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Exploring the Paths to Big Data Analytics Implementation Success in Banking and Financial Service: An Integrated Approach

Abstract

Purpose: Big data analytics (BDA) is recognized as a recent breakthrough technology with potential business impact, however, the roadmap for its successful implementation and the path to exploiting its essential value remains unclear. This study aims to provide a deeper understanding of the enablers facilitating BDA implementation in the banking and financial service sector from the perspective of interdependencies and interrelations.

Design/Methodology/Approach: We use an integrated approach that incorporates Delphi study, interpretive structural modelling (ISM) and fuzzy MICMAC methodology to identify the interactions among enablers that determine the success of BDA implementation. Our integrated approach utilizes experts' domain knowledge and gains a novel insight into the underlying causal relations associated with enablers, linguistic evaluation of the mutual impacts among variables, and incorporating two innovative ways for visualizing the results.

Findings: Our findings highlight the key role of enabling factors, including technical and skilled workforce, financial support, infrastructure readiness, and selecting appropriate big data technologies, that have significant driving impacts on other enablers in a hierarchical model. The results provide reliable, robust and easy to understand insights about the dynamics of BDA implementation in banking and financial service as a whole system while demonstrating potential influences of all interconnected influential factors.

Originality/Value: This study explores the key enablers leading to successful BDA implementation in the banking and financial service sector. More importantly, it reveals the interrelationships of factors by calculating driving and dependence degrees. This exploration provides managers with a clear strategic path toward effective BDA implementation.

Keywords: Big data analytics (BDA); Delphi; Interpretive structural modelling (ISM); Fuzzy MICMAC; Enablers; Banking and financial service.

Exploring the Paths to Big Data Analytics Implementation Success in Banking and Financial Service: An Integrated Approach

1. Introduction

Investment in big data analytics (BDA) has been a crucial managerial decision for the banking and financial service (BFS) sector, not only due to its potential to create business value (Popovič et al. 2018), but considering organizational changes and resource commitments that it might arise (Davenport and Harris 2007). BDA can better be defined by considering key characteristics of big data, besides encompassing elements of tools, infrastructure, and means of visualizing that ultimately generate managerial insights and add value to the decision-making process (Mikalef et al., 2018). According to the IDC institute's report in 2019, BDA investments are estimated to account for $26.3 billion in the BFS sectors. Recently, BFS sectors have started to expand their BDA teams to meet the growing needs. For instance, HSBC is planning to recruit 1,000 data scientists to improve customer experience and risk management with aid of BDA (LexisNexis 2019). The investment in BDA has brought tremendous benefits to BFS firms (Cohen, 2018). JP Morgan Chase, for instance, has detected fraud risk among its customers by monitoring buying patterns and spending behaviours, while American Express offers their customers data-driven promotions (e.g., mobile geo-targeted advertising) by analysing customers' social media data.

Despite the great benefits of BDA for performance and business value (Huang et al. 2020), many BFS firms are still lagging behind in adopting BDA technologies. One of the most common difficulties is that constantly increasing large volumes of data from various sources (e.g., transactions, customer profiles, and behavioural data) challenges BFS firms' data acquisition, processing, and interpretation capabilities (Baesens et al. 2016). Indeed, most of the valuable banking and finance-related data has not been analysed for the sake of strategic implications to inform managerial decisions in service innovation and personalization, value co-creation, and marketing strategies (Hung et al. 2020). Thus, BFS managers require a series of guidance on how their organisational conditions (e.g., business process, strategies, and organisational routines) can best fit BDA implementation (Srinivasan and Swink 2018; Wang et al. 2020).

Prior studies have provided exploratory discussions on the benefits, challenges and socio-economic impact of BDA in the context of banking and financial service (e.g. George et al. 2014; Hung et al. 2020; Kshetri 2016; Srivastava and Gopalkrishnan 2015) and other research concentrates on the technological features and applications of BDA in financial management (e.g. Óskarsdóttir et al. 2019; Pérez-Martín et al. 2018). Using the Delphi study, Kache and Seuring (2017) identify the challenges and opportunities of BDA in the supply chain management context. Similarly, Vidgen et al. (2017) recognize the value and challenges of BDA and conceptually develop an analytics eco-system framework. Although current literature has used the Delphi study to explore the BDA issues, there is no study to reveal what enablers would lead a BFS firm to achieve a successful BDA implementation. More importantly, the studies on BDA enablers factors, based on our knowledge, have not revealed how these factors are interrelated. It is therefore imperative to explore the key enablers leading to successful BDA implementation, considering their *interrelationships* by driving and dependence degrees. This exploration has the potential to provide BFS managers with a clear strategic path toward BDA effective implementation.

Specifically, this study aims to address three research questions (RQ):

RQ1: What are the key enablers of BDA implementation in the BFS context?

RQ2: How are the BDA enablers interrelated based on two criteria of dependence and driving powers?

RQ3: What is the roadmap ensuring BDA implementation success for BFS firms?

Our study fills this important gap in the literature by leveraging an integrated approach of Delphi study, interpretive structural modelling (ISM) and fuzzy Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (MICMAC) methodology to identify BDA enablers and examine interrelationships among these enablers. By BDA enablers in this study, we mean any factors including managerial or organisational, technology associated or data-related ones that enable the company to be successful in implementing BDA initiatives, covering influential factors from pre-adoption steps to implementation phases. Moreover, the interrelationship between BDA enablers referrers to the association between influential factors based on two criteria of dependence and driving powers. Understanding and representing the potential influences between important factors provides fresh insights into successfully implementing BDA in BFS firms. In this vein, our study seeks to progress beyond identifying and proposing a list of verified factors from experts' perspective in terms of exploring the enablers' interdependencies by calculating their driving and dependence powers. To address the research RQ1: a Delphi study is conducted to validate the list of the most important big data analytics enablers (BDAEs) in BFS firms, and to highlight other relevant context-based enablers based on the domain experts' knowledge and expertise. To respond to the RQ2, we developed a model using ISM as a mathematically derived methodology. We also directed Fuzzy MICMAC analysis to quantitatively assess the interdependencies among the enablers and computed the driving and dependent power of each of them. To address RQ3, the modelling process of ISM allows structuring a complex phenomenon through a set of interconnected matrices so that the complicated interrelationships among variables can be identified and quantified (Warfield 1994). Innovatively representing significant interconnectivity between enablers in proposed frameworks provide a deeper understanding for academic and practitioners.

This study offers several important contributions. Primarily, it is among the first research that unravels the paths to a successful BDA implementation using an integrated and structured empirical approach. The findings documented in our study provide empirical support for BFS firms to implement BDA. Second, our study adds value to BDA literature by identifying the key enablers of BDA implementation and exploring the linkages among these enablers to provide a clear pathway of BDA implementation through incorporating Delphi study with interpretive structural modelling (ISM) and fuzzy MICMAC methodology. Finally, we provide practical recommendations to BDA implementation, urging BFS practitioners to take into account these enablers in order to reap more values from BDA implementation. The paper proceeds as follows: the next section presents the big data and its potential impacts on the BFS sector. In section 3, we present the research design. Results and findings are described in section 4. Finally, section 5 and 6 provide the discussion, implications, limitations and future research.

2. Research Background

Big data analytics has been considered as one of the breakthrough technologies that can yield operational and strategic business values for businesses (Constantiou and Kallinikos 2015; Fichman et al. 2014). Adopting BDA enables banking and financial service organizations to meet the expectations of their consumers and even rejuvenate their business models. Since the financial crisis of 2008, BFS firms have been under intensive pressures to act in a manner meeting stakeholders' expectations and applicable laws and regulations. New legislations such as Payments Service Directive and Basel III ask BFS firms to be transparent and provide access to billions of accurate customers' data. On the other hand, new technologies such as BDA, Internet of Things (IoT) and Blockchain have the potentiality to change the market structure. BDA is used with the aim of obtaining various insights about the business and its surrounding environment, and consequently, making better decisions and more effective strategic movements. Various changes resulting from BDA have significantly altered businesses, especially active companies in the field of banking and financial services (Baesens et al. 2016).

Abbasi et al (2016) argue that big data has the potential to change the whole value chain of information in three ways: a) involving different set of people, processes, and technologies, b) greater amalgamation of technologies for analytics and knowledge extraction, and c) relying more on data scientists and analysts to support self-service and real-time decision making. Big data is believed to result in more efficient and effective operations or even can be seen as an empowering agent or stimulus, which enables creating new business models (Davenport et al. 2012; Davenport and Kudyba 2016; McAfee and Brynjolfsson 2012). Due to opportunities created by BDA, many monopolies have disappeared, and traditional frontiers of businesses have removed, and even companies have the chance to enter new industrial contexts (Woerner and Wixom 2015). Consequently, large companies such as Alibaba could enter the financial and banking sector and, by using their big data, are able to provide new services to their customers, without any need to traditional banks (Baesens et al. 2016). Therefore, BFS firms should consider big data as a double-edged sword to make fundamental changes in their business strategies (Bhimani 2015).

Although most studies have demonstrated the benefits of BDA applications, the implementation of BDA projects is complex and costly. Many firms have difficulties to unveil its business value. This is evident in the fact that around 60-85% of BDA projects fail to succeed (Henrion 2019). Particularly in the BFS sector, research on exploring strategic use of BDA is still in its early stages (Hung et al. 2020). Little is known about what the key enablers of BDA implementation are and how they are related. Thus, Liang and Liu's (2018) study has answered the call for more attention to management issues of BDA, including exploring the organisational factors that influence the adoption of BDA.

Prior research has explored the enablers of BDA implementation from the technological, data-related, and organizational perspectives (see left side of Figure 1). However, identifying enablers for implementing BDA is still not sufficient. It is important to explore interrelated, interdependent and holistic sets of BDA enablers that could provide a deeper understanding of BDA implementation (Delone and McLean 1992; Wang et al. 2019). To this end, fruitful BDA initiatives require an integrated model that reveals the interrelationships among various BDAEs and shows their driving and dependence powers. A combination of Delphi method, ISM, and fuzzy MICMAC approaches enabled us to finalize and validate the list of BDAEs in the BFS sector, extract their interdependencies, and visualizing the results (see right side of Figure 1).

Insert Figure 1 here

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3. Research Design

Given the exploratory and holistic nature of this research, we employed an integrated multi-method approach that combines both qualitative and quantitative methods to answer our research questions (Vidgen et al. 2017). Mangan et al. (2004, p. 569) point out that the advantage of utilizing a multi-method approach is to gain the ability to "compensate for the flaws, and leverage the strengths, of the various available methodologies". We selected an integrated Delphi and ISM fuzzy MICMAC approach that helps us build a structural model for a complex problem in a designed pattern. We developed a hierarchical model of variables to describe the phenomenon under the study accurately and systematically rather than considering each variable individually. ISM and fuzzy MICMAC method identify the interdependencies among variables and highlight the impacts they may have on each other through the paths and loops (Bhosale and Kant 2016; Cherrafi et al. 2017; Mishra et al. 2017; Venkatesh et al. 2015). To identify important BDAEs and interrelationships among them, the ISM methodology draws on consensus resulting from a Delphi method. Furthermore, we used fuzzy MICMAC to classify BDAEs based on their driving and dependence powers. The integrated Delphi-ISM-Fuzzy MICMAC approach that we used in our study provides us an appropriate way for exploratory theory building (Akkermans et al. 2003; Melnyk et al. 2009) and enables us to examine key enablers influencing BDA implementation in BFS sectors. An overview of our research process, which addresses three research objectives, is shown in Figure 2. In the first phase, we explored key enablers of BDA in BFS firms through literature review and Delphi study. In the second phase, we developed the conceptual model regarding the relationships of statements extracted from the analysis of structural self-interaction matrices. In the last phase, we built ISM and Fuzzy MICMAC models by utilizing experts' opinions. Our integrated research design allows for alternating between qualitative and quantitative approaches, thereby generating a clear picture of the complexity of BDA implementation. Further elaborations of each research question are presented in the following subsections.

Insert Figure 2 here

3.1 Delphi Study

In the current paper, we used the Delphi method to explore a list of key enablers related to BDA implementation and reach the consensus of panel members about these enablers as well as their contextual interrelationships. The Delphi study is a methodical analysis to gain insights into the most important factors of a complex phenomenon. The method is useful to collect group judgments while avoiding negative effects related to interpersonal biases, strong personalities, defensive attitudes and unproductive disagreements (Linstone and Turoff 2002). Okoli et al. (2010) define an expert as "an individual who has acquired knowledge in big data, gradually through a period of learning and experience" (p. 9). In this study, professionals with more than five years of experience in the field of BDA were recruited to make sure views of qualified experts would be collected (Okoli and Pawlowski 2004). We located our panel of professionals through searching and reviewing professional communities' members on big data in LinkedIn. We approached the project managers and IT specialists who worked for banks and financial institutions with experience in implementing big data in their institutions. Additionally, academic researchers with relevant publications (more than three quality papers published in peer-reviewed journals) have been contacted to participate in this study. Finally, we invited 35 experts fitting our selection criteria, of whom 22 accepted to participate in the first round of the study. However, we only received 20 valid questionnaires, as the other two questionnaires were not completed adequately, resulting in an effective response rate of 57%; no obvious response bias regarding our selection criteria was observed. Profile of respondents is provided in Table 1.

Insert Table 1 here

Data were collected during 6 months in four stages according to Bhosale and Kant (2016): the preparation stage and the three subsequent Delphi steps. During the preparation stage, planning of the study and establishment of the expert panel were performed. In the first round, brainstorming phase according to the approach used by Kasi et al. (2008) and also Wamba and Ngai (2015), the panel experts reviewed and examined important enablers from an initial online list of 23 items derived from literature review. We also asked the panellists to add up new enablers, if they were sufficiently considered significant to improve the success of big data projects, with special attention to the BFS domain. Subsequently, we carefully analysed the selected enablers and open-ended feedback that enabled us to generate a combined list of 27 enablers. Second round focused on narrowing down the list of enablers to a manageable set. In this phase, the experts have presented a randomized list of 27 enablers. The Likert-scale is used as an appropriate evaluation method which allows identifying items that are rated as the most important (von der Gracht 2012). We asked experts to rate enablers on a standard Likert-scale from strongly disagree to strongly agree, and deliver additional commentaries for justifying individual items and their overall opinion. A brief definition for each of the BDA enablers was provided to assure all the experts had the same understanding of each. After consolidating the experts' ratings, we followed Hsu and Sandford (2007) and defined a cut-off value. Finally, we extracted 19 enablers from the list with more than 70% of experts rated them positively (more than neutral) and their mean value greater than neutral (see Table 2). Through the rounds of three and four of Delphi study, the experts' consensus was achieved.

Insert Table 2 here

3.2 Interpretive Structural Modelling

As mentioned above, ISM as a logical mathematically derived methodology represents a complex phenomenon comprising the interrelated variables through a systematic process based on the structural modelling of interconnected matrices (Warfield 1994; Sage 1977). The ISM method is interpretive as it uses experts' judgment to specify the interrelationships among variables related to a complex problem (Sage 1977). One of the advantages of ISM methodology is that it enables transforming the vague and inadequately articulated rational representation of systems into visible and well-structured models. Other various attractive features of ISM, which make it suitable for this study, are:

- ISM provides a visual representation of a complex problem; it relies on knowledge and practical experience of experts to breakdown a complicated system into several segments and to construct an easily understandable model (Dwivedi et al. 2017).
- Applying ISM, an interactive learning process is enabled to structure variables of a complex to represent the contextual relationships among identified variables (Shukla and Mattar 2019).
- It has been increasingly used by researchers and pioneer organizations from diversified fields for finding solutions of complex issues or complicated problems (Mani et al. 2016).

- It requires a small group of experts to effectively identify the variables and analyse transitive interactions and relationships among them (Sindhu et al. 2016).

3.3 Fuzzy MICMAC

Duperrin and Godet (1973) introduced Matrice d'Impacts Croisés Multiplication Appliquée á un Classement (MICMAC) to systematically analyse the cross-impacts of variables in complex problems. We imported the result of ISM as an input into fuzzy MICMAC to identify the driving and dependence powers (Sharma and Gupta 1995) of BDAEs in the BFS sector. While the ordinary type of MICMAC analysis only considers binary relationships, fuzzy MICMAC more accurately differentiates the factors regarding their driving and dependence powers. We conducted the following steps to MICMAC analyze the BDAEs:

Step 1: Developing a binary direct relationship matrix

Step 2: Building linguistic assessment direct reachability matrix

Step 3: Shaping the fuzzy MICMAC-stabilized matrix

4. Results and Findings

In what follows, we discuss the logic of the ISM process in more detail. The result of each step is fully described and illustrated by their relevant outputs.

4.1 Identifying the Variables

The ISM process initiates by identifying the list of important components of a complex problem. As we noted before, the list of influential enablers was extracted and selected by conducting literature review and Delphi method. Reviewing prior work indicates 23 key enablers which resemble a summarized and synthesized form of important factors from relevant case studies, taxonomy orientated studies and wider research on the underlying successfully implementing big data projects. Through Delphi study, experts eliminated some BDAEs, which were similar in meaning or less valid in the BFS context. Moreover, expert panels suggested 4 new items due to their importance in BFS firms. Ultimately, our panelists selected 19 key BDAEs as important factors for implementing big data projects successfully. The justifications of BDAEs selection are summarized in Table 3.

Insert Table 3 here

4.2 Establishing the Contextual Relationship

In the ISM process, panel experts also determine and validate the contextual relationships among the variables. To this aim, seven members of the Delphi panel agreed to examine the associations between pairs of variables. These experts received a list of final BDAEs in a random-order and were asked to specify all pairwise relationships between them in an empty structural self-interaction matrix sheet. The results were then discussed with the experts, and contextual relationships were confirmed, reflecting the experts' agreement based on their judgement. The pairwise comparison of BDAEs is reflected in the structural self-interaction matrix (SSIM) in Table 4.

To configure the SSIM, the experts analyzed the interrelationships between the enablers. The logic of relations between the enablers are described in row (i) and column (j), by representing the following symbols: V, A, X and O:

V: enabler *i* will help achieve enabler *j*;

A: enabler *j* will be influenced or achieved by enabler *i*;

X: enablers *i* and *j* will support achieving each other; and

O: enablers *i* and *j* are not related.

Insert Table 4 here

4.3 Establishing the Contextual Relationship

According to SSIM results, we then developed the initial and final reachability matrices. The initial reachability matrix (IRM) is developed by converting the values of SSIM (i.e. V, A, X, O) into the binary format (i.e. 0, 1) as per the following rules (please see Table 5).

- When the (i, j) entry is V, then the (i, j) entry becomes 1 and the (j, i) entry becomes 0.
- When the (i, j) entry is A, then the (i, j) entry converts to 0 and the (j, i) entry is 1.
- When the (i, j) entry is X, then the (i, j) entry becomes 1 and the (j, i) entry also becomes 1.
- When the (i, j) entry is O, then the (i, j) entry becomes 0 and the (j, i) entry also becomes 0.

Insert Table 5 here

To develop the final reachability matrix (FRM), we need to identify transitive relationships, wherein established relation between the first and second variable, and between second and third variable could indicate the relation between first and third variables. If variable A is related to variable B (A→B) and variable B is related to variable C (B→C), then a transitive relationship exists between variables A and C (A→C)· Equation (1) indicates the transitivity process to develop the FRM from the IRM:

$$\text{If } (T_{ik} = 1) \wedge (T_{kj} = 1) \wedge (T_{ij} = 0), \text{ then } (T_{ij} = 1^*) \quad (1)$$

Where $k \neq i$ & $k \neq j$, T is IRM, i and j represent the rows and columns respectively, and k represents the (i, j) cell reference in the transitivity operation. Table 6 depicts the final reachability matrix.

Insert Table 6 here

4.4 Level Partitioning of the Reachability Matrix

After completing the FRM, we set the level partitions to define the hierarchy of variables. In the next step, FRM is assessed according to the antecedent and reachability sets for each of the identified enablers in the matrix (Warfield 1994). The reachability set is made up of the enabler itself and the other enablers, which it influences or helps to realize. The antecedent set is formed of the enabler itself with the other variables, which influence or help to achieve it. After setting the reachability and antecedent sets for each of the enablers, we specified the intersections of these two sets. Level I comprises those elements for which the reachability and intersection sets are identical. The top-level comprises the enablers: (9) *embedding big data in business processes,* (11) *appropriate organizational structures,* (14) *clear and justifiable business case,* (16) *big data analytics strategic alignment*, which exhibit high levels of dependency (Table 7). To recognize the next levels, this procedure is iterated, but for each iteration, the previously identified mutual variables are eliminated. The remaining intersection and reachability set at the second level are outlined under iteration II in Table 7: (3) *top management support*, (5) *data integrity*, (19) *empowering end-users.* Level III variables are (1) *big data governance*, (2) *creating data-driven culture*, (7) *big data security*, (10) *managing legacy systems dependency*, which are presented under iteration III in Table 7.

Enablers positioned in next level (iteration IV) are (6) *big data privacy*, (15) *scalability*, (17) *fault tolerance and reliability of big data technologies*, (18) *big data customization* *capability.* The lowest level of the model presented level V enablers (iteration V in Table 7) have the highest effects on the other enablers. In the last iteration (4) *technical and skilled workforce*, (8) *financial support*, (12) *infrastructure readiness*, and (13) *selecting appropriate big data technologies* enablers are identified.

Insert Table 7 here

4.5 Building the ISM Model

Developing the structural digraph or model is the final step in the ISM methodology. Figure 3, as a final ISM model, displays the representation of the BDAEs and their interrelationships based on the FRM (Table 6) and level partitioning of the reachability matrix (Table 7). The ISM model has five different levels, the highest level consists of four enablers: (9) *Embedding big data in business processes,* (11) *Appropriate organizational structures,* (14) *Clear and justifiable business case,* (16) *Big data analytics strategic alignment*. This level includes the enablers with the highest rank of dependency power but lower levels of driving power thus, they are considerably dependent on the enablers in the lower levels. The next level of the model represents (3) *Top management support*, (5) *Data integrity*, (19) *Empowering end-users,* which similarly have high dependence power but more driving power than the enablers do in the previous level. The next subsequent levels depict (1) *Big data governance*, (2) *Creating data-driven culture*, (7) *Big data security*, (10) *Managing legacy systems dependency* in level three, and (6) *Big data privacy*, (15) *Scalability,* (17) *Fault tolerance and reliability of big data technologies,* (18) *Big data customization capability*. These enablers have strong influential linkages to the level above, and impact enablers in below level. The final layer in the model represents the key enablers: (4) *Technical and skilled workforce*, (8) *Financial support*, (12) *Infrastructure readiness* and (13) *Selecting appropriate big data technologies*. These lowest-level enablers have the strongest driving power and therefore, influence over other linked factors in our model.

Insert Figure 3 here

4.6 Fuzzy MICMAC Analysis

Duperrin and Godet (1973) developed the MICMAC method to analyse the structure of complex systems. MICMAC analysis visualizes the variables of a complex system based on their dependence and driving power (Sharma and Gupta 1995). MICMAC analysis computes the driving and dependence power of each system variable by summing up across both horizontal and vertical axis. In binary MICMAC analysis, the sum of all 1s in the row provides the driving power of that variable, whereas the sum of 1s in the column specifies its dependence power. To increase the sensitivity and accuracy of the results, in this study, we used fuzzy MICMAC analysis to consider not only the existence of the relationships among the variables but also computing the strength of the relationships.

Exploring the key determinants of a complex system can best be accomplished by identifying the direct and indirect influences of the variables, characterizing the phenomenon under study (Saxena et al. 1992). Binary Matrix of Direct Influence (BMDI), in conventional MICMAC, is developed by converting the diagonal entries of IRM to zero. Every cell of BMDI indicates to what extent a variable directly influences the other variables. In fuzzy MICMAC, typically the triangular fuzzy linguistic terms are used to address the uncertainty resulting from the probable inaccuracy and ambiguity due to the human language and judgement. Thereby, we applied this fuzzy function to calculate the strength of contextual relationships among model variables based on our expert opinions. This function is defined by a triplet of an upper limit *r,* a lower limit *l*, and a value of m, where $l < m < r$. The membership function of triangular fuzzy number is defined by equation 2:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-l}{m-l} & l \leq x \leq m \\ \frac{r-x}{r-m} & m \leq x \leq r \\ 0 & otherwise \end{cases} \qquad (2)$$

Table 8 presents the triangular fuzzy linguistic scale for the evaluation of alternatives. The fuzzy MICMAC can analyse the experts' judgements about the interrelationships by qualitative consideration on linguistic variables, which are linked to the triangular fuzzy numbers.

Insert Table 8 here

We asked the same experts to rate the relationships between the BDAEs and used the linguistic terms in Table 8 to evaluate the influence of BDAEs on each other (Herrera et al. 2009). Then, we superimposed the values on the BMDI to obtain a linguistic assessment direct relationship matrix. In the next step, the matrix is multiplied repeatedly until the ranking of the dependence and driving power stabilized (Qureshi et al. 2008). This fuzzy multiplication is used to examine the indirect dependence and driving power of the variables, which are caused by the transmission of the dependences/influences through some other intermediate variables (Saxena et al. 1992). This operation allows us to find the BDAEs that may not possess strong dependence or driving power, but are significant elements for the system as a whole phenomenon (Villacorta et al. 2014). We followed the multiplication process based on the principle of fuzzy matrix multiplication in equation 3 (Kandasamy 2007) where $A = a_{in}$ and $B = b_{nj}$.

$$C = A.B = \max n\left[min\left(a_{in}, b_{nj}\right) \right] \quad (3)$$

The stabilized fuzzy MICMAC matrix for BDAEs in the BFS sector are presented in Table 9. Similar to binary MICMAC, adding the values in each row calculates the driving powers in fuzzy MICMAC and the dependence powers are computed by summing the values in each column. The MICMAC diagram in Figure 4 shows the driving and the dependency powers of BDAEs and classifies them in four quadrants as follows:

- *Autonomous*: variables with weak driving and weak dependence power, which are relatively disconnected from the other variables and thus have a low impact on the system.
- *Linkage*: variables with high dependency and high driving power, causing volatility in the system as any action on these variables affect other variables and themselves.
- *Dependent:* variables with high dependence power but weak driving power, affected by other factors but have no effects on the others.
- *Independent:* variables with weak dependency power but strong driving power, which are often termed as key variables.

Insert Figure 4 here

Insert Table 9 here

The fuzzy MICMAC analysis in Figure 4 illustrates that the majority of BDAEs are located within the independent and dependent quadrants. This means that some variables have strong impacts on several dependent factors and changes in these key enablers can largely affect the big data implementations. The key driving BDAEs such as (4) *technical and skilled workforce*, (6) *big data privacy*, (8) *financial support*, (12) *infrastructure readiness*, (13) *selecting appropriate big data technologies,* (15) *scalability,* (17) *fault tolerance and reliability of big data technologies,* and (18) *big data customization capability* are located in the independent quadrant. These factors have the maximum effects on other big data enablers in BFS firms, thus they should be cautiously managed. BDAEs in the independent quadrant are significant elements in big data implementation projects, they are also placed at the root of the ISM model.

Dependent quadrant has the most enablers. Eight enablers fell in this quadrant: (5) *Data integrity*, (7) *Big data security,* (9) *Embedding big data in business processes,* (11) *Appropriate organizational structures,* (14) *Clear and justifiable business case,* (16) *Big data analytics strategic alignment, and* (19) *Empowering end-users.* In the MICMAC diagram, none of the variables is positioned within the Autonomous quadrant. The absence of BDAEs in this indicates that all considered enablers have significant relationships. Four enablers are positioned in the Linkage area, underlining their unstable nature due to strong driving and dependency powers. Any change about the enablers in this quadrant would have a corresponding influence on other variables and feedback on themselves. These highly intercorrelated enablers are (1) *Big data governance*, (2) *Creating data-driven culture,* (3) *Top management support,* and (10) *Managing legacy systems dependency.*

5. Discussion

This paper aims to develop a robust model to identify the contributory enablers of big data implementation in the BFS sector. The ISM and fuzzy MICMAC analysis specify and quantify interrelationships among 19 BDAEs that we identified and validated them through literature review and Delphi study. The structural model resulted from ISM visually highlights the potential influences and dependencies of the enablers. The digraph model and MICMAC analysis show that in the first level, technical and skilled workforce, financial support, infrastructure readiness, and selecting appropriate big data technologies are the key enablers and have the maximum driving power in implementing big data projects in the BFS firms. This finding notes that the availability of appropriate resources (financial, technical human resources, and technologies) is crucial for big data projects, thereby BFS firms must ensure about the availability of required resources before initiating the BDA project. The literature has also underlined the links between big data project success and the presence of these key enablers (Janssen et al. 2017; Phillips-Wren and Hoskisson, 2015; Jharkharia and Shankar, 2005; Sun et al. 2014; Shukla and Mattar, 2019; Vidgen et al. 2017). Our study extends this line of research by criticality linking these separate enablers and their joint potential influence within the model. The BFS firms need to procure required technological, financial and human resources and use these core enablers effectively to obtain the fruitful outcomes.

The other key enablers, at the next level in the digraph, are big data privacy, scalability, reliability and big data customization capability. Managers, especially in the financial sector, have great concerns about privacy issues and are worried about the legal and ethical implications of collecting and unauthorized use of customers' data. Furthermore, the non-functional features of big data technologies and the ability to change the functions and its analytical capabilities regarding the end-users' requirements are significant elements in big data projects. The dependency of these BDAEs on the other enablers at the lower level signals that BFS firms need to use technical specialists and possess the other resources to manage the required features and address the privacy concerns.

Big data governance, creating data-driven culture, top management support, and managing dependency on legacy systems have high instability, thus managers should be very cautious about them. This characteristic means that if a big data project has any problems with one or more of these enablers, because of their large number of connections, further consequences might happen and the whole project can be affected. Most of the financial service providers have invested millions of dollars in their current systems and infrastructures and rely on them in performing their daily and critical operations. Consequently, managers are faced with the challenge of changing and integrating these legacy systems with big data technologies, while considering huge amounts of investments already made in their infrastructures. Additionally, healthy data-driven culture, effective big data governance, and support of top management have constructive influence on other enablers and even have positive feedback on themselves.

Data integrity, empowering end-users, embedding big data in business processes, appropriate organizational structures, clear and justifiable business case, and BDA strategic alignment are at the upper-middle and top levels with high dependency power. This finding shows that these enablers can be affected by the lower-level elements. BSF firms need to consider this result, such that success in each of factors in upper-middle and top levels is largely dependent on many other interconnected factors.

6. Conclusion

6.1. Theoretical Contributions

By using an exploratory integrated approach, this study seeks to enhance the knowledge of BDA enablers by analysing the interrelationships and influences they have on each other. To develop a valid and consistent theoretical foundation, our study identifies BDAEs and their contextualized interrelationships that are important in real-world big data practices, particularly in BFS context. The multi-method approach enabled us to advance our insight into the contextual interdependencies among BDAEs and their impacts on the successful big data project implementation.

We initially conducted the literature review and Delphi study to identify and finalize 19 BDAEs. Afterwards, we used the ISM and fuzzy MICMAC analysis to build a theoretical framework to assist us in understanding the interrelationships among these enablers. We employed the ISM methodology to develop a map for representing the complex interrelationships and the hierarchical structure of BDAEs.

This study contributes to the current knowledge of big data by moving beyond identifying and proposing a list of verified factors from expert perspective. In customising influential factors for BSF sector, our study revealed that 'strategic alignment', 'fault tolerance and reliability of big data technologies', 'big data customization capability' and 'empowering the end-users' are also amongst enables that determine initiatives success. It further explores the enablers' interdependencies by calculating their driving and dependence powers. Hence, our findings underline the BDAEs co-dependence and significant effects that they have on each other. The ISM hierarchical model highlights that technical and skilled workforce, financial support, infrastructure readiness, and selecting appropriate big data technologies are at the root level thus, they can be considered as the most critical BDAEs with significant driving power and effective in the success of other enablers. On the flip side, the position of the embedding big data in business processes, appropriate organizational structures, clear and justifiable business case, BDA strategic alignment enablers at the top of the ISM hierarchy implies their high dependency power. This finding indicates that it is important BSF firms closely manage the interconnected elements lower in the model to increase the likelihood of big data project success.

Further, we imported the results of the ISM as an input to the fuzzy MICMAC analysis to identify the driving power and dependence of BDAEs. The results revealed the high driving and dependency power of big data governance, creating data-driven culture, top management support, and managing dependency on legacy systems. These enablers are highly unstable and mere modifications in these enablers strongly affect other enablers and have a consolidated effect on big data projects performance. Therefore, our study suggests that the enabler position from viewpoint of effect on each other are different and factors with more driving power needs more attention in BDA projects and initiatives.

6.2. Practical implications

The findings of the current study advise that executing and running a big data project is a complex issue. Notably, it depends on the firms' ability to simultaneously harness critical capabilities and resources (skilled workers, financial resources, technology features, and readiness) within a business context (data-driven culture, top management support, privacy and security, organizational structures), including the data features (data governance and integrity), and deploy these synergistically (big data alignment and embedding in business process) to smooth the big data implementation process. Moreover, our results suggests that although different enablers discussed in this study are influential in successful implantation of BDA in BFS, the factors with more driving powers presented at lower level of Figure 3 and independent enablers in cluster IV of Figure 4 need more strategic attention. These factors with higher influence power or as independent enablers will drive other relevant factors that holistically would predict the success of BDA in a banking or financial service company. Thus, managers are expected to ensure if their company is financially and technically ready to step forward. More specifically, our findings provide BFS managers with clear strategic guidance and the pathway on how to implement BDA effectively. The structural model developed in this study shows a more realistic representation of the main enablers of big data projects. The prioritized contributory BDAEs provide useful empirical insights for managers and practitioners to realize the overall structure and importance of factors driving big data projects. The identified hierarchy and interdependencies of the BDAEs enable managers to understand a) key variables with high influence on other elements, b) highly sensitive factors with higher dependence and driving power, which both groups require continued attention for the successful implementation of BDA projects.

Furthermore, the results pinpoint critical factors with high driving power for big data projects, thereby, managers and practitioners need to pay particular attention to these key enablers. Moreover, the high driving and dependency power of some BDAEs like top management support, managing dependency on legacy systems indicates their unstable nature and provides useful guidance to managers, when embarking upon their big data transformational journey. Further, the prioritized contributory BDA enablers provide useful evidence for managers and practitioners to realize the overall structure and importance of factors driving big data projects. The identified hierarchy and mutual relationships of the BDAEs will help managers to understand a) key variables with high influence on other elements, b) highly sensitive factors with higher dependence and driving power, which both groups require continued attention for the successful implementation of BDA projects.

6.3. Limitations and Directions for Future Research

Although this study enhances understanding of the main BDAEs and their relative significance, the results of this study should be interpreted in light of its limitations. First, current paper findings are based on the participation of 20 professionals, and suffer from the subjective nature of experts' opinion and may not be generalizable to other contexts. However, the rich data resulting from our literature review in combination with the Delphi study provide an initial starting point for future research. Second, this study is designed and implemented based on the academics and experts judgement with experience in BFS sector, while future studies can analyse final users' viewpoints, external stakeholders especially customers, and regulation bodies concerns and experiences. Third, the resulting model has not been statistically validated and in the future research Structural Equation Modelling (SEM) can be applied for this purpose. Quantification of the BDAEs and their interrelationships by carefully adopting system dynamics, fuzzy analytical hierarchy process (FAHP) or fuzzy analytical process (FANP) are also recommended. Researchers also can take advantage of simulation approaches and use dynamic models or agent-based modelling for understanding the interactions and assessing important effects. This study focuses on the enablers of BDA in BFS and future studies can identify influential factors in other data-driven industries and compare the results. Finally, we examined all enablers and their interrelations regardless of a BDA project lifecycle, so a separate future study can determine which enabler would play an essential role in any of the project phases from pre-adoption to post-implantation and use.

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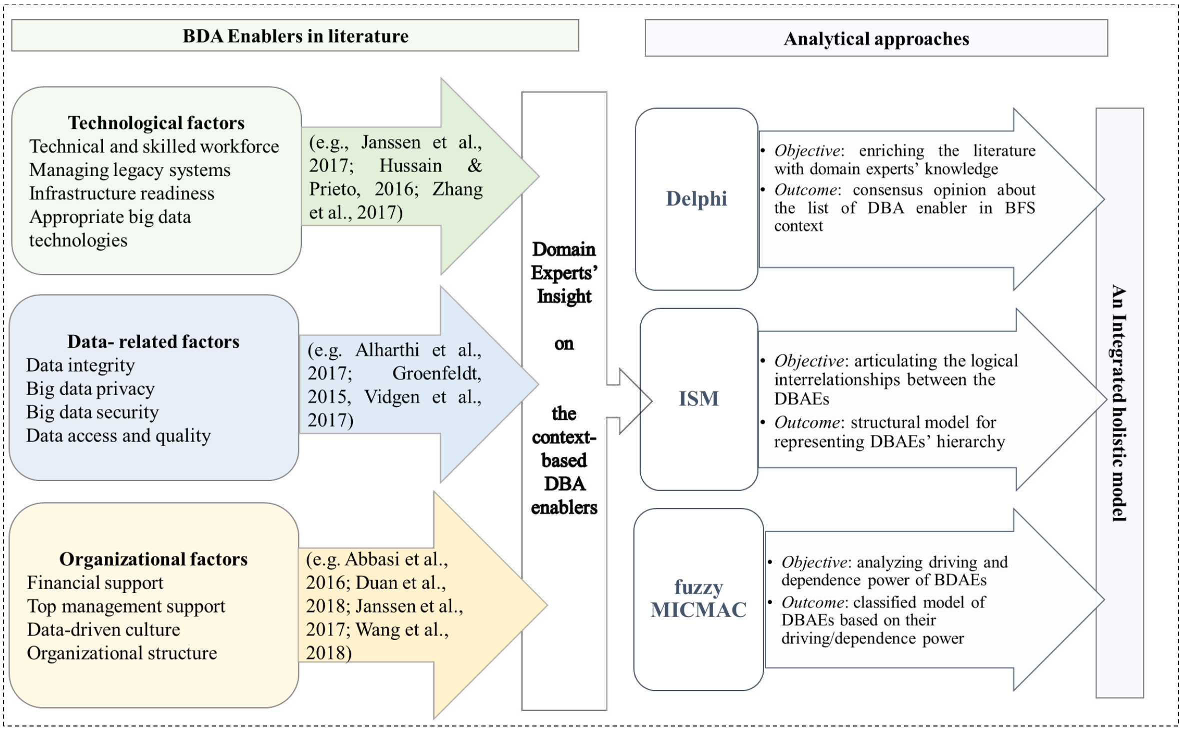

Figure 1. Literature review on BDA enablers (left side) and the development of an integrated model in this study (right side)

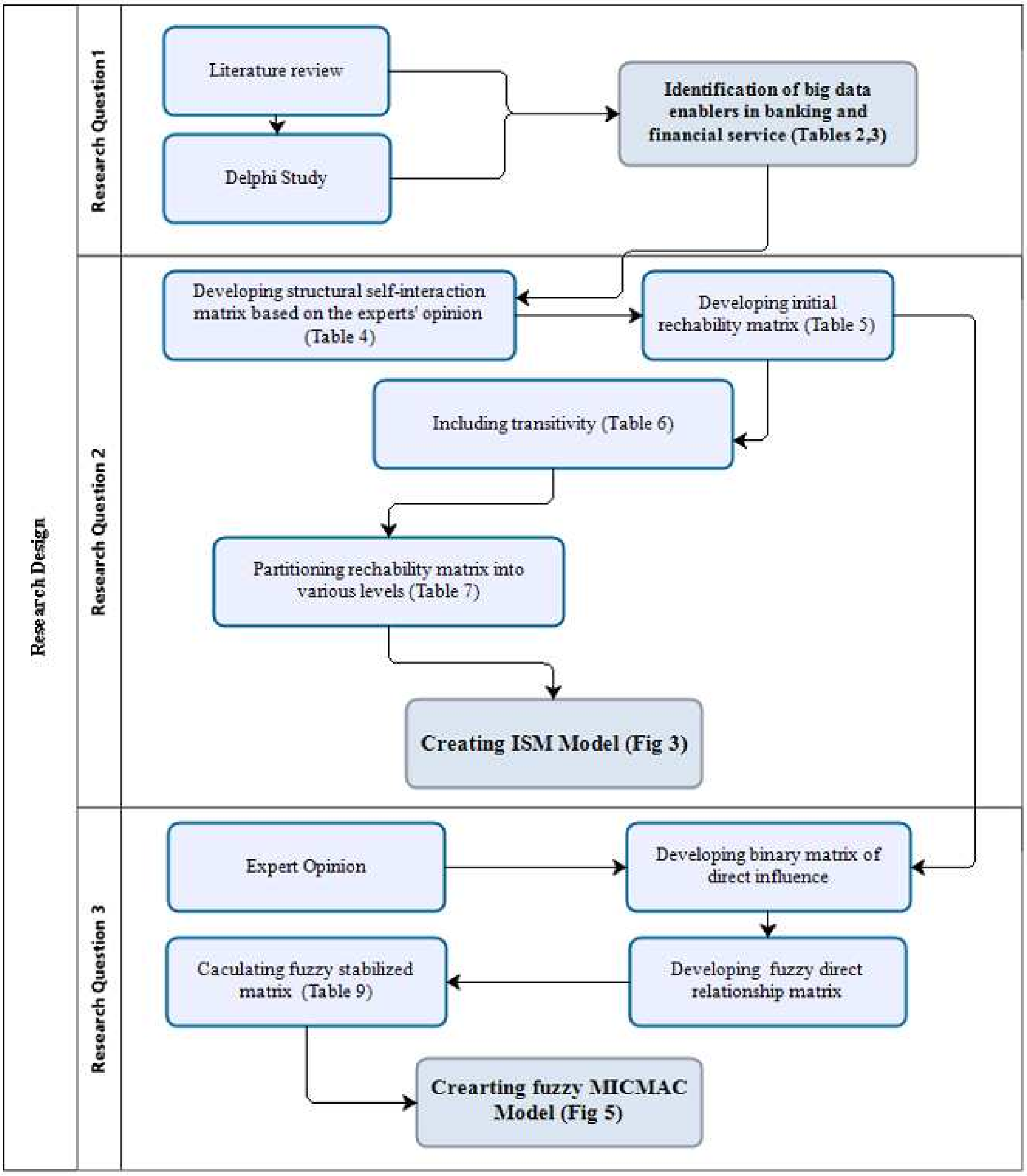

Figure 2. Research design

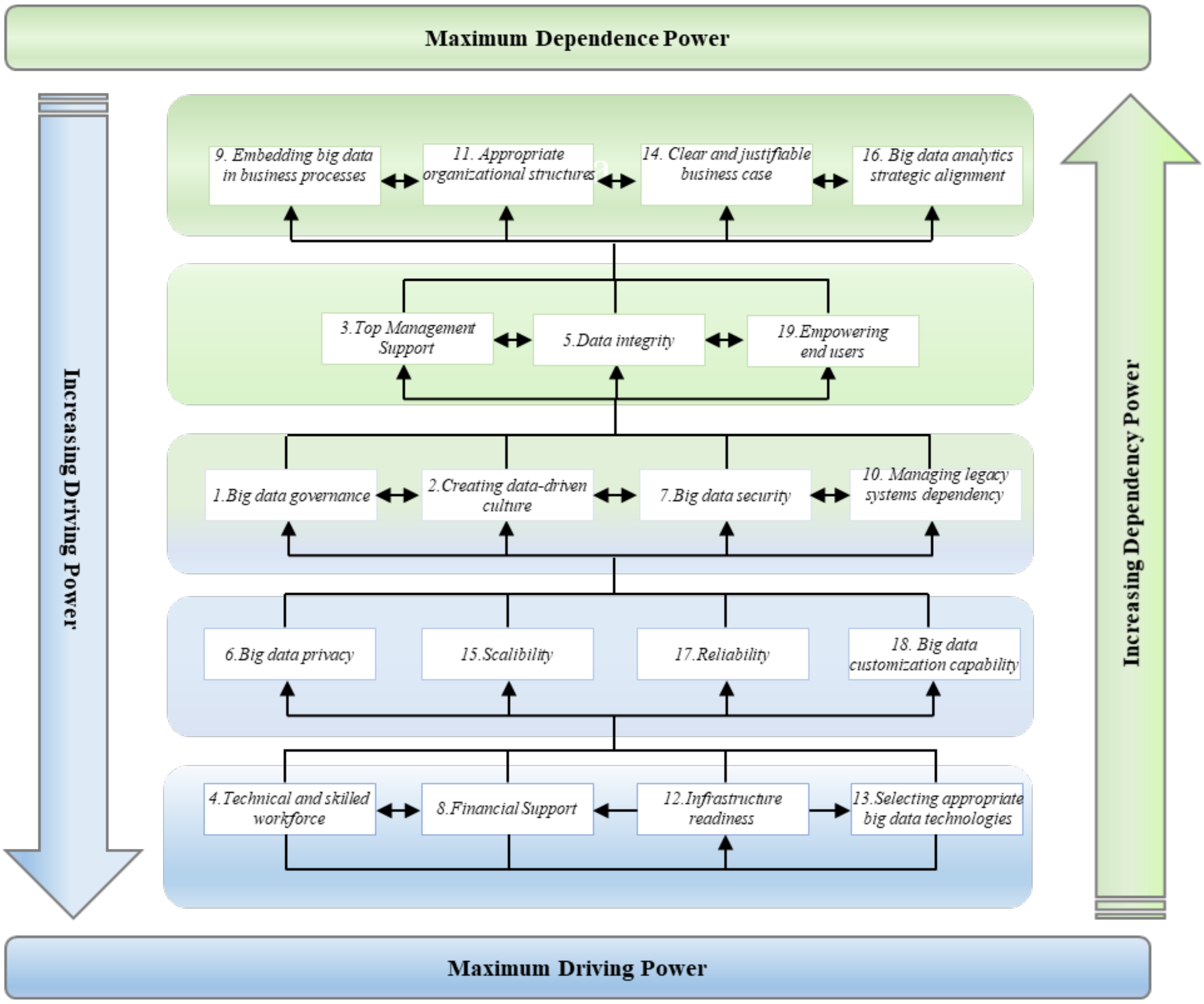

Figure 3. ISM model of BDA Enablers

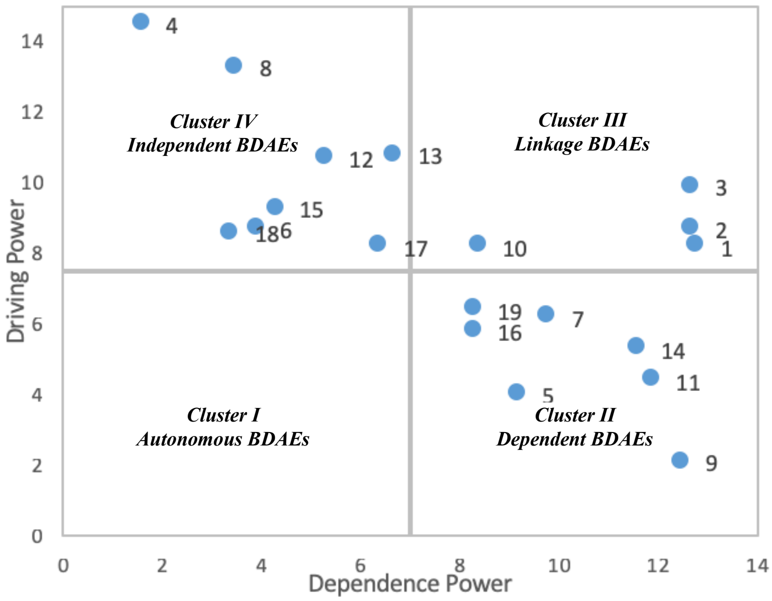

Figure 4. MICMAC diagram

Table 1. Profile of respondents

	Professional (14)	Academic (6)
Age	*n* (%)	*n* (%)
30-40	3 (15%)	4 (20%)
40-50	6 (30%)	2 (10%)
50-60	4 (20%)	
More than 60	1 (5%)	
Gender		
Female	3 (15%)	2 (10%)
Male	11 (55%)	4 (20%)
Related experience		
5-10 year	2 (10%)	1 (5%)
10-15 year	7 (35%)	4 (20%)
More than 15 year	5 (25%)	1 (5%)
Academic qualification		
Doctorate	1 (5%)	6 (30%)
Master's degree	11 (55%)	
Bachelor degree	2 (10%)	

Table 2. Primary perspectives about enablers for BDA implementation in BFS

Item	Score							Mean
	1	2	3	4	5	6	7	
Data integrity	0	0	0	0	3	4	13	6.5
Technical and skilled workforce	0	0	0	0	4	4	12	6.4
Big data privacy	0	0	0	1	3	6	10	6.25
Big data security	0	0	0	0	3	9	8	6.25
Financial support	0	0	1	0	2	8	9	6.2
Top management support	0	0	1	1	4	6	8	5.95
Data-driven culture	1	0	1	2	3	4	9	5.7
Appropriate organizational structures	0	1	1	2	4	5	7	5.6
Managing legacy systems dependency	0	1	2	2	3	4	8	5.55
Infrastructure readiness	0	1	2	1	4	5	7	5.55
Embedding big data in business processes	0	1	2	2	4	5	6	5.4
Selecting appropriate big data technologies	0	0	2	2	7	4	5	5.4
Big data governance	0	1	1	2	6	7	3	5.3
Clear and justifiable business case	0	0	2	3	7	5	3	5.2
Scalability	1	1	1	2	4	7	4	5.2
Big data customization capability	0	0	1	4	8	5	2	5.15
Fault tolerance and reliability of big data technologies	0	1	2	2	6	7	2	5.1
Big data analytics strategic alignment	0	2	3	1	4	7	3	5
Empowering the end-users	1	0	2	2	7	5	3	5.05
Handling data heterogeneity	1	1	2	3	9	3	1	4.55
Data access	0	2	2	4	8	3	1	4.55
Big data timeliness	1	1	3	5	8	2	0	4.2
Existence of enough storage	1	2	4	4	7	2	0	4
Legal and regulatory support	1	3	4	5	4	2	1	3.9
Data quality	2	2	3	8	4	0	1	3.7
Integrating current infrastructure with big data technologies	2	3	2	7	5	1	0	3.65
Sharing of operational/strategic data between different units	2	3	4	8	2	1	0	3.4

BDAEs	Justifications provided by panel	Studies that supports the experts' view
Big data governance	● Big data governance could be a potential approach for enhancing data quality, maintaining data value and achieving insights in business decisions. ● Big data governance practices could leverage enterprise-wide and external data resources for creating business insights to overcome market competition. ● The proper data governance enables firms to tackle the avalanche of heterogeneous data, information, and knowledge from a complex array of internal and external resources ● A strong governance protocol provides clear guidelines for big data availability, criticality, authenticity, sharing and retention enabling BFS firms to harness big data effectively from the time it is acquired, stored, analysed, and finally used.	Abbasi et al. (2016); Hashem et al. (2015); Kache and Seuring (2017); Otto (2011); Wang et al. (2018)
Data-driven culture	● Successfully implementing big data initiatives requires radical changes to organizational mindset and culture in order to leverage capabilities and gain the most of big data capabilities ● Establishing data curiosity and data-driven thinking is vital in today's businesses ● A data-driven culture constitutes patterns of behaviour, practices, and beliefs that are consistent with the principles of analytical decision-making.	Davenport (2014); Duan et al. (2020); Dutta and Bose, (2015); Gillon et al. (2014); Holsapple et al. (2014); McAfee and Brynjolfsson (2012); Wedel and Kannan (2016)
Top management support	● The success of big data analytics needs management teams with clear visions and aims. ● Big data initiatives require top management to provide continued support. ● Top management team needs to be involved in laying out the big data strategy.	Lamba and Singh (2018); McAfee and Brynjolfsson (2012)
Technical and skilled workforce	● The lack of knowledgeable technical workforce is leading to a huge shortage in the big data talent market ● It is crucial to get experts on board with knowledge of analysing big data and gaining insight from it, but such experts who can also effectively communicate with business persons are scarce ● The adequacy of the firm's skilled human resources for various tasks is determinant in big data initiatives ● Data scientists are expected to not only understand IT and sophisticated analytics, also be capable of successfully collaborating with decision-makers	Janssen et al. (2017); Keeso (2014); Richey et al. (2016); Sun et al. (2018)
Data integrity	● Information systems in BFS firms are often fragmented and isolated in separated silos, which hinders the aggregation of big data. ● BFS firms often experience "tower of Babel" in which systems are extremely isolated from each other	Vidgen et al. (2017)
Big data privacy	● Analysing customer data invariably raises privacy issues related to data ownership and the extent to which BFS firms are allowed to use this big data ● BDA could potentially disclose sensitive personal data, as it uncovers the hidden connections between apparently disparate pieces of data	Chintamaneni (2016); Jain et al. (2016)
Big data security concerns	● Data security requires highly efficient methods and algorithms to deal with huge volumes of data ● Inappropriate disclosure, unauthorized access, disruption, inspection, modification, recording, and destruction would damage the BFS firms' reputation and legitimacy	Abbasi et al. (2016); Siddiqa et al. (2016)
Financial support	● Due to the immense cost of big data sets' storing and analysing, and shortage of skilled workforce, companies have difficulties to allocate the required budget for attaining big data technologies. ● Many big data initiatives have been barricaded by the high cost of erecting infrastructure to support the daily collection, storage, and analysis of potentially hundreds of millions of data points	Wang et al. (2018)
Embedding big data in business processes	● Big data initiatives require changes in the business process. ● Integrating related business processes to standardize the data-driven activities results in improving the big data chain ● Incorporating BDA into business processes could maximize the re-usage of data and extract the value of big data	Chen and Nath (2018); Huang and Rust (2013); Janssen et al. (2017)
Managing legacy systems dependency	● Integrating big data technologies with legacy systems and infrastructures can be a challenging task ● Managers faces the challenge of transforming, merging and integrating big data into the legacy systems which results in considerable investments ● Determining the modernization scope for integrating big data with legacy systems properly guarantee organizational agility	Hussain and Prieto (2016)
Appropriate organizational structures	● To actualize big data capabilities, BFS firms are required to redesign organizational structure that effectively advances, mobilizes and utilizes the essential technical and human resources	Günther et al. (2017); Peppard and Ward (2004); Sharma et al. (2014)
Infrastructures readiness	● Most of the existing IT infrastructures have not been designed to fulfil the growing requirements of BDA ● The efficiency of the BDA can be determined by the infrastructure quality ● Infrastructure readiness is an essential prerequisite for managing big data, facilitating sorting and processing of large volumes of data with high velocity through greater network latency ● Effective big data implementation requires advanced IT infrastructures with improved processing capacity and following the best practices of data management to deploy innovative tools and techniques	Alharthi et al. (2017); Arunachalam et al. (2018); Ekbia et al. (2015); Shukla and Mattar (2019); Vidgen et al. (2017); Zhang et al. (2017)
Selecting appropriate big data technologies	● Big data tools and technologies are not only costly but may not be the best fit for any situation ● BFS firms need to identify and evaluate candidate technologies based on the desired big data applications and quality attribute requirements and select an appropriate architecture to fully utilize big data capabilities.	Lamba and Singh (2018)
Clear and justifiable business case	● Companies face difficulties in proving the values of big data investments as there is a lack of solid justification to convince stakeholders for investing ● Benefits ambiguity and uncertainty on big data values make stakeholders hesitant about implementing big data analytics	Arunachalam et al (2018); Lee (2017); Richey et al. (2016); Sanders (2016)
Scalability	● A large scale and huge volume of speedy non-homogenous data is a critical challenge that necessitates systems and infrastructures with scale-up capacity	Arunachalam et al. (2018) ; Sun et al. (2016)
Big data analytics strategic alignment	● Strategic alignment of big data endeavours with business strategies is indicated as an important factor, which facilitates big data implementation and success in the BFS firms ● To unlock the competitive advantage and maximize the value from big data applications, big data strategy should be aligned with corporate strategy and design high-level plans for analytical capabilities of the company based on the business strategies	Newly discovered from this study
Fault Tolerance and reliability of big data technologies	● Achieving adaptive fault tolerance and optimal systems in the big data context and providing reliable service is crucial from experts' viewpoint. ● Employing functionally-equivalent components to tolerate faults could improve big data analytics capability ● Having fault tolerance strategy for different users and reliability and availability of analytical functions in business dynamic environment should be considered in big data implementation	Newly discovered in this study
Big data customization capability	● Tailoring big data with business variability, complexity, and the institutional context and Defining a tailored analytics model based on bank's dynamic environment enables banks to take advantage of big data applications	Newly discovered in this study
Empowering the end-users	● Preparing key employees to use big data analytics can derive full value from big data resources and expand the role of analytics into all types of decisions in big data assimilation in BFS firms ● Empowering the users with the skill to apply data and analytics to solve business questions and considering user abilities in exploiting big data applications could overcome the barriers of big data analytics implementation	Newly discovered in this study

Table 4. Structural self-interaction matrix

Enablers (i)	*Enablers (j)*																		
	19	18	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1
1- Big data governance	V	A	O	O	O	V	A	A	A	A	V	A	V	O	V	A	A	X	
2- Creating data-driven culture	V	O	O	V	O	O	O	O	X	O	V	A	V	O	O	A	A		
3- Top management support	V	A	A	X	A	A	O	X	V	A	V	V	A	A	V	A			
4- Technical and skilled workforce	V	V	V	V	V	V	V	V	V	V	V	A	V	V	V				
5- Data integrity	O	O	O	O	O	V	A	A	O	A	V	A	O	O					
6- Big data privacy concern	A	O	O	O	O	O	O	O	V	O	V	A	X						
7- Big data security concern	A	O	O	O	O	V	A	A	V	V	V	A							
8- Financial support	V	O	O	O	V	V	V	O	O	V	V								
9- Embedding big data in business processes	A	A	A	X	A	O	A	A	A	A									
10- Managing legacy systems dependency	O	O	O	O	O	V	A	A	O										
11- Appropriate organizational structures	X	O	O	A	O	A	O	O											
12- Infrastructure readiness	O	V	V	O	V	V	V												
13- Selecting appropriate big data technologies	O	V	V	O	V	X													
14- Clear and justifiable business case	A	A	A	A	A														
15- Scalability	O	O	O	O															
16- Big data analytics strategic alignment	O	A	O																
17- Reliability of big data technologies	O	O																	
18- Big data customization capability	O																		
19- Empowering the end-users																			

Table 5. Initial reachability matrix

Enablers (i)	Enablers (j)																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Big data governance	1	1	0	0	1	0	1	0	1	0	0	0	0	1	0	0	0	0	1
Creating Data-driven Culture	1	1	0	0	0	0	1	0	1	0	1	0	0	0	0	1	0	0	1
Top management support	1	1	1	0	1	0	0	1	1	0	1	1	0	0	0	1	0	0	1
Technical and Skilled workforce	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
Data integrity	0	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0
Big data privacy concern	0	0	1	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0
Big data security concern	0	0	1	0	0	1	1	0	1	1	1	0	0	1	0	0	0	0	0
Financial support	1	1	0	1	1	1	1	1	1	1	0	0	1	1	1	0	0	0	1
Embedding big data in business processes	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0
Managing legacy systems dependency	1	0	1	0	1	0	0	0	1	1	0	0	0	1	0	0	0	0	0
Appropriate organizational structures	1	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	1
Infrastructure Readiness	1	0	1	0	1	0	1	0	1	1	0	1	1	1	1	0	1	1	0
Selecting appropriate big data technologies	1	0	0	0	1	0	1	0	1	1	0	0	1	1	1	0	1	1	0
Clear and justifiable business case	0	0	1	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0
Scalability	0	0	1	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0
Big data analytics strategic alignment	0	0	1	0	0	0	0	0	1	0	1	0	O	1	0	1	0	0	0
Fault Tolerance and reliability of big data technologies	0	0	1	0	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0
Big data customization capability	1	0	1	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0
Empowering the end-users	0	0	0	0	0	1	1	0	1	0	1	0	0	1	0	0	0	0	1

Table 6. Final reachability matrix

Enablers (i)	Enablers (j)																		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Big data governance	1	1	1*	0	1	1*	1	0	1	1*	1*	0	1*	1	0	1*	0	0	1
Creating data-driven culture	1	1	1*	0	1*	1*	1	0	1	1*	1	0	0	1*	0	1	0	0	1
Top management support	1	1	1	1*	1	1*	1*	1	1	1*	1	1	1*	1*	1*	1	1*	1*	1
Technical and Skilled workforce	1	1	1	1	1	1	1	1*	1	1	1	1	1	1	1	1	1	1	1
Data integrity	0	0	1*	0	1	0	0	0	1	0	1*	0	1*	1	0	1*	0	0	0
Big data privacy concern	1*	1*	1	0	1*	1	1	1*	1	1*	1	1*	0	1*	0	1*	0	0	1*
Big data security concern	1*	1*	1	0	1*	1	1	1*	1	1	1	1*	1*	1	0	1*	0	0	1*
Financial support	1	1	1*	1	1	1	1	1	1	1	1*	1*	1	1	1	1*	1*	1*	1
Embedding big data in business processes	0	0	1*	0	0	0	0	0	1	0	1*	0	0	1*	0	1	0	0	0
Managing legacy systems dependency	1	1*	1	0	1	0	1*	1*	1	1	1*	1*	1*	1	0	1*	0	0	1*
Appropriate organizational structures	1	1	0	0	1*	1*	1*	0	1	0	1	0	0	1*	0	1*	0	0	1
Infrastructure readiness	1	1*	1	0	1	1*	1	1*	1	1	1*	1	1	1	1	1*	1	1	1*
Selecting appropriate big data technologies	1	1*	1*	0	1	1*	1	0	1	1	1*	0	1	1	1	1*	1	1	0
Clear and justifiable business case	1*	1*	1	0	1*	0	1*	1*	1*	0	1	1*	1	1	1*	1*	1*	1*	1*
Scalability	1*	1*	1	0	1*	0	0	1*	1	0	1*	1*	1*	1	1	1*	0	0	1*
Big data analytics strategic alignment	1*	1*	1	0	1*	0	0	1*	1	0	1	1*	1*	1	0	1	0	0	1*
Fault tolerance and reliability of big data technologies	1*	1*	1	0	1*	0	0	1*	1	0	1*	1*	1*	1	0	1*	1	0	1*
Big data customization capability	1	1*	1	0	1*	0	0	1*	1	0	1*	1*	1*	1	0	1	0	1	1*
Empowering the end-users	1*	1*	1*	0	0	1	1	0	1	1*	1	0	0	1	0	1*	0	0	1

Note: 1* indicates transitivity

Iteration I Enablers	Reachability Set	Antecedent Set	Intersection	Level
1.Big data governance	1,2,3,5,6,7,9,10,11,13,14,16,19	1,2,3,4,6,7,8,10,11,12,13,14,15,16,17,18,19	1,2,3,6,7,10,11,13,14,16,19	
2.Creating data-driven culture	1,2,3,5,6,7,9,10,11,14,16,19	1,2,3,4,6,7,8,10,11,12,13,14,15,16,17,18,19	1,2,3,6,7,10,11,14,16,19	
3.Top management support	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	1,2,3,4,5,6,7,8,9,10,12,13,14,15,16,17,18,19	1,2,3,4,5,6,7,8,9,10,12,13,14,15,16,17,18,19	
4.Technical and skilled workforce	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	3,4,8	3,4,8	
5.Data integrity	3,5,9,11,13,14,16	1,2,3,4,5,6,7,8,10,11,12,13,14,15,16,17,18	3,5,11,13,14,16	
6.Big data privacy concern	1,2,3,5,6,7,8,9,10,11,12,14,16,19	1,2,3,4,6,7,8,11,12,13,19	1,2,3,6,7,8,11,12,19	
7.Big data security concern	1,2,3,5,6,7,8,9,10,11,12,13,14,16,19	1,2,3,4,6,7,8,10,11,12,13,14,19	1,2,3,6,7,8,10,11,12,13,14,19	
8.Financial support	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	3,4,6,7,8,10,12,14,15,16,17,18	3,4,6,7,8,10,12,14,15,16,17,18	
9.Embedding big data in business processes	3,9,11,14,16	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	3,9,11,14,16	I
10.Managing legacy systems dependency	1,2,3,5,7,8,9,10,11,12,13,14,16,19	1,2,3,4,6,7,8,10,12,13,19	1,2,3,7,8,10,12,13,19	
11.Appropriate organizational structures	1,2,5,6,7,9,11,14,16,19	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	1,2,5,6,7,9,11,14,16,19	I
12.Infrastructure readiness	1,2,3,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	3,4,6,7,8,10,12,14,15,16,17,18	3,6,7,8,10,12,14,15,16,17,18	
13.Selecting appropriate big data technologies	1,2,3,5,6,7,9,10,11,13,14,15,16,17,18	1,3,4,5,7,8,10,12,13,14,15,16,17,18	1,3,5,7,10,13,14,15,16,17,18	
14.Clear and justifiable business case	1,2,3,5,7,8,9,11,12,13,14,15,16,17,18,19	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	1,2,3,5,7,8,9,11,12,13,14,15,16,17,18,19	I
15.Scalability	1,2,3,5,8,9,11,12,13,14,15,16,19	3,4,8,12,13,14,15	3,8,12,13,14,15	
16.Big data analytics strategic alignment	1,2,3,5,8,9,11,12,13,14,16,19	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19	1,2,3,5,8,9,11,12,13,14,16,19	I
17.Fault tolerance and reliability of big data technologies	1,2,3,5,8,9,11,12,13,14,16,17,19	3,4,8,12,13,14,17	3,8,12,13,14,17	
18.Big data customization capability	1,2,3,5,8,9,11,12,13,14,16,18,19	3,4,8,12,13,14,18	3,8,12,13,14,18	
19.Empowering the end-users	1,2,3,6,7,9,10,11,14,16,19	1,2,3,4,6,7,8,10,11,12,14,15,16,17,18,19	1,2,3,6,7,10,11,14,16,19	

Iteration II Enablers	Reachability Set	Antecedent Set	Intersection	Level
1.Big data governance	1,2,3,5,6,7,10,13,19	1,2,3,4,6,7,8,10,12,13,15,17,18,19	1,2,3,6,7,10,13,19	
2.Creating data-driven culture	1,2,3,5,6,7,10,19	1,2,3,4,6,7,8,10,12,13,15,17,18,19	1,2,3,6,7,10,19	
3.Top management support	1,2,3,4,5,6,7,8,10,12,13,15,17,18,19	1,2,3,4,5,6,7,8,10,12,13,15,17,18,19	1,2,3,4,5,6,7,8,10,12,13,15,17,18,19	II
4.Technical and skilled workforce	1,2,3,4,5,6,7,8,10,12,13,15,17,18,19	3,4,8	3,4,8	
5.Data integrity	3,5,13	1,2,3,4,5,6,7,8,10,12,13,15,16,17,18	3,5,13	II
6.Big data privacy concern	1,2,3,5,6,7,8,10,12,19	1,2,3,4,6,7,8,12,13,19	1,2,3,6,7,8,12,19	
7.Big data security concern	1,2,3,5,6,7,8,10,12,13,19	1,2,3,4,6,7,8,10,12,13,19	1,2,3,6,7,8,10,12,13,19	
8.Financial support	1,2,3,4,5,6,7,8,10,12,13,15,17,18,19	3,4,6,7,8,10,12,15,17,18	3,4,6,7,8,10,12,15,17,18	
10.Managing legacy systems dependency	1,2,3,5,7,8,10,12,13,19	1,2,3,4,6,7,8,10,12,13,19	1,2,3,7,8,10,12,13,19	
12.Infrastructure Readiness	1,2,3,5,6,7,8,10,12,13,15,17,18,19	3,4,6,7,8,10,12,15,17,18	3,6,7,8,10,12,15,17,18	
13.Selecting appropriate big data technologies	1,2,3,5,6,7,10,13,15,17,18	1,3,4,5,7,8,10,12,13,15,17,18	1,3,5,7,10,13,15,17,18	
15.Scalability	1,2,3,5,8,12,13,15,19	3,4,8,12,13,15	3,8,12,13,15	
17.Fault tolerance and reliability of big data technologies	1,2,3,5,8,12,13,17,19	3,4,8,12,13,17	3,8,12,13,17	
18.Big data customization capability	1,2,3,5,8,12,13,18,19	3,4,8,12,13,18	3,8,12,13,18	
19.Empowering the end-users	1,2,3,6,7,10,19	1,2,3,4,6,7,8,10,11,12,15,17,18,19	1,2,3,6,7,10,19	II

Iteration III Enablers	Reachability Set	Antecedent Set	Intersection	Level
1.Big data governance	1,2,6,7,10,13	1,2,4,6,7,8,10,12,13,15,17,18	1,2,6,7,10,13	III
2.Creating data-driven culture	1,2,6,7,10	1,2,4,6,7,8,10,12,13,15,17,18	1,2,6,7,10	III
4.Technical and skilled workforce	1,2,4,6,7,8,10,12,13,15,17,18	4,8	4,8	
6.Big data privacy concern	1,2,6,7,8,10,12	1,2,4,6,7,8,12,13	1,2,6,7,8,12	
7.Big data security concern	1,2,6,7,8,10,12,13	1,2,4,6,7,8,10,12,13	1,2,6,7,8,10,12,13	III
8.Financial support	1,2,4,6,7,8,10,12,13,15,17,18	4,6,7,8,10,12,15,17,18	4,6,7,8,10,12,15,17,18	
10.Managing legacy systems dependency	1,2,7,8,10,12,13	1,2,4,6,7,8,10,12,13	1,2,7,8,10,12,13	III
12.Infrastructure Readiness	1,2,6,7,8,10,12,13,15,17,18	4,6,7,8,10,12,15,17,18	6,7,8,10,12,15,17,18	
13.Selecting appropriate big data technologies	1,2,6,7,10,13,15,17,18	1,4,7,8,10,12,13,15,17,18	1,7,10,13,15,17,18	
15.Scalability	1,2,8,12,13,15	4,8,12,13,15	8,12,13,15	
17.Fault tolerance and reliability of big data technologies	1,2,8,12,13,17	4,8,12,13,17	8,12,13,17	
18.Big data customization capability	1,2,8,12,13,18	4,8,12,13,18	8,12,13,18	

Iteration IV Enablers	Reachability Set	Antecedent Set	Intersection	Level
4.Technical and skilled workforce	4,6,8,12,13,15,17,18	4,8	4,8	
6.Big data privacy	6,8,12	4,6,8,12,13	6,8,12	IV
8.Financial support	4,6,8,12,13,15,17,18	4,6,8,12,15,17,18	4,6,8,12,15,17,18	
12.Infrastructure Readiness	6,8,12,13,15,17,18	4,6,8,12,15,17,18	6,8,12,15,17,18	
13.Selecting appropriate big data technologies	6,13,15,17,18	4,8,12,13,15,17,18	13,15,17,18	
15.Scalability	8,12,13,15	4,8,12,13,15	8,12,13,15	IV
17.Fault tolerance and reliability of big data technologies	8,12,13,17	4,8,12,13,17	8,12,13,17	IV
18.Big data customization capability	8,12,13,18	4,8,12,13,18	8,12,13,18	IV

Iteration V Enablers	Reachability Set	Antecedent Set	Intersection	Level
Technical and skilled workforce	4,8,12,13	4,8	4,8	V
Financial support	4,8,12,13	4,8,12	4,8,12	V
Infrastructure Readiness	8,12,13	4,8,12	8,12	V
Selecting appropriate big data technologies	13	4,8,12,13	13	V

Table 8. Triangular fuzzy linguistic scale

Linguistic terms	Triangular fuzzy number	Triangular membership function
No influence	(0,0,0)	
Very low influence	(0,0.1,0.3)	
Low influence	(0.1,0.3,0.5)	
Medium influence	(0.3,0.5,0.7)	
High influence	(0.5,0.7,0.9)	
Very high influence	(0.7,0.9,1)	
Complete influence	(1,1,1)	

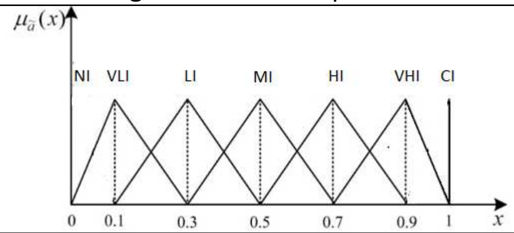

Table 9. Stabilized matrix for BDAEs

#	*Enablers*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Driving
1	Big data governance	0	0.9	0	0	0.9	0	0.9	0	0.7	0.9	0.9	0	0.7	0.7	0	0.7	0	0	0.9	**8.2**
2	Creating data-driven culture	0.9	0	0.9	0	0	0.9	0.9	0	0.7	0.9	0.7	0	0	0.7	0	0.7	0.5	0	0.9	**8.7**
3	Top management support	0.9	0.9	0	0.7	0.7	0	0.7	0.9	0.7	0.5	0.9	0.7	0	0	0	0.9	0.7	0	0.7	**9.9**
4	Technical and skilled workforce	0.9	0.9	0.9	0	0.9	0.9	0.7	0	0.9	0.7	0.9	0.9	0.9	0.7	0.9	0.9	0.9	0.9	0.7	**14.5**
5	Data integrity	0	0	0.7	0	0	0	0.7	0	0.7	0	0	0	0.7	0.5	0	0	0	0	0.7	**4**
6	Big data privacy concern	0.9	0.9	0.9	0	0.7	0	0.9	0	0.7	0.9	0.7	0.7	0	0.7	0	0	0	0	0.7	**8.7**
7	Big data security concern	0.9	0	0.9	0	0.7	0.9	0	0	0.7	0.7	0.7	0	0	0.7	0	0	0	0	0	**6.2**
8	Financial support	0.9	0.9	0	0.9	0.9	0.7	0.9	0	0.9	0.9	0	0	0.9	0.9	0.9	0.9	0.9	0.9	0.9	**13.3**
9	Embedding big data in business processes	0	0	0.7	0	0	0	0	0	0	0	0.7	0	0	0	0	0.7	0	0	0	**2.1**
10	Managing legacy systems dependency	0.7	0.9	0.9	0	0.9	0	0.7	0.7	0.9	0	0.9	0.7	0	0.9	0	0	0	0	0	**8.2**
11	Appropriate organizational structures	0.7	0.9	0	0	0.7	0	0	0	0.7	0	0	0	0	0.7	0	0	0	0	0.7	**4.4**
12	Infrastructure readiness	0.7	0.9	0.9	0	0.9	0	0.9	0	0.9	0.7	0	0	0.7	0.9	0.9	0	0.9	0.7	0.7	**10.7**
13	Selecting appropriate big data technologies	0.7	0.7	0.9	0	0.7	0	0.9	0	0.7	0.5	0.9	0	0	0.7	0.9	0.7	0.9	0.9	0.7	**10.8**
14	Clear and justifiable business case	0.9	0.7	0.9	0	0	0	0	0	0	0	0.7	0	0.7	0	0.7	0.7	0	0	0	**5.3**
15	Scalability	0.7	0.7	0.9	0	0.7	0	0	0.7	0.5	0.5	0.7	0.7	0.9	0.9	0	0.7	0.7	0	0	**9.3**
16	Big data analytics strategic alignment	0.7	0.9	0.9	0	0	0	0	0	0.5	0	0.7	0	0.7	0.7	0	0	0	0	0.7	**5.8**
17	Fault tolerance and reliability of big data technologies	0.9	0.9	0.5	0	0.5	0	0	0.5	0.5	0.7	0.9	0.9	0.5	0.5	0	0.9	0	0	0	**8.2**
18	Big data customization capability	0.7	0.7	0.9	0	0	0	0.7	0.7	0.9	0.5	0.7	0.7	0	0.7	0	0.5	0.9	0	0	**8.6**
19	Empowering the end-users	0.7	0.9	0.9	0	0	0.5	0.9	0	0.9	0	0.9	0	0	0.7	0	0	0	0	0	**6.4**
	Dependence Power	12.8	12.7	12.7	1.6	9.2	3.9	9.8	3.5	12.5	8.4	11.9	5.3	6.7	11.6	4.3	8.3	6.4	3.4	8.3	