been examined from a wide variety of theoretical lenses, but the RBV and the DCV have been common denominators. The RBV of the firm articulates two alternative sources of competitive advantage: the heterogeneity of the firm's strategic resources, and the perfect immobility of these resources across the firm (Barney, 1991). As proposed by Hambrick (1987), an effective combination of a firm's physical, human, and organizational capital resources is a rare resource and is imperfectly imitable. Imitability of a firm's resources can be avoided in the nexus of interpersonal relations among managers, the firm's culture, the firm's reputation among suppliers and customers, and information processing systems (Barney, 1991). Hence, firms can achieve imperfect imitability through the development of BDA capabilities, as this creates an evidence-based decision environment and data-driven culture.

Teece and Pisano (1994) highlight the shortcomings of RBV, as it is relatively static and is not compatible with the rapidly changing business environment. They claim that dynamic capabilities are the source of competitive advantage, based on the notion that competitive advantage entails both the exploitation of existing internal and external firm-specific capabilities and flourishing new ones. The fundamental idea of dynamic capability is tacit knowledge; this is the nexus of coordinative management processes because the behavior, processes, and operations of a firm are difficult to replicate. Another shortcoming of RBV is that it does not explain the evolution of resources over time. Firms must have the stability to continue delivering value in their idiosyncratic way but be agile and adaptive enough to reform as and when needed (Mikalef et al. 2019). BDA capabilities essentially require the processing of data and information from inside and outside the organization, and swift responses to a change in the firm and market dynamics.

The points of commonality in the above theories are the inimitability and synchronization of resources, processes, and capabilities. However, to survive and thrive in a turbulent business environment, adaptability and evolution are key. The DCV, in addition to the acknowledgment of inimitability and synchronization of resources, processes, and capabilities, emphasizes the dynamicity of resources, business operations, and capabilities in response to changes in the external environment. Moreover, the BDA capabilities of the firm provide an environment of close-knit business functions. The tacit knowledge acquired through an environment where business functions are close-knit and synchronized is difficult for competitors to imitate. This study underpins BDA capabilities as the dynamic capability of competitive advantage. The following subsections present background literature regarding the classification of BDA capabilities and empirical studies on the link between BDA capabilities and firm performance.

### 2.1. BDA capabilities

Holistic characterization of BDA capabilities has been the subject of recent literature. For instance, Akhtar, Frynas, and Mellahi (2019: 252) characterize BDA capabilities as a balanced combination of requisite human resource, big-data skills, advanced technologies supported by large datasets to generate analytical reports and actionable insights utilized, produced, and processed by mathematical, statistical techniques, and machine learning tools for enhanced performance.

In their *Harvard Business Review* article, Brynjolfsson and McAfee (2012) report that data-driven firms are 6 percent more profitable and 5 percent more productive than their rivals. Moreover, an effective combination of infrastructure, HR, and management capabilities of firms is significant for the successful adoption of BDA and superior financial and operational performance. The technical challenge of using big data is real, but the managerial challenge is even greater, dealing from top to bottom of the organizational hierarchy. To cope with this challenge, Brynjolfsson and McAfee (2012) further suggest five areas for firms to focus more, i.e., technology, leadership, decision-making, talent management, and company culture. Barton and Court (2012) support the idea of the interconnection of technology, people, and management in a big data environment, and emphasize the integrated approach to model building, data sourcing, and organizational transformation to benefit from big data.

Akter, Wamba, Gunasekaran, Dubey, and Childe (2016) categorize BDA capabilities into three typologies: BDA technology capabilities, BDA management capabilities, and BDA talent capabilities. The adoption of BDA capabilities involves a three-stage process: acceptance, assimilation, and routinization incorporated into corporate commitment (Singh & El-Kassar, 2019; Teece, 2003). Wang, Kung, Gupta, and Ozdemir (2019) highlight sets of primary BDA capabilities such as data integration, analytical, analytical person, predictive, and data interpretation capabilities and complementary organizational resources such as data governance, evidence-based decision-making, improvisational, and planned dynamic capabilities. Merely 4 percent of 400

**Table 1**
Taxonomy of BDA capabilities.

| Relevant studies | Infrastructure capability | Human resource capability | Management capability |
|---|---|---|---|
| Barton and Court (2012) | Data and IT platform | People | Managers |
| Brynjolfsson and McAfee (2012) | IT infrastructure | Skills and knowledge of data scientist | Corporate strategy |
| Davenport and Patil (2012) | Connectivity, compatibility, and modularity | Data scientist | Analytics management at core businesses and operational functions |
| Wixom, Yen, and Relich (2013) | Data and BA tools | IT team | IT strategy |
| Kiron, Prentice, and Ferguson (2014) | Organizational openness, compatibility analytics technology and collaborative use of technology | Analytical talent, technical and business knowledge and organization's effectiveness in disseminating insights | Analytics planning, sharing and coordinating, investment, control on analytics as a whole |
| Wamba et al. (2015) | Connectivity, compatibility, and modularity | Management | Management, technical and business relations |
| Ransbotham et al. (2015) | Infrastructure and processes | Managerial decision making | Technical knowledge and skills |
| Ren et al. (2017) | BDA infrastructure capabilities | BDA personnel expertise capabilities | BDA management capabilities |
| Lozada, Arias-Pérez, and Perdomo-Charry (2019) | Tangibles (data, technology and basic resources) | Human skills | Intangibles (data-driven culture and organizational learning) |
| Rialti, Zollo, Ferraris, and Alon (2019) | BDA infrastructure flexibility | BDA personnel expertise | BDA management capabilities |
| Mikalef et al. (2019) | Tangible (basic resources, data, technology) | Human skills (technical and managerial skills) | Intangible (data-driven culture and organizational learning) |

companies have capabilities (i.e., the right people, tools, data intention focus, and analytical insights), and these firms have better financial and non-financial performance (Wegener & Sinha, 2013). Four areas are crucial for building up firms' data analytics capabilities: state-of-the-art tools and processes, quality data, data-savvy people, and incentives that promote analytical decision-making (Wegener & Sinha, 2013).

Existing literature essentially categorizes BDA capabilities that are linked to better financial and non-financial performance into three groups: infrastructure, management, and HR capabilities. Table 1 presents some selected studies relying on this taxonomy of BDA capabilities.

### 2.2. BDA capabilities and firm performance

A substantial number of studies in the previous literature have explored the positive relationship between BDA capabilities and firm performance and agreed upon the significance of evidence-based decision-making. Bharadawaj (2000) investigated a significant and positive association between IT capabilities and firm performance. Business process performance and decision-making performance were found to have mediating effects on the positive relationship between information management capabilities and firm performance (Aydiner et al. 2019a, 2019b). Akter et al. (2016) examined the mediating role of business strategy alignment in firm performance through BDA capabilities. Ferraris et al. (2018) conducted an empirical analysis of the data collected from Italian firms and concluded that decisions based on big data might be effective for better firm performance. To implement BDA in the healthcare setting successfully, Wang, Kung, and Byrd (2018: 10) recommend five strategies: (1) the implementation of big data governance, (2) the creation of an information-sharing culture, (3) the training of key personnel to use BDA, (4) the integration of cloud computing into the organization's BDA, and (5) the generation of new business ideas from BDA.

Akhtar et al. (2019) explored the significant positive relationship between big-data-savvy teams, big-data-driven actions, and firm performance. They further identified the skills and techniques used by big-data-savvy teams. It is unlikely to be known by one professional, so the authors emphasize the diversity of skills and knowledge of big-data-savvy teams. Mikalef et al. (2019) found that BDA capabilities such as tangible, intangible, and human skills have a positive association with innovation through the mediating effect of dynamic capabilities. They also note the moderating impact of environmental factors such as dynamism, heterogeneity, and hostility on the link between BDA capabilities and innovation. An organizational culture that deploys resources synergistically and relies on evidence-based decision-making produces more competitive performance gains. In a more recent study, Amankwah-Amoah and Adomako (2019) adopted a different approach to studying the effect of BDA on firm performance by developing a four-domain framework that explains how different approaches to BDA adoption and implementation may lead to failure. Furthermore, firms that possess ordinary BDA capabilities and simple data are more likely to emerge with business failure.

Table 2 provides a summary of selected previous studies reporting on the link between BDA capabilities and firm performance, adopting various theoretical lenses. Our conceptual framework delineating the interdependence of BDA capabilities and the effect of these capabilities on firm performance is shown in Fig. 1.

## 3. Research methodology

The application of MCDM methods to organizational decision-making problems is burgeoning because of their unique approach of ranking all the possible criteria and determining the relative weight of each criterion (Arda, Delen, Tatoglu, & Zaim, 2017). The integrated MCDM methodology proposed in this study consists of three main stages: determination of BDA capabilities, prioritization of BDA capabilities, and analysis of the linkage between BDA capabilities and firm performance. The BDA capabilities are determined based on previous studies (Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien, 2005). In the second stage, two MCDM techniques-intuitionistic fuzzy decision-making trial and evolution laboratory (IF-DEMATEL) and analytic network process (ANP)-are synergistically applied. IF-DEMATEL is applied to explain the interactions between the BDA capabilities and determine the network relationship map (NRM); then, the ANP is conducted to identify the importance weights of the BDA capabilities. In the final stage, simple additive weighting (SAW) is performed to obtain the effect of BDA capabilities on firm performance based on six measures. The technical background of the methods applied is elaborated in the following subsections.

### 3.1. IF-DEMATEL

DEMATEL has been employed in various areas ranging from knowledge management (Wu, 2008), portfolio selection criteria (Varma & Sunil Kumar, 2012), and emergency management (Li, Hu, Zhang, Deng, & Mahadevan, 2014) to green supply chain management (Kaur,

**Table 2**
Summary of studies on BDA capabilities and firm-level performance outcomes.

| Study | Theoretical framework | BDA capabilities | Performance outcome |
|---|---|---|---|
| Bharadawaj (2000) | Resource-based view | IT infrastructure, human IT resources, and IT-enabled intangibles | Firm performance |
| Santhanam and Hartono (2003) | Resource-based view | Profit ratios and cost ratios | Firm performance |
| Tippins and Sohi (2003) | Resource-based view | IT knowledge, IT operations and IT objects | Firm performance |
| Bhatt and Grover (2005) | Resource-based view | IT infrastructure quality, IT business experience, and relationship infrastructure | Competitive advantage |
| Ravichandran and Lertwongsatien (2005) | Resource-based view | IS planning sophistication, systems development capabilities, IS support maturity and IS operations capability | Firm performance |
| Ray, Muhanna, and Barney (2005) | Resource-based view | Technical IT skills, generic IT, IT spending, shared knowledge, flexible IT infrastructure, and IT complementarities | Performance of the customer service process |
| Fink and Neumann (2007) | IT infrastructure | Business capability, behavioral capability, and technical capability | IT-independent organizational agility |
| Kim, Shin, Kim, and Lee (2011) | Dynamic capabilities | IT management capabilities and IT personnel capabilities | Firm performance |
| Mithas, Ramasubbu, and Sambamurthy (2011) | Resource-based view | Performance management capability, customer management capability, and process management capability | Firm performance |
| Bronzo et al. (2013) | Dynamic capabilities | Leadership and strategy, process documentation, the measure of performance processes, organizational structure, people management, culture, and values of the organization, client orientation, supplier orientation, systems, and IT. | Firm performance |
| Cao, Duan, and Li (2015) | Information processing view and contingency theory | Data-driven environment and information processing capability | Decision-making effectiveness |
| Wu, Straub, and Liang (2015) | Resource-based view | Decision-making structure, formal process, communication approach, product strategic alignment, quality strategic alignment and market strategic alignment | Organizational performance |
| Akter et al. (2016) | Resource-based view and socio-materialism | Big data management capability, big data technology capability, and big data talent capability | Firm performance |
| Vidgen, Shaw, and Grant (2017) | Resource-based view | Technology, organization, process, and people | Value creation |
| Aydiner et al. (2019a, 2019b) | Resource-based view | Data acquisition and processing, prescriptive analytics, predictive analytics, and descriptive analytics | Firm performance |
| Akhtar et al. (2019) | The resource-based view and human capital theory | Multi-disciplinary skills and data-driven insights of the big data-savvy teams. | Business performance |
| Dubey et al. (2019) | Resource-based view, institutional theory, and big data culture | Tangible resources (data connectivity, technology, basic resources) and human skills. | Manufacturing performance |
| Mikalef et al. (2019) | The resource-based view and dynamic capabilities | Tangible (basic resource and data), human skills (technical and managerial skills), and intangible (organizational learning and data-driven culture). | Innovation |
| Wang et al. (2019) | The resource-based view and configuration theory | Primary capabilities (e.g., analytical personal skills, data integration, analytical, predictive, data interpretation capabilities) and complementary organizational resources (e.g., evidence-based decision making, data governance, improvisational and planned dynamic capabilities). | Quality of healthcare |

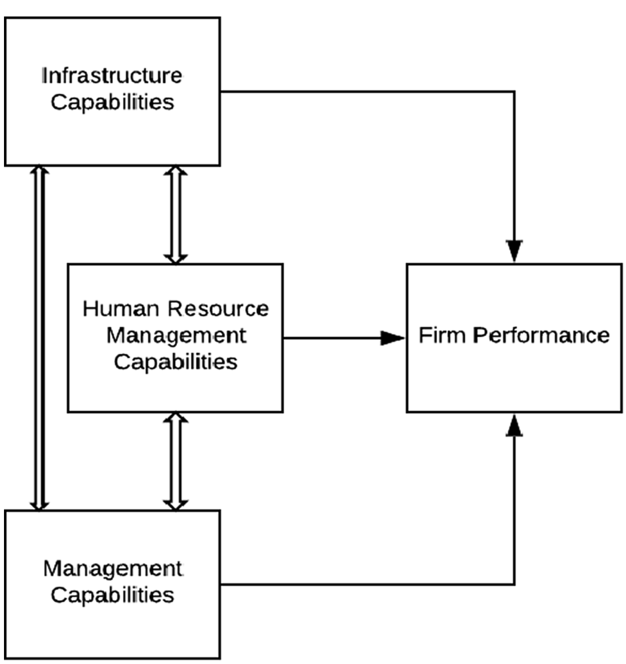


**Fig. 1.** Conceptual model.

Sidhu, Awasthi, Chauhan, & Goyal, 2017). However, due to the insufficiency of DEMATEL in handling uncertainty and vagueness in various MCDM situations, IF-DEMATEL is conducted to reveal the links among the BDA capabilities within the proposed methodology. Fig. 2 presents a flowchart of the proposed methodology, including the main steps of IF-DEMATEL. These steps are derived from earlier studies (Büyüközkan, Güleryüz, & Karpak, 2017; Xie, Duan, Sun, & Du, 2014) and explained as follows.

*Step 1*. Determine the experts: Managers and professionals with relevant knowledge and expertise are consulted for the linking of listed BDA capabilities.

*Step 2*. Determine the scale of evaluation: In the proposed methodology, the scale used by Büyüközkan et al. (2017) is adopted, as shown in Table 3. Different from the classical fuzzy expressions, which are represented by sole membership degrees, there exist three dimensional characterization of intuitionistic fuzzy numerals, namely membership, non-membership and hesitancy degrees, respectively.

*Step 3*. Determine the importance weights of the decision-makers: Prioritization is computed via the scale provided in Table 4, and the related operations are performed based on Boran, Genc, Hurt, and Akay (2009).

The formula indicated in Eq.1 is performed, and each decision-maker's importance weight is found.

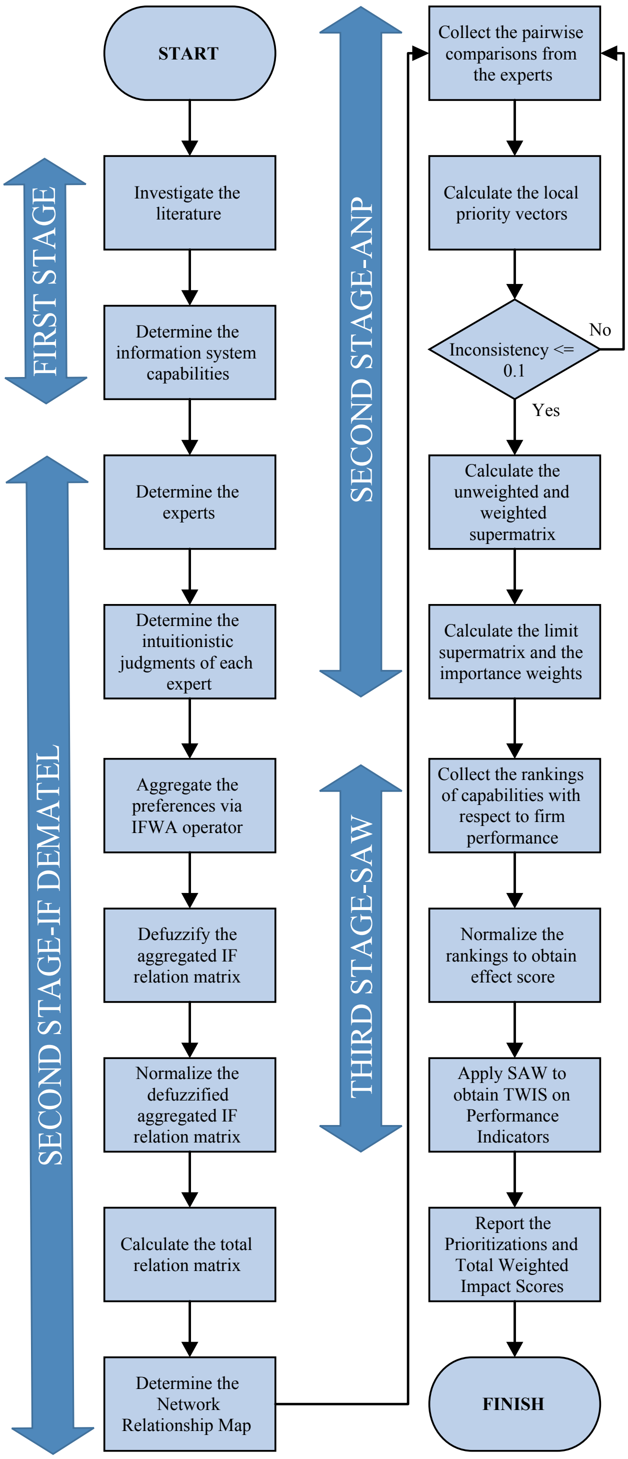


**Fig. 2.** Flow-chart of the proposed methodology.

**Table 3**
Linguistic terms used in IF-DEMATEL.

| Definition of linguistic terms | Intuitionistic fuzzy number | | |
|---|---|---|---|
| Very high influence (VH) | [0.90 | 0.10 | 0.00] |
| High influence (H) | [0.75 | 0.20 | 0.05] |
| Medium influence (M) | [0.50 | 0.45 | 0.05] |
| Low influence (L) | [0.35 | 0.60 | 0.05] |
| No influence (N) | [0.00 | 1.00 | 0.00] |

**Table 4**
Linguistic scale for determining the importance of decision-makers.

| Definition of linguistic terms | Intuitionistic fuzzy number | | |
|---|---|---|---|
| Very important (VI) | [0.90 | 0.10 | 0.00] |
| Important (I) | [0.75 | 0.20 | 0.05] |
| Medium important (MI) | [0.50 | 0.45 | 0.05] |
| Unimportant (U) | [0.35 | 0.60 | 0.05] |
| Very unimportant (VU) | [0.10 | 0.90 | 0.00] |

$$\lambda_k = \frac{\left(\mu_k + \Pi_k\left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)}{\sum_{k=1}^{l}\left(\mu_k + \Pi_k\left(\frac{\mu_k}{\mu_k + \nu_k}\right)\right)} \tag{1}$$

The sum of the relative importance weights must be equal to 1, as shown in Eq. (2).

$$\sum_{k=1}^{l} \lambda_k = 1 \tag{2}$$

*Step 4*. Determine each participant's intuitionistic judgments and aggregate their preferences via the intuitionistic fuzzy weighted averaging (IFWA) operator, as indicated in Eq. (3) (Xu, 2007).

$$\begin{aligned} r_{ij} &= IFWA_\lambda(r_{ij}^{(1)}. r_{ij}^{(2)}. \cdots . r_{ij}^{(l)}) = \lambda_1 r_{ij}^{(1)} \oplus \lambda_2 r_{ij}^{(2)} \oplus \cdots \oplus \lambda_l r_{ij}^{(l)} = \\ &= [1 - \textstyle\prod_{k=1}^{l}(1-\mu_{ij}^{(k)})^{\lambda_k}. \prod_{k=1}^{l}(\nu_{ij}^{(k)})^{\lambda_k}. \prod_{k=1}^{l}(1-\mu_{ij}^{(k)})^{\lambda_k} \\ &\quad - \textstyle\prod_{k=1}^{l}(\nu_{ij}^{(k)})^{\lambda_k}] \\ r_{ij} &= (\mu_{ij}. \nu_{ij}. \pi_{ij})\mu_{ij} = (1 - \textstyle\prod_{k=1}^{l}(1-\mu_{ij}^{(k)})^{\lambda_k}). \ \nu_{ij} = (\prod_{k=1}^{l}(\nu_{ij}^{(k)})^{\lambda_k}). \\ \pi_{ij} &= (\textstyle\prod_{k=1}^{l}(1-\mu_{ij}^{(k)})^{\lambda_k} - \prod_{k=1}^{l}(\nu_{ij}^{(k)})^{\lambda_k}) \end{aligned} \tag{3}$$

*Step 5*. Defuzzify the aggregated intuitionistic fuzzy relation matrix utilizing the formula in Eq. (4), as proposed by Xie et al. (2014).

$$\bar{r}_{ij} = \mu_{ij}^{(k)} - \nu_{ij}^{(k)} + (2\beta - 1)\pi_{ij}^{(k)} \tag{4}$$

$$X = \begin{bmatrix} 0 & \cdots & \bar{r}_{1n} \\ \vdots & \ddots & \vdots \\ \bar{r}_{n1} & \cdots & 0 \end{bmatrix}$$

*Step 6*. Normalize the defuzzified aggregated intuitionistic fuzzy relation matrix (X) by applying Eq. (5) and find N, as indicated in Eq. (6).

$$\lambda = min\left[\frac{1}{\max 1 \le i \le n \sum_{j=1}^{n}|z_{ij}|}. \frac{1}{\max 1 \le j \le n \sum_{i=1}^{n}|z_{ij}|}\right] \quad i.\ j \in \{1.2. \cdots .n\} \tag{5}$$

$$N = \lambda x X \tag{6}$$

*Step 7*. Obtain the total relation matrix by performing the formula, as shown in Eq. (7).

$$T = N(I - N)^{-1} \tag{7}$$

*Step 8*. Determine the NRM by eliminating the values under the mean in the total relation matrix.

### 3.2. ANP

Among all MCDMs, the analytical hierarchy process (AHP) and ANP are the most commonly used and acknowledged as the most effective techniques (Chen et al., 2019).

After obtaining the NRM via IF-DEMATEL, ANP is applied. The reason for choosing ANP is its superiority in addressing complicated network structures. ANP is the generalized version of the AHP, proposed by Saaty (1996), who coined the AHP. There are various applications of ANP in the literature, including IS project selection (Lee &

Kim, 2000), planning of product mix (Chung, Lee, & Pearn, 2005), selection of shipping registry (Chou, 2018), and the assessment of lean and green performance (Farias, Santos, Gohr, de Oliveira, & Amorim, 2019).

The steps of ANP are briefly explained below (Kilic, Zaim, & Delen, 2015; Saaty & Vargas, 2013).

*Step 1*. Collect the pairwise comparisons from the participants: The judgments of each participant concerning each criterion are obtained.

Let A indicate the pairwise comparison values between the factors obtained. The pairwise comparison value in the comparison matrix A is indicated by $a_{ij}$, as shown in Eq. (8).

$$A = \begin{bmatrix} a_{11} & a_{12} & . & . & . & a_{1n} \\ a_{21} & a_{22} & . & . & . & a_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n1} & . & . & . & a_{nn} \end{bmatrix} \tag{8}$$

*Step 2*. Calculate the local priority vectors: To find a local priority vector ($w$), indicated in Eq. (9), the normalized matrix B consisting of $b_{ij}$ values is firstly constructed as in Eq. (10) by applying Eq. (11).

$$Aw = \lambda_{\max} w \tag{9}$$

$$B = \begin{bmatrix} b_{11} & b_{12} & . & . & . & b_{1n} \\ b_{21} & b_{22} & . & . & . & b_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ b_{n1} & b_{n1} & . & . & . & b_{nn} \end{bmatrix} \tag{10}$$

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i = 1, \ldots, n \quad j = 1, \ldots, n \tag{11}$$

The normalized pairwise comparison matrix B, as shown in Eq. (12), is constructed. The $b_{ij}$ values in matrix B are the normalized values that are obtained via Eq. (13).

$$B = \begin{bmatrix} b_{11} & b_{12} & . & . & . & b_{1n} \\ b_{21} & b_{22} & . & . & . & b_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ b_{n1} & b_{n1} & . & . & . & b_{nn} \end{bmatrix} \tag{12}$$

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \quad i = 1, \ldots, n \quad j = 1, \ldots, n \tag{13}$$

Then the eigenvalues (wi) are computed via Eq. (14), and the eigenvector (W) is constructed.

$$W = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix}, \ and \ \ w_i = \frac{\sum_{i=1}^{n} b_{ij}}{n} \quad for \quad i = 1, 2, \ldots, n \tag{14}$$

*Step 3*. Check the inconsistency: All the pairwise comparison matrices are checked. The inconsistency should be at most 0.1. Firstly, $\lambda_{\max}$ is obtained by applying Eq. (15); then, the inconsistency value is checked by applying Eqs. (16) and (17). CI, RI, and CR represent consistency indicators, random indicator, and consistency ratio, respectively. Table 5 includes the RI obtained from a standard random index table, as shown in Table 3. Hence, all the pairwise matrices are checked by applying the formulae provided in Eqs. (16) and (17).

**Table 5**
Random indices for the sizes of matrices.

| n | 1–2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|
| RI | 0.0 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

$$W' = AW = \begin{bmatrix} w'_1 \\ w'_2 \\ \vdots \\ w'_n \end{bmatrix}, \ and \ \ \lambda_{\max} = \frac{1}{n}\left(\frac{w'_1}{w_1} + \frac{w'_2}{w_2} + \ldots + \frac{w'_n}{w_n}\right) \tag{15}$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{16}$$

$$CR = \frac{CI}{RI} \tag{17}$$

*Step 4*. Calculate the unweighted and weighted supermatrix: The unweighted supermatrix is built by inserting the local priority vectors in the appropriate columns; then, cluster weights are considered, and a weighted supermatrix is obtained.

*Step 5*. Limit supermatrix: The limit supermatrix is obtained by getting enough power of the weighted supermatrix. Later, all the values in a row become identical and indicate the priority value. Moreover, all the priority values add up to 1.

### 3.3. Simple additive weighting (SAW)

SAW is a simple but effective multi-attribute decision-making method (MADM). It is one of the most frequently used MADM techniques and provides the weighted average (Alinezhad, Amini, & Alinezhad, 2009). SAW provides a global (total) score by adding contributions from each attribute. The global score of the alternative can be shown in Eq. (18) (Yoon & Hwang, 1995). Within the equation, $w_j$ shows the weight of the attribute j, while $r_{ij}$ indicates the normalized value of alternative i with respect to attribute j. Linear normalization is used within the SAW technique.

$$V(a_i) = \sum_{j=1}^{n} w_j * r_{ij} \tag{18}$$

Within the proposed study, this section will provide the total impact score (TIS) of BDA capabilities on six firm performance measures.

### 3.4. IF-DEMATEL, ANP, and SAW

At times, ANP alone is used for decision-making problems. However, the integration of ANP with other MCDM methods has been utilized in solving complex problems. Wu (2008) first jointly applied DEMATEL and ANP to evaluate and select knowledge management strategies. DEMATEL constructs interrelations among criteria before applying ANP to assign weights to criteria. DEMATEL and ANP complement one another and compensate for each other's weaknesses (Horng, Liu, Chou, Yin, & Tsai, 2014).

In this study, IF-DEMATEL is implemented to examine the interdependence of the BDA capabilities of the firms. Finding the interdependencies between the capabilities is crucial to reveal the importance level of factors in complex decision-making. The application of ANP in complex decision-making problems ranks the important factors and effectively demonstrates the connections between factors. Ultimately, SAW is applied to obtain the total effect of BDA capabilities on firm performance measures.

### 3.5. Variable measurement

The measures used in this study are drawn from the prior literature on BDA, and IT/IS management (Aydiner et al. 2019a, 2019b; Ravichandran & Lertwongsatien, 2005) and already have shown satisfactory levels of construct reliability with Cronbach alpha values well above the acceptable threshold value of 0.70 (Nunnally & Bernstein, 1994). Then, the variables constituting the underlying dimensions of BDA capabilities, including infrastructure, HR, and management capabilities, as well as firm performance, were shortlisted based on their relative importance following discussions with experienced managers and professionals in the relevant application area. To establish further the content validity of the scales used in this study, three CTOs in Pakistan were interviewed who provided us with their views on BDA capabilities based on their knowledge and experience. Each of the underlying dimensions of BDA capabilities consists of five items, while firm performance contains six items. The operationalization of this study's scales (along with the actual wording of the questions) and their sources are reproduced in Appendix 1.

### 3.6. Data collection

We adopted a selected multiple case study approach to acquire the necessary data in assessing the relative importance of BDA capabilities and the relationships of these capabilities with firm performance. First, we identified the firms listed on the Pakistan Stock Exchange with a well-established IT infrastructure and digital platforms that could provide information-rich cases to illuminate our research questions (Yin, 2018). Initially, we identified 40 manufacturing firms meeting our selection criteria. We contacted the selected firms by sending an invitation letter with an interview brief to the chief technology officer (CTO) or a senior executive in charge of IT/IS of each target firm, inviting them to participate in our study. Following the initial contact with the targeted firms, we concluded our case selection stage as eight firms were willing to take part in our study, exhibiting a satisfactory level of variation in terms of firm-specific characteristics. The participants were assured that their names, the firm, contact information, and other personal information of any kind would not be revealed at any stage of this study. The features of the participants and sample firms are shown in Table 6.

## 4. Data analysis

The data analysis consists of two stages. The first stage involves the application of two MCDM techniques, namely IF-DEMATEL and ANP, while the second stage involves the implementation of the SAW method. These two stages are described in the following subsections.

### 4.1. First stage

In this stage, first, IF-DEMATEL is applied to reveal the NRM. The brief explanations of the steps involved in IF-DEMATEL implementation are as follows.

*Step 1*. Determine the experts: A series of interviews are conducted with CTOs of case study firms (decision-makers) to evaluate the interaction between the BDA capabilities.

*Step 2*. Determine the scale of evaluation: The scale of evaluation is determined (see Table 7.

*Step 3*. Determine the importance weights of the decision-makers: Since there is a compromise judgment of decision-makers in the IF-DEMATEL process, this step is skipped.

*Step 4*. Determine each decision-maker's intuitionistic judgments and aggregate their preferences via the IFWA operator: The decision-makers' intuitionistic judgments between the capabilities are obtained and indicated in Table 7. The abbreviations of linguistic terms, as shown in Table 3, are used. Since there is compromise judgment of decision-makers, aggregation is not required.

*Step 5*. Defuzzify the aggregated intuitionistic fuzzy relation matrix: The intuitionistic fuzzy relation matrix is defuzzified via Eq. (4) and indicated in Table 8.

*Step 6*. Normalize the defuzzified aggregated intuitionistic fuzzy relation matrix (X): Normalization is performed using Eq. (5), and the normalized matrix is provided in Appendix 2.

*Step 7*. Obtain the total relation matrix: The total relation matrix is obtained by performing Eq. (7) and indicated in Appendix 3.

*Step 8*. Determine the Network Relationship Map (NRM).

NRM is obtained by eliminating the values under the mean value in the total relation matrix. It is computed that the mean value in the total relation matrix is $-0.005$. Hence, the eliminated values become 0 while the others become 1 and are indicated in Table 9.

As shown in NRM (Table 9), the first row has the value of 1 in the BDA capabilities columns of C3, C4, C5, C7, C9, C10, C13, and C15, indicating that C1 affects the capabilities of C3, C4, C5, C7, C9, C10, C13, and C15, respectively. Similarly, the interrelationships among the capabilities are interpreted and used as input in ANP.

The network structure of ANP is constructed based on NRM obtained from IF-DEMATEL, as indicated in Fig. 3. For the sake of simplicity and to save space, the inner steps of ANP methodology are demonstrated considering one decision-maker's judgments. Similar steps are applied for the other decision-makers. The application steps of ANP are as follows.

*Step 1*. Collect the pairwise comparisons from the decision-makers: The judgments of each decision-maker with respect to each affecting criterion are obtained.

All the pairwise comparisons are collected from the eight participants considering the NRM provided in Table 9. It is seen that C1 affects the capabilities C3, C4, and C5 in Group 1 (infrastructure capabilities), C7, C9, and C10 in Group 2 (HR capabilities), and C13 and C15 in Group 3 (management capabilities). Hence, the first pairwise comparison matrix is constructed with respect to C1 for each group, as provided in Tables 9–11. The proposed ANP structure is shown in Fig. 3. The same procedure is applied for all the remaining capabilities from C2 to C15.

*Step 2*. Calculate the local priority vectors: The local priority vectors for all pairwise comparison matrices indicated in Tables 9–12 are shown in Table 13.

*Step 3*. Check the inconsistency: The inconsistency ratios are computed as 0.10, 0.5, and 0 for the three pairwise comparison matrices, respectively. Hence, the results indicate that the matrices are consistent.

*Step 4*. Calculate the unweighted and weighted supermatrix: The unweighted and weighted supermatrices are obtained via Super Decisions software and provided in Appendices 4 and 5.

*Step 5*. Limit supermatrix: The final matrix is the limit supermatrix,

**Table 6**
Characteristics of participants and sample firms.

| Participant | Position | Industry | Year of establishment | Allocation of IT expenditure in the budget (%) | Work experience in this firm (years) | Duration of the interview (minutes) |
|---|---|---|---|---|---|---|
| 1 | CTO | Chemical | 1981 | 1–5 | 20 | 42 |
| 2 | CTO | Textile | 1951 | 1–5 | 10 | 52 |
| 3 | CTO | Textile | 1970 | 6–10 | 20 | 39 |
| 4 | CTO | Textile | 1987 | 11–15 | 20 | 55 |
| 5 | CTO | Chemical | 1980 | 1–5 | 5 | 47 |
| 6 | CTO | Textile | 1951 | 1–5 | 10 | 50 |
| 7 | CTO | Textile | 1956 | 1–5 | 5 | 48 |
| 8 | CTO | Energy | 1963 | 20 | 5 | 41 |

**Table 7**
The judgments of the participants for the BDA capabilities.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | N | N | VH | VH | VH | N | H | L | H | M | N | N | M | L | H |
| **C2** | N | N | VH | VH | VH | H | M | VH | N | N | L | N | N | N | L |
| **C3** | VH | M | N | L | N | H | VH | VH | M | VH | N | N | L | M | L |
| **C4** | VH | M | VH | N | H | N | N | N | L | M | N | N | M | L | N |
| **C5** | N | N | L | M | N | M | L | L | N | N | N | N | L | N | M |
| **C6** | N | N | VH | VH | VH | N | N | VH | VH | VH | N | N | M | VH | VH |
| **C7** | L | VH | VH | M | M | VH | N | VH | VH | VH | L | N | M | M | H |
| **C8** | N | M | VH | M | M | VH | VH | N | H | VH | N | N | L | L | H |
| **C9** | L | N | L | L | N | VH | VH | VH | N | VH | N | N | H | H | VH |
| **C10** | H | N | H | L | N | VH | VH | VH | VH | N | N | N | M | H | H |
| **C11** | VH | H | M | L | VH | H | VH | M | L | VH | N | VH | H | VH | VH |
| **C12** | VH | H | VH | VH | VH | H | VH | L | L | L | VH | N | M | M | H |
| **C13** | N | L | H | M | H | N | N | L | M | L | N | H | N | VH | VH |
| **C14** | M | L | L | L | L | L | N | H | VH | VH | M | L | VH | N | VH |
| **C15** | L | M | VH | VH | VH | L | N | H | H | H | M | H | VH | VH | N |

**Note:** Acronyms are provided in Table 3.

**Table 8**
The de-fuzzified relation matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | −1 | −1 | 0.8 | 0.8 | 0.8 | −1 | 0.55 | −0.25 | 0.55 | 0.05 | −1 | −1 | 0.05 | −0.25 | 0.55 |
| **C2** | −1 | −1 | 0.8 | 0.8 | 0.8 | 0.55 | 0.05 | 0.8 | −1 | −1 | −0.25 | −1 | −1 | −1 | −0.25 |
| **C3** | 0.8 | 0.05 | −1 | −0.25 | −1 | 0.55 | 0.8 | 0.8 | 0.05 | 0.8 | −1 | −1 | −0.25 | 0.05 | −0.25 |
| **C4** | 0.8 | 0.05 | 0.8 | −1 | 0.55 | −1 | −1 | −1 | −0.25 | 0.05 | −1 | −1 | 0.05 | −0.25 | −1 |
| **C5** | −1 | −1 | −0.25 | 0.05 | −1 | 0.05 | −0.25 | −0.25 | −1 | −1 | −1 | −1 | −0.25 | −1 | 0.05 |
| **C6** | −1 | −1 | 0.8 | 0.8 | 0.8 | −1 | −1 | 0.8 | 0.8 | 0.8 | −1 | −1 | 0.05 | 0.8 | 0.8 |
| **C7** | −0.25 | 0.8 | 0.8 | 0.05 | 0.05 | 0.8 | −1 | 0.8 | 0.8 | 0.8 | −0.25 | −1 | 0.05 | 0.05 | 0.55 |
| **C8** | −1 | 0.05 | 0.8 | 0.05 | 0.05 | 0.8 | 0.8 | −1 | 0.55 | 0.8 | −1 | −1 | −0.25 | −0.25 | 0.55 |
| **C9** | −0.25 | −1 | −0.25 | −0.25 | −1 | 0.8 | 0.8 | 0.8 | −1 | 0.8 | −1 | −1 | 0.55 | 0.55 | 0.8 |
| **C10** | 0.55 | −1 | 0.55 | −0.25 | −1 | 0.8 | 0.8 | 0.8 | 0.8 | −1 | −1 | −1 | 0.05 | 0.55 | 0.55 |
| **C11** | 0.8 | 0.55 | 0.05 | −0.25 | 0.8 | 0.55 | 0.8 | 0.05 | −0.25 | 0.8 | −1 | 0.8 | 0.55 | 0.8 | 0.8 |
| **C12** | 0.8 | 0.55 | 0.8 | 0.8 | 0.8 | 0.55 | 0.8 | −0.25 | −0.25 | −0.25 | 0.8 | −1 | 0.05 | 0.05 | 0.55 |
| **C13** | −1 | −0.25 | 0.55 | 0.05 | 0.55 | −1 | −1 | −0.25 | 0.05 | −0.25 | −1 | 0.55 | −1 | 0.8 | 0.8 |
| **C14** | 0.05 | −0.25 | −0.25 | −0.25 | −0.25 | −0.25 | −1 | 0.55 | 0.8 | 0.8 | 0.05 | −0.25 | 0.8 | −1 | 0.8 |
| **C15** | −0.25 | 0.05 | 0.8 | 0.8 | 0.8 | −0.25 | −1 | 0.55 | 0.55 | 0.55 | 0.05 | 0.55 | 0.8 | 0.8 | −1 |

**Table 9**
The network relation matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 |
| **C2** | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **C3** | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 |
| **C4** | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **C5** | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **C6** | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| **C7** | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| **C8** | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| **C9** | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 |
| **C10** | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| **C11** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| **C12** | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 |
| **C13** | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| **C14** | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 |
| **C15** | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |

as shown in Appendix 6. All the rows have the same value and represent the importance weight of the capabilities. Similarly, all the required operations are performed for the other decision-makers, and the importance weights for each decision-maker are given in Table 14. Moreover, the overall, within-cluster, and cluster importance weights are shown in Table 15.

### 4.2. Second stage

In the SAW method, the aim is to find the total impact of BDA capabilities on the firm performance measures, including market share (FP1), sales growth (FP2), product development (FP3), cost saving (FP4), number of new product and service projects (FP5), and return on sales (FP6). First, participants were asked to rank the BDA capabilities' impact on firm performance measures. The rankings of capabilities' effects on each firm performance measure are provided in Appendix 7.

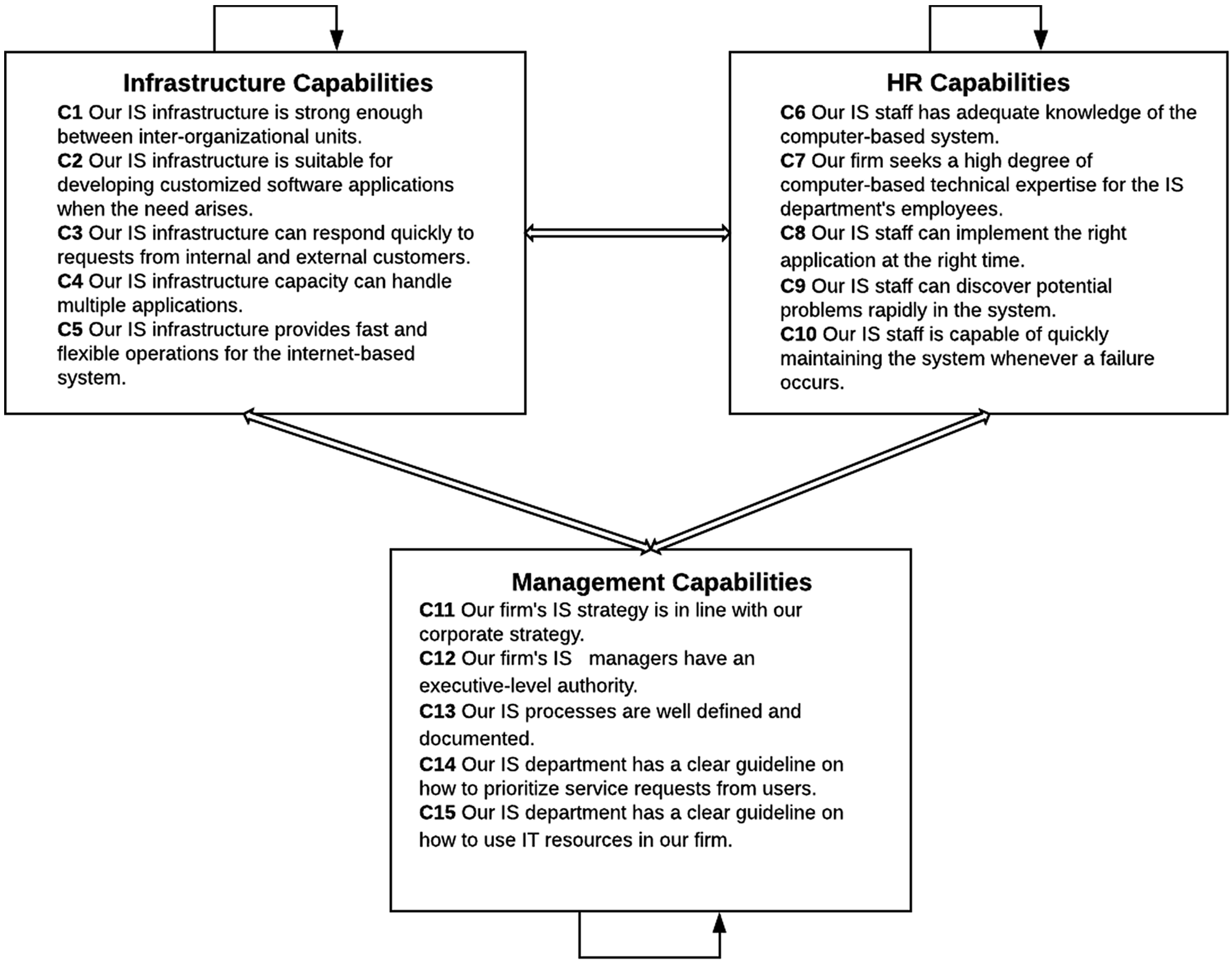


**Fig. 3.** ANP structure.

**Table 10**
Pairwise comparison with respect to "C1" within "Group 1"

| | C7 | C9 | C10 |
|---|---|---|---|
| C7 | 1 | 2 | 2 |
| C9 | 1/2 | 1 | 1/2 |
| C10 | 1/2 | 2 | 1 |

**Table 11**
Pairwise comparison with respect to "C1" within "Group 2".

| | C3 | C4 | C5 |
|---|---|---|---|
| C3 | 1 | 1/4 | 2 |
| C4 | 4 | 1 | 3 |
| C5 | 1/2 | 1/3 | 1 |

**Table 12**
Pairwise comparison with respect to "C1" within "Group 3.

| | C13 | C15 |
|---|---|---|
| C13 | 1 | 1 |
| C15 | 1 | 1 |

**Table 13**
Local priority vectors with respect to "C1" for each group.

| Group 1 | | Group 2 | | Group 3 | |
|---|---|---|---|---|---|
| C3 | 0.218 | C7 | 0.493 | C13 | 0.5 |
| C4 | 0.630 | C9 | 0.196 | C15 | 0.5 |
| C5 | 0.152 | C10 | 0.311 | | |

Next, the ranking values are normalized; the normalized rankings are provided in Appendix 8. For instance, while normalizing C1′s effect on firm performance measures (first column in Appendix 7), the smallest rank value (1.33) in Appendix 7 is converted to the highest normalized value (1) in Appendix 8. However, in implementing the SAW procedure, linear normalization should be applied for each firm performance measure considering all the BDA capabilities. In the last stage, the importance weights of BDA capabilities are multiplied by the normalized values, and the total impact score of all BDA capabilities' effects on each performance measure is obtained.

## 5. Discussion and conclusion

This study examined the relative importance of BDA capabilities and their impact on firm performance by applying an integrated MCDM technique. Drawing on pertinent literature and employing a multiple case study approach, a set of fifteen BDA capabilities were identified.

**Table 14**
Importance weight of each BDA capability according to each participant.

| | Cap. # | Part. 1 | Part. 2 | Part. 3 | Part. 4 | Part. 5 | Part. 6 | Part. 7 | Avg. (%) |
|---|---|---|---|---|---|---|---|---|---|
| **INFRASTRUCTURE CAPABILITIES** | C1 | 0.1397 | 0.1428 | 0.1095 | 0.1362 | 0.1386 | 0.1417 | 0.1342 | **13.47** |
| | C2 | 0.0433 | 0.0373 | 0.0756 | 0.0380 | 0.0367 | 0.0336 | 0.0487 | **4.48** |
| | C3 | 0.1002 | 0.1030 | 0.0987 | 0.1123 | 0.0984 | 0.0952 | 0.0671 | **9.65** |
| | C4 | 0.1273 | 0.1150 | 0.1358 | 0.1096 | 0.1221 | 0.1230 | 0.1531 | **12.66** |
| | C5 | 0.0397 | 0.0376 | 0.0492 | 0.04 | 0.0687 | 0.0566 | 0.1074 | **5.71** |
| **HR CAPABILITIES** | C6 | 0.0467 | 0.0585 | 0.0480 | 0.0452 | 0.0413 | 0.0458 | 0.0335 | **4.56** |
| | C7 | 0.0576 | 0.0238 | 0.0648 | 0.0558 | 0.0344 | 0.0384 | 0.0504 | **4.65** |
| | C8 | 0.0468 | 0.0460 | 0.0516 | 0.0488 | 0.0410 | 0.0561 | 0.0382 | **4.70** |
| | C9 | 0.0472 | 0.0616 | 0.0415 | 0.0566 | 0.0549 | 0.0640 | 0.0539 | **5.43** |
| | C10 | 0.0657 | 0.0784 | 0.0581 | 0.0611 | 0.0805 | 0.0593 | 0.0603 | **6.63** |
| **MANAGEMENT CAPABILITIES** | C11 | 0.0033 | 0.0019 | 0.0022 | 0.0032 | 0.0017 | 0.0031 | 0.0037 | **0.28** |
| | C12 | 0.0347 | 0.0235 | 0.0202 | 0.0342 | 0.0186 | 0.0328 | 0.0322 | **2.81** |
| | C13 | 0.0856 | 0.0907 | 0.0807 | 0.0942 | 0.0979 | 0.0774 | 0.0813 | **8.69** |
| | C14 | 0.0829 | 0.0953 | 0.0836 | 0.0907 | 0.0844 | 0.0884 | 0.0666 | **8.46** |
| | C15 | 0.0786 | 0.0838 | 0.0799 | 0.0734 | 0.0802 | 0.0840 | 0.0687 | **7.84** |

This entire set of BDA capabilities is categorized into three major clusters, labeled infrastructure, human resources, and management capabilities. Each cluster consists of five BDA capabilities. Table 15 displays the ranking of the whole set of 15 BDA capabilities based on the weights of importance. Likewise, it is possible to rank BDA capabilities clusters with respect to their total scores by adding the individual scores of BDA capabilities constituting each cluster. At the cluster level, the analysis indicates that infrastructure capabilities (45.96%) have the highest level of priority, followed by the management capabilities (28.07%) and HR capabilities (25.97%) clusters, respectively.

As mentioned earlier, Table 15 indicates the relative importance of each BDA capability within its own cluster. Of the five BDA capabilities constituting the infrastructure capabilities cluster, the BDAs represented as C1 (29.31%), C4 (27.55%), and C3 (20.99%) have the highest level of importance not only within their own cluster but also within the entire set of BDAs. These three BDA capabilities are essentially linked with capacity-building and speed and are in line with the findings of previous studies suggesting the need to develop the right culture and infrastructure to benefit from BDA capabilities (Akhtar et al., 2019; Jagadeish et al. 2014; Ransbotham, Kiron, & Prentice, 2015).

Within the management capabilities cluster, C13 (30.95%), C14 (30.14%), and C15 (27.93%) have the highest level of importance and feature as the fourth, fifth, and sixth most important BDAs within the whole set. These three BDAs are related to the standardization of operations and processes within the IS department. In contrast, C11 (alignment of IS strategy with corporate strategy) and C12 (executive-level authority of IS managers) are the least important BDA capabilities not only in the management capabilities cluster but also within the whole list of 15 BDA capabilities. This finding suggests that the IS department has not yet been acknowledged as a department of primary significance in the organization. This explains the misconception that investment in the establishment and maintenance of IS infrastructure is an expense rather than a long-term investment with larger benefits. Another prevailing misconception is that the function of the IS department is limited to data storage, whereas IS infrastructure is more than just storage, and there is a dire need to explore its full potential.

The lowest rank of HR capabilities corroborates earlier studies emphasizing the need to bridge the talent gap (Accenture and GE 2015; Gartner, , 2016). Within the HR capabilities cluster, C10 (25.51%) and C9 (20.91%) feature by far as the most important BDA capabilities related to the skillset of the IS department for the swift detection and fixing of problems that occur in maintaining operations. On the other hand, C7 (17.91%) and C6 (17.58%) are found to be the least important HR capabilities, suggesting that investment in equipment alone will yield no return for the firms unless HR capabilities are developed. This finding reiterates the importance of the capacity-building of existing employees and hiring educated and trained employees, given the lack of standardized IT/IS education in Pakistan.

Table 16 illustrates the results of the SAW analysis, indicating the total effect of BDA capabilities on firm performance measures. In addition, Table 17 provides a detailed picture of the ranks showing the individual effect of each BDA capability on firm performance measures.

The SAW results in Table 16 show that from the full set of six performance measures, BDA capabilities are linked most with return on sales (21.52%), product development (18.41%), and the number of new products and services projects (17.74%). In contrast, sales growth (14.77%) and market share (11.08%) are the two market-related performance measures that are least related to BDA capabilities. While these findings cast some light on the potential link between BDA capabilities and firm performance measures, BDA capabilities tend to be more closely related to financial and operational performance measures. However, the influence of BDA capabilities on market-related firm performance is somewhat limited. These results, in general, tend to support the findings of earlier empirical studies undertaken in both other emerging and developed countries (Akhtar et al., 2019; Akter et al., 2016; Dubey, Gunasekaran, Childe, Blome, & Papadopoulos, 2019; Mikalef et al. 2019).

The SAW results in Table 17 illustrate that C11 is the most impactful BDA capability in market performance (FP1), whereas the BDA capabilities of C1, C4, C5, C6, C7, C8, C9, C10, C12, C13, and C15 have the least effect on FP1. In terms of sales growth (FP2), the BDA capabilities of C8, C11, and C14 have the most impact, while C4, C5, C6, C9, C12, and C15 have the least impact on sales growth. Regarding product development (FP3), the BDA capabilities of C4, C7, and C9 have the highest effect, while C15 has the least effect on FP3. Likewise, for cost saving (FP4), the BDA capabilities of C6, C10, and C13 have the most impact, with C2 and C4 having the least impact on FP4. As for the number of new products and service projects (F5), C11 is found to be the least impactful BDA capability, while C5, C12, and C15 have the highest impact. Finally, the firm performance measure of return on equity (F6) is affected most by the BDA capabilities of C1, C2, C3, C8, and C14, with C11 having the least impact on FP6.

The extant literature features the moderating effect of data-driven culture and evidence-based decision-making on firm performance. This study applied a different approach and explored that infrastructure capabilities are the most important capabilities amongst other BDA capabilities and are highly related to firm performance, substantiating the findings of previous studies (Akter et al., 2016; Dubey et al., 2019; Mikalef et al. 2019).

The quantitative and qualitative analysis reveals that firms are

**Table 15**
Overall, inter and intra-cluster relative weights.

| | Capability | Overall (%) | Ranking | Within cluster (%) | Cluster weight (%) |
|---|---|---|---|---|---|
| **INFRASTRUCTURE CAPABILITIES** | C1. Our IS infrastructure is strong enough between inter-organizational units. | 13.47 | 1 | 29.31 | **45.96** |
| | C2. Our IS infrastructure is suitable for developing customized software applications when the need arises. | 4.48 | 13 | 9.74 | |
| | C3. Our IS infrastructure can respond quickly to requests from internal and external customers. | 9.65 | 3 | 20.99 | |
| | C4. Our IS infrastructure capacity can handle multiple applications. | 12.66 | 2 | 27.55 | |
| | C5. Our IS infrastructure provides fast and flexible operations for the internet-based system. | 5.71 | 8 | 12.42 | |
| **HR CAPABILITIES** | C6. Our IS staff has adequate knowledge of the computer-based system. | 4.56 | 12 | 17.58 | **25.97** |
| | C7. Our firm seeks a high degree of computer-based technical expertise for the IS department's employees. | 4.65 | 11 | 17.91 | |
| | C8. Our IS staff can implement the right application at the right time. | 4.70 | 10 | 18.09 | |
| | C9. Our IS staff can discover potential problems rapidly in the system. | 5.43 | 9 | 20.91 | |
| | C10. Our IS staff is capable of quickly maintaining the system whenever a failure occurs. | 6.63 | 7 | 25.51 | |
| **MANAGEMENT CAPABILITIES** | C11. Our firm's IS strategy is in line with our corporate strategy. | 0.28 | 15 | 0.99 | **28.07** |
| | C12. Our firm's IS managers have an executive-level authority. | 2.81 | 14 | 10.00 | |
| | C13. Our IS processes are well defined and documented. | 8.69 | 4 | 30.95 | |
| | C14. Our IS department has a clear guideline on how to prioritize service requests from users. | 8.46 | 5 | 30.14 | |
| | C15. Our IS department has a clear guideline on how to use IT resources in our firm. | 7.84 | 6 | 27.93 | |

**Table 16**
Total impact score and ranking for each performance measure.

| | Total impact score | Percentage | Rank |
|---|---|---|---|
| FP1 (Market share) | 0.4176 | 0.1108 | **6** |
| FP2 (Sales growth) | 0.5567 | 0.1477 | **5** |
| FP3 (Product development) | 0.6939 | 0.1841 | **2** |
| FP4 (Cost saving) | 0.6212 | 0.1648 | **4** |
| FP5 (Number of new product and service projects) | 0.6685 | 0.1774 | **3** |
| FP6 (Return on sales - profit/total sales) | 0.8113 | 0.2152 | **1** |

developing BDA capabilities, yet those firms need to prioritize the right combination of BDA capabilities to achieve the goals of better firm performance and competitive advantage.

### 5.1. Managerial implications

This study gives a clear picture to the senior management of how developing BDA capabilities contributes to firm performance and identifies areas where firms need to focus more to maximize the utility of BDA. Like other key emerging markets, Pakistan is driven by the need to develop a technologically advanced business environment. This study highlights and ranks the BDA capabilities of Pakistani firms and their relationships with the firm performance so that top management can devise strategies based on their strengths and weaknesses. The sample firms can increase their operational efficiency by developing an integrated IS and IT system with their stakeholders, as they invest both financially and non-financially to build BDA capabilities, As put forward by CTOs during interviews, the top management of participant firms are showing interest in increasing the investment in IS infrastructure and are also hiring skilled employees to perform jobs that require advanced knowledge and skill set in data analysis. This study paints a picture of an increasing trend in the industry regarding decision-making based on data analysis.

A crucial next step in this stream of research would be to produce a practical guide and toolkit that helps IT/IS managers and practitioners to assess and combine their perspectives in terms of developing superior BDA capabilities. The inventory may contain practical suggestions for building a data-driven culture.

### 5.2. Limitations and future research

While this study contributes to the BDA literature by applying MCDM techniques, it is subject to certain limitations. Our findings should be treated as exploratory, as they are based on a limited number of companies from a single emerging country. Further research can be undertaken with a larger sample set by extending the geographical boundaries. A larger number of participants would obviously lead to more reliable and rigorous interview outcomes. This study relies on the measures of firm performance based on the perception of respondents, which may potentially introduce biases and measurement error. Although it would be promising to make use of the objective measures of firm performance, gaining access to such measures that involve various dimensions of firm performance is a major obstacle. Therefore, further studies should employ a mix of hard and soft measures to obtain a more accurate evaluation of firm performance. While using an integrated MCDM methodology has some apparent merits, other MCDM tools, such as TOPSIS, VIKOR, and Choquet integral, could also be utilized jointly to evaluate the BDA dynamics. Moreover, new research, including more capabilities or examining external factors that influence developing BDA capabilities, is definitely called for.

**Table 17**
Ranking the effect of each capability for firm performance measures.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **FP1** | 6 | 5 | 5 | 6 | 6 | 6 | 6 | 6 | 6 | 6 | **1** | 6 | 6 | 4 | 6 |
| **FP2** | 3 | 4 | 3 | 5 | 5 | 5 | 3 | 2 | 5 | 4 | 2 | 5 | 4 | 2 | 5 |
| **FP3** | 5 | 3 | 2 | **1** | 4 | 2 | **1** | 4 | **1** | 5 | 3 | 4 | 5 | 6 | 2 |
| **FP4** | 4 | 6 | 6 | 4 | 3 | **1** | 2 | 3 | 4 | **1** | 4 | 2 | **1** | 5 | 3 |
| **FP5** | 2 | 2 | 4 | 2 | **1** | 3 | 5 | 5 | 3 | 3 | 6 | **1** | 2 | 3 | **1** |
| **FP6** | **1** | **1** | **1** | 3 | 2 | 4 | 4 | **1** | 2 | 2 | 5 | 3 | 3 | **1** | 4 |

## Appendix 1. . Measurement of scales

**Section 1- Big data analytics capabilities**

**A- Infrastructure capabilities** — Aydiner et al. (2019a, 2019b)

C1 Our IS infrastructure is strong enough between inter-organizational units.
C2 Our IS infrastructure is suitable for developing customized software applications when the need arises.
C3 Our IS infrastructure can respond quickly to requests from internal and external customers.
C4 Our IS infrastructure capacity can handle multiple applications.
C5 Our IS infrastructure provides fast and flexible operations for the internet-based system.

**B- Human resource capabilities** — Ravichandran and Lertwongsatien (2005), Aydiner et al. (2019a, 2019b)

C6 Our IS staff has adequate knowledge of the computer-based system.
C7 Our firm seeks a high degree of computer-based technical expertise for the IS department's employees.
C8 Our IS staff can implement the right application at the right time.
C9 Our IS staff can discover potential problems rapidly in the system.
C10 Our IS staff is capable of quickly maintaining the system whenever a failure occurs.

**C- Management capabilities** — Aydiner et al. (2019a, 2019b)

C11 Our firm's IS strategy is in line with our corporate strategy.
C12 Our firm's IS managers have an executive-level authority.
C13 Our IS processes are well defined and documented.
C14 Our IS department has a clear guideline on how to prioritize service requests from users.
C15 Our IS department has a clear guideline on how to use IT resources in our firm.

**Section 2- Firm performance** — Ravichandran and Lertwongsatien (2005), Aydiner et al. (2019a, 2019b)

FP1 Market share
FP2 Sales growth
FP3 Product development
FP4 Cost-saving
FP5 Number of new product and service projects introduced
FP6 Return on sales (profit/total sales)

## Appendix 2. . Normalized relation matrix

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | −0.076 | −0.076 | 0.0608 | 0.0608 | 0.0608 | −0.076 | 0.0418 | −0.019 | 0.0418 | 0.0038 | −0.076 | −0.076 | 0.0038 | −0.019 | 0.0418 |
| **C2** | −0.076 | −0.076 | 0.0608 | 0.0608 | 0.0608 | 0.0418 | 0.0038 | 0.0608 | −0.076 | −0.076 | −0.019 | −0.076 | −0.076 | −0.076 | −0.019 |
| **C3** | 0.0608 | 0.0038 | −0.076 | −0.019 | −0.076 | 0.0418 | 0.0608 | 0.0608 | 0.0038 | 0.0608 | −0.076 | −0.076 | −0.019 | 0.0038 | −0.019 |
| **C4** | 0.0608 | 0.0038 | 0.0608 | −0.076 | 0.0418 | −0.076 | −0.076 | −0.076 | −0.019 | 0.0038 | −0.076 | −0.076 | 0.0038 | −0.019 | −0.076 |
| **C5** | −0.076 | −0.076 | −0.019 | 0.0038 | −0.076 | 0.0038 | −0.019 | −0.019 | −0.076 | −0.076 | −0.076 | −0.076 | −0.019 | −0.076 | 0.0038 |
| **C6** | −0.076 | −0.076 | 0.0608 | 0.0608 | 0.0608 | −0.076 | −0.076 | 0.0608 | 0.0608 | 0.0608 | −0.076 | −0.076 | 0.0038 | 0.0608 | 0.0608 |
| **C7** | −0.019 | 0.0608 | 0.0608 | 0.0038 | 0.0038 | 0.0608 | −0.076 | 0.0608 | 0.0608 | 0.0608 | −0.019 | −0.076 | 0.0038 | 0.0038 | 0.0418 |
| **C8** | −0.076 | 0.0038 | 0.0608 | 0.0038 | 0.0038 | 0.0608 | 0.0608 | −0.076 | 0.0418 | 0.0608 | −0.076 | −0.076 | −0.019 | −0.019 | 0.0418 |
| **C9** | −0.019 | −0.076 | −0.019 | −0.019 | −0.076 | 0.0608 | 0.0608 | 0.0608 | −0.076 | 0.0608 | −0.076 | −0.076 | 0.0418 | 0.0418 | 0.0608 |
| **C10** | 0.0418 | −0.076 | 0.0418 | −0.019 | −0.076 | 0.0608 | 0.0608 | 0.0608 | 0.0608 | −0.076 | −0.076 | −0.076 | 0.0038 | 0.0418 | 0.0418 |
| **C11** | 0.0608 | 0.04183 | 0.0038 | −0.019 | 0.0608 | 0.0418 | 0.0608 | 0.0038 | −0.019 | 0.0608 | −0.076 | 0.0608 | 0.0418 | 0.0608 | 0.0608 |
| **C12** | 0.0608 | 0.04183 | 0.0608 | 0.0608 | 0.0608 | 0.0418 | 0.0608 | −0.019 | −0.019 | −0.019 | 0.0608 | −0.076 | 0.0038 | 0.0038 | 0.0418 |
| **C13** | −0.076 | −0.019 | 0.0418 | 0.0038 | 0.0418 | −0.076 | −0.076 | −0.019 | 0.0038 | −0.019 | −0.076 | 0.0418 | −0.076 | 0.0608 | 0.0608 |
| **C14** | 0.0038 | −0.019 | −0.019 | −0.019 | −0.019 | −0.019 | −0.076 | 0.0418 | 0.0608 | 0.0608 | 0.0038 | −0.019 | 0.0608 | −0.076 | 0.0608 |
| **C15** | −0.019 | 0.0038 | 0.0608 | 0.0608 | 0.0608 | −0.019 | −0.076 | 0.0418 | 0.0418 | 0.0418 | 0.0038 | 0.0418 | 0.0608 | 0.0608 | −0.076 |

## Appendix 3. . The total relation matrix

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | −0.0669 | −0.0694 | 0.0443 | 0.0424 | 0.0340 | −0.0729 | 0.0322 | −0.0203 | 0.0377 | 0.0039 | −0.0746 | −0.0709 | 0.0058 | −0.0193 | 0.0247 |
| **C2** | −0.0707 | −0.0616 | 0.0461 | 0.0486 | 0.0518 | 0.0383 | −0.0006 | 0.0441 | −0.0785 | −0.0717 | −0.0159 | −0.0709 | −0.0798 | −0.0818 | −0.0396 |
| **C3** | 0.0436 | −0.0067 | −0.0634 | −0.0179 | −0.0795 | 0.04105 | 0.0555 | 0.0666 | 0.0261 | 0.0670 | −0.0811 | −0.0859 | −0.0178 | 0.0073 | −0.0111 |
| **C4** | 0.0596 | −0.0014 | 0.0342 | −0.0786 | 0.0237 | −0.0808 | −0.0609 | −0.0790 | −0.0305 | −0.0177 | −0.0610 | −0.0607 | −0.0070 | −0.0328 | −0.0838 |
| **C5** | −0.0655 | −0.0532 | −0.0319 | −0.0022 | −0.0704 | −0.0076 | −0.0279 | −0.0331 | −0.0755 | −0.0782 | −0.0446 | −0.0420 | −0.0220 | −0.0717 | −0.0172 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C6** | −0.0685 | −0.0824 | 0.0436 | 0.0400 | 0.0267 | −0.0730 | −0.0764 | 0.0559 | 0.0626 | 0.0627 | −0.0831 | −0.0734 | 0.0118 | 0.0591 | 0.0493 |
| **C7** | −0.0312 | 0.0370 | 0.0592 | 0.0018 | −0.0111 | 0.0635 | −0.0724 | 0.0728 | 0.0641 | 0.0664 | −0.0423 | −0.0893 | 0.0022 | 0.0092 | 0.0403 |
| **C8** | −0.0750 | −0.0058 | 0.0536 | −0.0017 | −0.0172 | 0.0642 | 0.0461 | −0.0510 | 0.0494 | 0.0650 | −0.0810 | −0.0834 | −0.0167 | −0.0092 | 0.0346 |
| **C9** | −0.0268 | −0.0744 | −0.0103 | −0.0205 | −0.0795 | 0.0530 | 0.0393 | 0.0670 | −0.0400 | 0.0750 | −0.0782 | −0.0705 | 0.0469 | 0.0554 | 0.0645 |
| **C10** | 0.0277 | −0.0780 | 0.0404 | −0.0200 | −0.0837 | 0.0540 | 0.0475 | 0.0697 | 0.0834 | −0.0413 | −0.0846 | −0.0810 | 0.0141 | 0.0523 | 0.0482 |
| **C11** | 0.0424 | 0.0247 | 0.0197 | −0.0062 | 0.0587 | 0.0375 | 0.0454 | 0.0153 | −0.0065 | 0.0565 | −0.0877 | 0.0343 | 0.0394 | 0.0551 | 0.0660 |
| **C12** | 0.0506 | 0.0317 | 0.0642 | 0.0591 | 0.0620 | 0.0323 | 0.0465 | −0.0126 | −0.0175 | −0.0127 | 0.0341 | −0.0887 | 0.0022 | −0.0002 | 0.0354 |
| **C13** | −0.0595 | −0.0120 | 0.0256 | 0.0004 | 0.0297 | −0.0699 | −0.0720 | −0.0226 | −0.0061 | −0.0256 | −0.0522 | 0.0490 | −0.0682 | 0.0471 | 0.0428 |
| **C14** | −0.0005 | −0.0273 | −0.0150 | −0.0181 | −0.0225 | −0.0179 | −0.0653 | 0.0394 | 0.0600 | 0.0580 | −0.0057 | −0.0116 | 0.0605 | −0.0577 | 0.0614 |
| **C15** | −0.0153 | −0.0071 | 0.0539 | 0.0491 | 0.0453 | −0.0190 | −0.0673 | 0.0345 | 0.0337 | 0.0364 | −0.0130 | 0.0264 | 0.0546 | 0.0528 | −0.0681 |

## Appendix 4. . The unweighted supermatrix

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | 0.000 | 0.000 | 0.000 | 0.478 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.667 | 0.370 | 0.238 | 0.000 | 1.000 | 0.000 |
| **C2** | 0.000 | 000 | 0.000 | 0.256 | 0.000 | 0.000 | 0.286 | 0.000 | 0.000 | 0.000 | 182 | 0.432 | 0.000 | 0.000 | 0.000 |
| **C3** | 0.218 | 0.297 | 0.000 | 0.138 | 0.000 | 0.634 | 0.143 | 1.000 | 0.000 | 0.333 | 0.209 | 0.135 | 0.701 | 0.000 | 0.249 |
| **C4** | 0.630 | 0.540 | 0.000 | 0.000 | 1.000 | 0.192 | 0.571 | 0.000 | 0.000 | 0.000 | 0.133 | 0.085 | 0.193 | 0.000 | 0.594 |
| **C5** | 0.151 | 0.163 | 0.000 | 0.128 | 0.000 | 0.174 | 0.000 | 0.000 | 0.000 | 0.000 | 0.106 | 0.110 | 0.106 | 0.000 | 0.157 |
| **C6** | 0.000 | 0.387 | 0.509 | 0.000 | 0.000 | 0.000 | 0.224 | 0.509 | 0.128 | 0.097 | 0.099 | 0.333 | 0.000 | 0.000 | 0.000 |
| **C7** | 0.493 | 0.443 | 0.139 | 0.000 | 0.000 | 0.000 | 0.000 | 0.267 | 0.256 | 0.105 | 0.101 | 0.667 | 0.000 | 0.000 | 0.000 |
| **C8** | 0.000 | 0.169 | 0.167 | 0.000 | 0.000 | 0.630 | 0.431 | 0.000 | 0.138 | 0.200 | 0.052 | 0.000 | 0.000 | 0.169 | 0.271 |
| **C9** | 0.196 | 0.000 | 0.084 | 0.000 | 0.000 | 0.218 | 0.207 | 0.121 | 0.000 | 0.598 | 0.051 | 0.000 | 0.000 | 0.387 | 0.085 |
| **C10** | 0.311 | 0.000 | 0.101 | 0.000 | 0.000 | 0.151 | 0.138 | 0.103 | 0.478 | 0.000 | 0.697 | 0.000 | 0.000 | 0.443 | 0.644 |
| **C11** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 288 | 0.000 | 0.000 | 0.000 |
| **C12** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.365 | 0.000 | 0.550 | 0.000 | 0.413 |
| **C13** | 0.500 | 0.000 | 0.000 | 0.000 | 0.000 | 0.387 | 0.327 | 0.000 | 0.413 | 0.413 | 0.235 | 0.338 | 0.000 | 0.667 | 0.327 |
| **C14** | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.443 | 0.413 | 0.000 | 0.327 | 0.327 | 0.281 | 0.205 | 0.240 | 0.000 | 0.260 |
| **C15** | 0.500 | 0.000 | 0.000 | 0.000 | 0.000 | 0.169 | 0.260 | 1.000 | 0.260 | 0.260 | 0.120 | 0.169 | 0.210 | 0.333 | 0.000 |

## Appendix 5. . The weighted supermatrix

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | 0.000 | 0.000 | 0.333 | 0.478 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.222 | 0.123 | 0.079 | 0.000 | 0.333 | 0.000 |
| **C2** | 0.000 | 0.000 | 0.000 | 0.256 | 0.000 | 0.000 | 0.095 | 0.000 | 0.000 | 0.000 | 0.061 | 0.144 | 0.000 | 0.000 | 0.000 |
| **C3** | 0.073 | 0.148 | 0.000 | 0.138 | 0.000 | 0.211 | 0.048 | 0.333 | 0.000 | 0.111 | 0.070 | 0.045 | 0.350 | 0.000 | 0.083 |
| **C4** | 0.210 | 0.270 | 0.000 | 0.000 | 1.000 | 0.064 | 0.190 | 0.000 | 0.000 | 0.000 | 0.044 | 0.028 | 0.096 | 0.000 | 0.198 |
| **C5** | 0.050 | 0.082 | 0.000 | 0.128 | 0.000 | 0.058 | 0.000 | 0.000 | 0.000 | 0.000 | 0.035 | 0.037 | 0.053 | 0.000 | 0.052 |
| **C6** | 0.000 | 0.194 | 0.170 | 0.000 | 0.000 | 0.000 | 0.075 | 0.170 | 0.064 | 0.032 | 0.033 | 0.111 | 0.000 | 0.000 | 0.000 |
| **C7** | 0.164 | 0.222 | 0.046 | 0.000 | 0.000 | 0.000 | 0.000 | 0.089 | 0.128 | 0.035 | 0.034 | 0.222 | 0.000 | 0.000 | 0.000 |
| **C8** | 0.000 | 0.085 | 0.056 | 0.000 | 000 | 0.210 | 0.144 | 0.000 | 0.069 | 0.067 | 0.017 | 0.000 | 0.000 | 0.056 | 0.090 |
| **C9** | 0.065 | 0.000 | 0.028 | 0.000 | 0.000 | 0.073 | 0.069 | 0.040 | 0.000 | 0.199 | 0.017 | 0.000 | 0.000 | 0.129 | 0.028 |
| **C10** | 0.104 | 0.000 | 0.034 | 0.000 | 0.000 | 0.050 | 0.046 | 0.034 | 0.239 | 0.000 | 0.232 | 0.000 | 0.000 | 0.148 | 0.215 |
| **C11** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.096 | 0.000 | 0.000 | 0.000 |
| **C12** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.122 | 0.000 | 0.275 | 0.000 | 0.138 |
| **C13** | 0.167 | 0.000 | 0.000 | 0.000 | 0.000 | 0.129 | 0.109 | 0.000 | 0.206 | 0.138 | 0.078 | 0.113 | 0.000 | 0.222 | 0.109 |
| **C14** | 0.000 | 0.000 | 0.333 | 0.000 | 0.000 | 0.148 | 0.138 | 0.000 | 0.164 | 0.109 | 0.094 | 0.068 | 0.120 | 0.000 | 0.087 |
| **C15** | 0.167 | 0.000 | 0.000 | 0.000 | 0.000 | 0.056 | 0.087 | 0.333 | 0.130 | 0.087 | 0.040 | 0.056 | 0.105 | 0.111 | 0.000 |

## Appendix 6. . The limit supermatrix

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **C1** | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 | 0.140 |
| **C2** | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 | 0.043 |
| **C3** | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 | 0.100 |
| **C4** | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 | 0.127 |
| **C5** | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 | 0.040 |
| **C6** | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 |
| **C7** | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 | 0.058 |
| **C8** | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 |
| **C9** | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 | 0.047 |
| **C10** | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 | 0.066 |
| **C11** | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 | 0.003 |
| **C12** | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 | 0.035 |
| **C13** | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 | 0.086 |
| **C14** | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 | 0.083 |
| **C15** | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 | 0.079 |

**Appendix 7. . Average rankings of firm performance measures for BDA capabilities**

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **FP1** | 4.67 | 4.33 | 4.67 | 4.50 | 4.33 | 6.00 | 5.00 | 5.33 | 6.00 | 5.33 | 2.67 | 5.00 | 4.67 | 3.67 | 5.33 |
| **FP2** | 3.33 | 3.67 | 2.67 | 4.00 | 4.33 | 3.67 | 3.33 | 2.33 | 4.00 | 3.67 | 3.00 | 4.67 | 3.67 | 3.33 | 5.33 |
| **FP3** | 4.50 | 3.67 | 2.33 | 1.67 | 3.67 | 2.33 | 2.50 | 4.33 | 2.00 | 3.67 | 3.67 | 4.00 | 4.00 | 4.67 | 2.33 |
| **FP4** | 4.33 | 4.33 | 5.00 | 4.00 | 3.67 | 2.33 | 2.67 | 2.67 | 3.33 | 2.67 | 3.67 | 2.33 | 2.33 | 4.00 | 2.67 |
| **FP5** | 2.83 | 2.67 | 4.33 | 3.17 | 2.33 | 3.00 | 3.83 | 4.67 | 3.00 | 3.00 | 4.33 | 2.00 | 3.00 | 3.50 | 2.00 |
| **FP6** | 1.33 | 2.33 | 2.00 | 3.67 | 2.67 | 3.67 | 3.67 | 1.67 | 2.67 | 2.67 | 3.67 | 3.00 | 3.33 | 1.83 | 3.33 |

**Appendix 8. . Normalized average rankings of firm performance measures for BDA capabilities**

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 | C10 | C11 | C12 | C13 | C14 | C15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **FP1** | 0.29 | 0.54 | 0.43 | 0.37 | 0.54 | 0.39 | 0.50 | 0.31 | 0.33 | 0.50 | 1.00 | 0.40 | 0.50 | 0.50 | 0.38 |
| **FP2** | 0.40 | 0.64 | 0.75 | 0.42 | 0.54 | 0.64 | 0.75 | 0.71 | 0.50 | 0.73 | 0.89 | 0.43 | 0.64 | 0.55 | 0.38 |
| **FP3** | 0.30 | 0.64 | 0.86 | 1.00 | 0.64 | 1.00 | 1.00 | 0.38 | 1.00 | 0.73 | 0.73 | 0.50 | 0.58 | 0.39 | 0.86 |
| **FP4** | 0.31 | 0.54 | 0.40 | 0.42 | 0.64 | 1.00 | 0.94 | 0.63 | 0.60 | 1.00 | 0.73 | 0.86 | 1.00 | 0.46 | 0.75 |
| **FP5** | 0.47 | 0.88 | 0.46 | 0.53 | 1.00 | 0.78 | 0.65 | 0.36 | 0.67 | 0.89 | 0.62 | 1.00 | 0.78 | 0.52 | 1.00 |
| **FP6** | 1.00 | 1.00 | 1.00 | 0.45 | 0.88 | 0.64 | 0.68 | 1.00 | 0.75 | 1.00 | 0.73 | 0.67 | 0.70 | 1.00 | 0.60 |

## Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2020.03.028.

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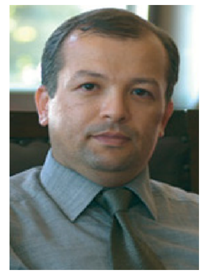

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