sustainability

MDPI

Article

Identifying the Key Big Data Analytics Capabilities in Bangladesh's Healthcare Sector

Md Ahsan Uddin Murad [1,2,*], Dilek Cetindamar [1] and Subrata Chakraborty [1,3]

[1] Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney, NSW 2007, Australia; dilek.cetindamarkozanoglu@uts.edu.au (D.C.); subrata.chakraborty@une.edu.au (S.C.)
[2] Government of the People's Republic of Bangladesh, Dhaka 1208, Bangladesh
[3] School of Science and Technology, Faculty of Science, Agriculture, Business and Law, University of New England, Armidale, NSW 2351, Australia
* Correspondence: mdahsan.uddinmurad@student.uts.edu.au or murad.ahsan@gmail.com

Abstract: The study explores the crucial big data analytics capabilities (BDAC) for healthcare in Bangladesh. After a rigorous and extensive literature review, we list a wide range of BDAC and empirically examine their applicability in Bangladesh's healthcare sector by consulting 51 experts with ample domain knowledge. The study adopted the DEcision MAking Trial and Evaluation Laboratory (DEMATEL) method. Findings highlighted 11 key BDAC, such as using advanced analytical techniques that could be critical in managing big data in the healthcare sector. The paper ends with a summary and puts forward suggestions for future studies.

Keywords: big data analytics; DEMATEL; developing countries; big data analytics capabilities; Bangladesh; healthcare

check for updates

Citation: Uddin Murad, M.A.; Cetindamar, D.; Chakraborty, S. Identifying the Key Big Data Analytics Capabilities in Bangladesh's Healthcare Sector. *Sustainability* **2022**, *14*, 7077. https://doi.org/10.3390/su14127077

Academic Editor: Mihajlo (Michael) Jakovljevic

Received: 18 April 2022
Accepted: 6 June 2022
Published: 9 June 2022

1. Introduction

Big data allows drawing internal associations and uncovering hidden patterns, trends, correlations, customer preferences, and facilitating firms making informed decisions [1,2]. However, pulling useable business insights from the internal association of big data requires an understanding of how to build capabilities to handle big data and overcome the related organizational challenges in applying those capabilities [3]. Therefore, besides technology, an organization must focus on building capabilities that are 'hard to imitate' by competitors [4]. These are widely known as big data analytics capabilities (BDACs) [5]. BDAC is a set of special capabilities that generate knowledge about self-transformation [6]. Those capabilities are distinct and interwoven to mutually support each other in materializing business goals in a big data environment [7].

Several studies admit that BDAC is becoming a vital business competence in decision-making [8]. A data-driven firm is reported to be six percent more profitable and five percent more productive than its counterparts [9]. On the other hand, apart from the traditional goal of making a firm profitable, sustainability becomes an arguably equally important milestone for the business, which is why BDA is considered a great instrument to achieve sustainability besides profitability [10]. Leveraging BDA in improving sustainability in different sectors such as food, energy, water [11], supply chain sustainability [12], and business sustainability [13] is already empirically tested. Therefore, identifying the key BDAC is crucial to yielding expected benefits from data concerning both financial and sustainability performance. However, it is impossible to have all BDACs immediately, nor are all BDACs not equally important for all organizations. Therefore, an organization should recognize the most relevant and vital capabilities it should have. This article endeavors to shed some light on what crucial BDACs exist in the healthcare sector in a developing country context.

Developing a core BDAC unique to an organization requires a detailed analysis of its contexts, such as the sector or the country where that organization is operating. Divergent views on what constitutes BDAC [14] and the existing BDAC measurement scales [15] pose an important question for organizations: What are the key BDACs most aligned with an organization? If a firm randomly picks any of the BDACs from the existing studies available in the literature without taking into consideration the context, it is likely that BDA implementation may not bring the expected yield. For example, a recent study in the healthcare sector found five unique BDACs: analytical capability for patterns of care, unstructured data analytical capability, decision support capability, predictive capability, and traceability [16] to realize potential benefits from BDA incorporation into the firm. This set of BDACs is significantly different from the existing BDAC lists portrayed in the literature. Another recent study uncovered five aggregate dimensions of human-related BDA capabilities, namely: Personnel Capability, Management Capability, Organizational Capability, Culture and Governance Capability and Strategy and Planning Capability [17]. These dimensions of human capabilities are significantly different from the widely accepted BDA capability list posed by [18]. Another recent study identifies different sets of BDACs for specific sectors such as healthcare. A study by [19] identified five unique sets of BDACs required to yield benefits of BDA implementation in healthcare. This implies, therefore, that more context-specific empirical investigations are required to develop the most relevant unique BDAC sets for that particular context. Otherwise, all investments in big data technologies are unlikely to bring advantages to an organization or a country. Therefore, we have crafted our research quest through framing the following research question:

(Q1) **What are the key big data analytics capabilities in the context of Bangladesh healthcare?**

Our literature review points out the lack of studies addressing the unique contexts of developing countries and their health sectors [5]. Hence, this paper aims to identify a BDAC set that might fit the specific context of Bangladesh's healthcare sector and derive some suggestions for big data practitioners and policymakers regarding their deployment. Further, the study might also be relevant, subject to further investigation, for countries within the same classification as Bangladesh, based on the global socio-economic report [20]. Our study offers to the BDAC literature an empirically tested BDAC list in the context of a developing economy healthcare sector. Hence, our study exemplifies how academic studies need to pay attention to a realistic assessment of the context-specific requirements before launching long-run investments in big data technologies.

The paper has five sections. After this introduction, section two will provide an overview of the literature facilitated to prepare the list of major BDACs. Section three will present the empirical investigation of Bangladesh's public hospital supply chain and introduce the popular multi-criteria decision-making (MCDM) technique, DEMATEL, used to analyze the data. Then, section four discusses the findings and analysis of the results. The final section will introduce contributions, implications, limitations of the study, and suggestions for future studies.

2. Background

In recent years, the business utility of big data has attracted much attention from both academics and executives [21]. Firms are also investing in big data analytics (BDA) to outperform competitors through accelerating innovation [22]. Even though many organizations leverage competitive advantages through big data, the past literature presents a limited focus on understanding the BDACs required to extract value from big data [23]. Just having BDA practice within firms does not, however, guarantee favorable results unless big data is well managed. Effective big data management utilizing different BDAC supports firms to leverage BDA [24].

BDACs are an organizational ability with the necessary tools and techniques to process big data to produce internal associations, patterns, and insights [1]. It acts as an organization enabling firms to process and analyze internal and external data (such as supply chain) [25]. BDACs provide the necessary competencies for a firm to provide business insights by capturing and analyzing big data. In doing so, BDAC holistically utilizes a firm's data, technology, and talent as an organization-wide process [4,7,18,26]. A set of interconnected capabilities is required for a firm to form BDAC; however, there is no consensus on the capability sets in that process. Some studies conceptualize BDAC as a unidimensional construct [1,27,28], while others [7,18,29] consider it as a multi-dimensional higher-order construct. For example, a study [18] splits BDACs into three sub-categories: BDA infrastructure flexibility, BDA management capabilities, and BDA personal expertise capabilities. Under these three categories, the research model enlisted 11 BDACs, as shown in Figure 1.

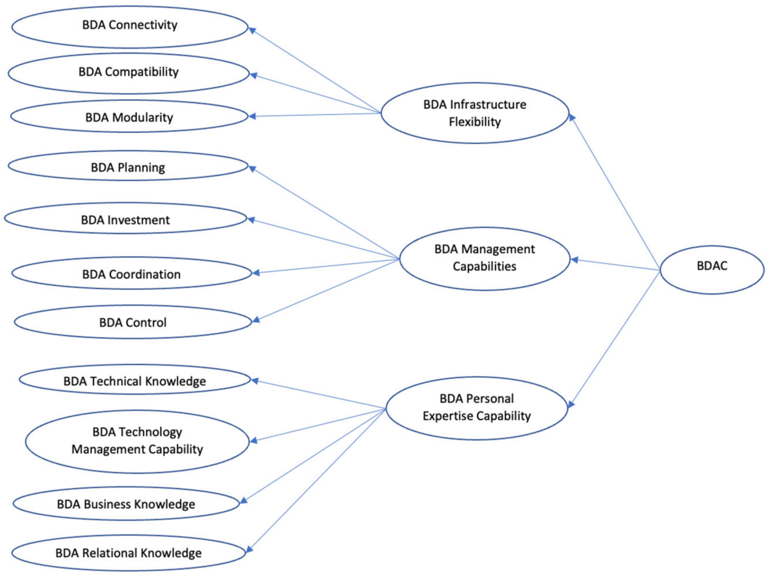

Figure 1. Example of how BDACs are presented in current research frameworks, adapted from [18].

Considering the unstructured nature of big datasets, the patterns observed are exposed to a wide range of probable causal relations [30]. Therefore, experts with different levels of data analytic capability will see additional insights from the same big dataset. Investigations of BDACs have endeavored to clarify the skill set required to yield maximum business benefits from owning big data. Hence, our literature review highlights different BDAC frameworks.

There is still no consensus on the BDACs set; therefore, the extant studies show that the number of constructs used to define BDAC varies from four to forty-nine capabilities. Table 1 summarizes the existing capabilities pooled from the information-systems literature.

Table 1. BDAC in different studies.

Reference	Total Number of Constructs Defining BDAC	Major BDACs Listed
[25,31–34]	4	Advanced Analytical Techniques, Data Visualization Techniques, Use of Dashboard, Deploying Dashboard across Manager's Devices
[1,27,28,35]	5	Advanced Analytical Techniques, Multiple Data Sources, Data Visualization Techniques, Use of Dashboard, Deploying Dashboard across Manager's Devices
[9]	15	Infrastructure capability with five sub capabilities such as flexibility; Talent capability; Management capability

Table 1. *Cont.*

Reference	Total Number of Constructs Defining BDAC	Major BDACs Listed
[8,36,37]	8	Parallel Computing, Real-time access to data, Capability to handle semi-structured data, Accuracy of data, Data-driven intelligence, Good infrastructure, Interchangeability of services, Proficient technical experts
[6]	16	Data capabilities such as identifying data sources; technology capabilities such as having the latest technology; talent capabilities such as having expertise in data analytics; business capabilities such as relying on big data to enhance innovativeness
[38]	18	BDA infrastructure capability; BDA Management Skills; BDA technical skills; Organization learning capability; and Data-driven decision-making capability.
[4]	32	Tangible assets such as basic resources; Human skills such as technical skills; Intangible assets such as Data-driven culture.
[7,18,39,40]	49	BDA infrastructure capability and BDAC talent capability

Even though many studies confirm that BDACs positively impact firm performance [7–9,18,32,34,41–52], academic research on understanding essential BDACs is still scarce [3]. Further, effectively utilizing the big data-specific resources of a firm is fundamental in attaining a competitive edge over the competitors [4]. That is why firms must consider achieving business-specific "hard to imitate" BDACs besides technology [4]. However, the literature warns about two features of BDAC [53,54]: (1) there is no one size fit for all BDAC sets, and (2) utilizing BDACs is not a static process. In this backdrop, researchers need to find ways of identifying the key BDAC sets aligned to the business, and context is vital before devising a strategic roadmap to achieve those on time. Thus, this paper aims to identify the most crucial BDAC in the health sector of a developing country, Bangladesh; this is discussed in the following Methodology section.

3. Methodology

3.1. Research Context

The research context is the healthcare industry in a developing country. The absence of appropriate information technology (IT) infrastructure, a fundamental requirement of BDA adoption, is considered one of the most significant barriers to technology adoption in developing countries [54]. Hence, our research could help us to understand developing key BDACs to fight this infrastructure challenge in developing countries. Developed nations are already ahead with superior Information and Communication Technology (ICT) infrastructure, ready to embrace new big data technology. Nevertheless, the high volume of medical data generating even higher velocities and varieties adds extra complexity to already hampered efforts of transforming healthcare big data to business value even in wealthy nations such as the USA [50]. So, it is implied that developing countries will face more challenges in handling big medical data. A separate investigation in the developing country context will help us to grasp the actual scenario of big data adoption. Our endeavor to rank the capabilities required for BDA adoption in the healthcare context of a developing economy is, therefore, an important area to explore.

The healthcare sector meets the needs of Bangladesh's 150 million population. ICT often receives less priority in developing countries [55], and Bangladesh is no exception. Bangladesh spends USD 2.3 billion on health [56]; however, there is a limited health technology development plan. The health sector of Bangladesh is fast-moving toward technology integration in their management and operations level through the implementation of projects such as the e-Health and Health Information System [56]. The project will automatically gather data from all national to local-level facilities by affording them internet access to build up a health database to perform better management activities. The gradual integration of such technology in Bangladesh's healthcare will generate a large volume of data which will necessitate BDA adoption. The world economic perspective report categorizes countries with similar situations as developing countries [20]. Overall technological advancements in all those other countries such as Pakistan, India, and Nepal are more or less similar to Bangladesh. So, our research might provide a good illustration of a typical developing country context.

The healthcare supply chain is a vast interconnected subsector such as pharmaceuticals, hospital equipment, plants, etc. It is unrealistic to study a whole complex sector in one study. Our focus will therefore be on the territory hospital settings of Bangladesh's divisional (state) headquarters. The reason behind the choice is twofold: First, Bangladesh is still in the early stage of technology adoption, so targeting big hospitals could give a sizeable ICT infrastructure, and second, remote areas and other sectors were difficult to access due to the COVID-19 pandemic.

3.2. Research Design

Three fundamental pillars of our research are: identify an existing body of knowledge through a literature survey to shortlist an exhaustive list of BDACs from the literature, take expert opinion in two stages to narrow down the list and identify the relative rank of the BDACs and finally apply MCDM approach to rank the BDACS. In the existing literature survey, we were aware of loopholes in the traditional literature review approach, such as shortlisting only the literature that supports the researchers' views. To avoid such biases, we followed a novel approach posed by [57] and later used by some other recent investigations such as [17]. We followed an established way of applying the MCDM approach for this research for quantitative analysis. Our research methodology used DEMATEL, and the framework is depicted in Figure 2. DEMATEL is a powerful and complex factor [58]. DEMATEL is a micro-oriented approach that helps decision makers determine the intensity of the relationship among factors [59]. DEMATEL was proposed by the science and human affairs program of the Battelle Memorial Institute of Geneva in 1973. DEMATEL analysis generates graphics output (known as digraph) of a causal relationship between factors and factors that have a central role, i.e., the critical success factor, which must be observed more in the further learning process [60,61]. The method retrieves the relationships between the cause and effect of a set of factors administering the system. Figure 2 below shows our methodology adopted in this paper.

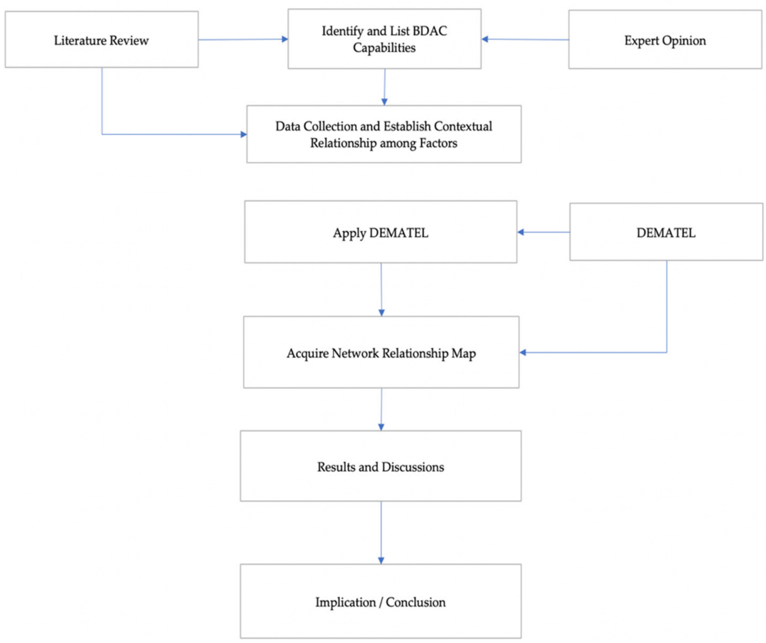

Figure 2. Research Methodology, adapted from [59].

3.3. Data Collection

The main data collection is based on a survey conducted by one of Bangladesh's top three leading market research firms. Data were collected from October 2021 to November 2021. Initially, we talked with a few prominent BDA practitioners to achieve an overall understanding of BDA in Bangladesh. A final experts' list was identified using the snowball approach. When we contacted 67 BDA expert practitioners, 53 agreed to participate in the survey. DEMATEL approach entails shortlisting factors first. Twenty BDACs were shortlisted for DEMATEL analysis through expert face to face interviews. The interview guideline posed by [62] was adopted to grasp the most important research opinion from the subjective opinion of semi-structured discussion. A questionnaire was developed using 20 BDACs shortlisted from initial expert opinion. Each of the 53 experts were provided with a direct relation 20 $\times$ 20 matrix to evaluate the influence degree of an actor on the others through a pairwise comparison. For comparison, the experts expressed their opinions ranging from "no influence" to "very high influence". The verbal variable is then converted to absolute numbers as described in the next paragraph (stage two data collection). The questionnaire was distributed to 53 experts, and 51 valid questionnaires were shortlisted for further analysis. The total usable response rate was 96%. One reason for the high rate of questionnaire response is that the respondents were chosen very carefully and were briefed elaborately on the research and research context. Table 2 summarizes the overall data collection demographic portfolio.

Table 2. Demography of the participants.

Variable	Frequency	Percentage
Age		
18–26	15	28.3
27–35	12	22.64
36–43	17	32.07
43–50	6	11.32
50+	3	5.66
Gender		
Male	41	77.36
Female	12	22.64
Education		
No Formal Education	0	0
Primary Education	0	0
Secondary Education	1	1.88
College qualification	2	3.77
Undergraduate Degree	26	49.05
Postgraduate Degree	24	45.28
Experience		
Less than one year	0	0
2–5 years	2	3.77
6–10 years	14	26.41
11–15 years	21	39.62
16–20 years	7	13.20
Over 20 years	9	16.98

Table 2. *Cont.*

Variable	Frequency	Percentage
Industry		
Administrative and support service activities	3	5.66
Education	4	7.54
Utility Services	2	3.77
Financial and Insurance Services	4	7.54
ICT	11	20.75
Manufacturing	6	11.32
Professional, Scientific and technical activities	6	11.32
Public administration and defense	10	18.86
Real estate activities	4	7.54
Other service activities	3	5.66
Firm Size (employees)		
1–20	1	1.88
20–50	12	22.64
50–100	7	13.2
101–250	12	22.64
251–500	6	11.32
501–1000	3	5.66
1001–3000	6	11.32
3001–6000	5	9.43
6000+	1	1.88

3.4. Data Analysis

We have selected DEMATEL for three reasons. First, it provides effective cause–effect relationships among conflicting factors. Second, the method prioritizes the most influential factors, thus giving performance improvement insights. Third, the pictorial presentation that DEMATEL presents through diagraphs helps demonstrate complex and conflicting situations. DEMATEL is mainly practical and helpful for visualizing complicated causal relationships and has been successfully applied in many fields [63–65]. The main advantages of DEMATEL involve its ability to account for indirect relations that can serve to compromise a standard cause and effect model. Therefore, it is particularly suitable for analyzing a mix of quantitative and qualitative data, as it is necessary to entirely explore the relationship among success factors [54].

The DEMATEL method has two phases. In the first phase, experts provide opinions in two stages. In stage one (of the first phase), experts present their thoughts to shortlist the criteria (capabilities in our case). In stage two, experts provide opinions on the relative importance of one criterion over others under a set rule. In the second phase, expert opinions are statistically analyzed using a five-step DEMATEL mathematical procedure. The whole process is discussed in the following paragraphs.

(1) First phase—stage one: Finding a set of BDAC through a literature survey and expert opinions

A rigorous literature review identifies 89 must-have to should-have fundamental BDACs. After primary scrutiny and removing duplication, 49 shortlisted BDAC were presented to the experts for further shortlisting in terms of their alignment with the research context. At the literature survey stage, thematic content analysis was conducted using enhancing transparency in reporting the synthesis of qualitative research (ENTREQ) statements [66]. The ENTREQ statement was later followed by similar studies [44] to rank critical factors using MCDM. The literature investigation was conducted in August 2021 and subsequently updated in October 2021, and articles published from 2010 to 2021 in SCOPUS, Web of Science, and Google Scholar were considered. Only peer-reviewed journal articles written in English were counted for further analysis. Apart from articles from these three research outlets, some grey literature such as government websites and annual reports were also surveyed. After removing duplicity and using three stages of screening (title, abstract, and full text), 54 journal articles and three grey literature reports were shortlisted to extract the BDACs.

Even though opinions from all 51 experts were taken at stage two, the brief list of BDACs at stage one was based on the view of an expert team, a smaller number of experts with the highest number of years of experience in the BDA field. The expert team (for stage one) comprises twelve experts: three senior policy experts from the health ministry of Bangladesh, two director-level hospital managers, five university professors, and two BDA industry practitioners registered with BASIS (the apex IT services association of Bangladesh). Experts were selected purely on their experience and direct involvement in BDA practices. Relevant work experience of the experts ranged from 15 to 39 years. Based on the experts' opinion in stage one, a final shortlist of BDACs was prepared for stage two.

(2) First phase—stage two: Expert opinion on the relative importance of shortlisted capabilities

Stage one resulted in a shortlist of twenty BDACs pertinent to our research context. In stage two, expert opinions were requested on the relationship between those factors, which were further analyzed with DEMATEL. All expert respondents were informed about DEMATEL, including the method, the way they both work, and the probable results they create. A publicly available video tutorial link on DEMATEL was supplied to understand the methods better. The core objectives of the study were explained to the experts and they were provided with a 20 × 20 matrix (twenty capabilities were identified from stage one) to generate the direct relationship matrix among the capabilities. Finally, the DEMATEL method was applied step by step on collected opinions.

This study designed a DEMATEL questionnaire consisting of two parts. The first part uses a five-point Likert scale to identify the strength of importance for each variable to meet the data prerequisite to apply DEMATEL. The second part indicates the degree of influence (from 0 to 4, where 0 represents 'no influence' and 4 represents the 'very high influence') by pairwise relation for each variable to explore the causal effect between and among the variables. The data were collected by face-to-face interviews with BDA experts in Bangladesh's health sector. We also performed a pre-test interview to verify the validity of the questionnaire. We carefully explained and confirmed their full understanding of each question during the interviews and asked open-ended relevant questions at the end of the interviews. The results of each questionnaire were integrated by the arithmetic mean. The purpose of the DEMATEL inquiry in this study was the analysis component structure of each factor, the direction, and the intensity of direct and indirect relationships that flow between apparently well-defined components. Experts' knowledge is checked and analyzed to better understand the component elements and how they are interrelated. A DEMATEL analysis illustrates the interrelated structure of components of the problem and finds the central ones to avoid 'overfitting' in decision-making.

- **Second Phase: Applying the DEMATEL method**

There are five steps in applying the DEMATEL method, summarized with results from our study in the following paragraphs.

Step 1: Generate the direct relation matrix

An $n \times n$ matrix is first generated to identify the relations model among the n criteria. The effect of the element in each row is exerted on the element of each column of this matrix.

If multiple experts' opinions are used, all experts must complete the matrix. The arithmetic mean of all experts' opinions is used, and then a direct relation matrix X is generated.

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

Table A1 (in the Appendix A) shows the direct relation matrix, which is the same as the pairwise comparison matrix of the experts.

Step 2: Compute the normalized direct-relation matrix

The sum of all rows and columns of the matrix is calculated directly to normalize. The largest number of the row and column sums can be represented by k. In normalization, each element of the direct-relation matrix must be divided by k.

$$k = max\left\{max\sum_{j=1}^{n} x_{ij}, \sum_{i=1}^{n} x_{ij}\right\}$$

$$N = \frac{1}{k} * X$$

Table A2 (in the Appendix A) shows the normalized direct-relation matrix.

Step 3: Compute the total relation matrix

After calculating the normalized matrix, the fuzzy total relation matrix can be computed as follows:

$$T = \lim_{k \to +\propto}\left(N^1 + N^2 + \ldots + N^k\right)$$

In other words, an $n \times n$ identity matrix is first generated, and then this identity matrix is subtracted from the normalized matrix, and the resulting matrix is reversed. The normalized matrix is multiplied by the resulting matrix to obtain the total relation matrix.

$$T = N \times (1 - N)^{-1}$$

The total relation matrix is presented in Table A3 (in Appendix A).

Step 4: Set the threshold value

The threshold value must be obtained to calculate the internal relations matrix. Accordingly, partial relations are neglected, and the network relationship map (NRM) is plotted. Only relations whose values in matrix T are greater than the threshold value are depicted in the NRM. It is sufficient to calculate the average values of the matrix T to determine the threshold value for the relations. After the threshold intensity is determined, all values in matrix T smaller than the threshold value are set to zero; the causal relation mentioned above is not considered. In this study, the threshold value is equal to 0.465. All the values in matrix T smaller than 0.465 are set to zero. The model of significant relations is presented in Table A4 (in the Appendix A).

Step 5: Final output and create a causal diagram

The next step is to find out the sum of each row and each column of T (in step 3). The sum of rows (D) and columns (R) can be calculated as follows:

$$\mathrm{D} = \sum\nolimits_{j=1}^{n} T_{ij}$$

$$\mathrm{R} = \sum\nolimits_{i=1}^{n} T_{ij}$$

Then, the values of D + R and D − R can be calculated by D and R, where D + R represents the degree of importance of factor *i* in the entire system, and D − R represents the net effects that factor *i* contributes to the system.

The sum of rows and columns are represented by vectors D and R, respectively. If r1(i = 1) represents the horizontal sum of row one of matrix *T*, then r1 represents the sum of the possible direct and indirect relationship of the 1st factor with other factors. The same rule is applied for vertical sum di. A causal and effect diagram is acquired from the data set of horizontal axis vector (D + R) named 'prominence' and (D − R) called 'relation'. The horizontal axis (D + R), made by adding D to R, reveals the relative importance of each criterion. The vertical axis (D − R), produced by subtracting R from D, divides criteria into cause-and-effect groups. The criterion falls in the cause group if the relations vector is positive. The sum of (ri + di) represents the 'centrality,' indicating the system's total effects (contributed or experienced) of factor *i*. [59,67]. Table 3 shows the final output.

Table 3. The final output.

	R	**D**	**D + R**	**D − R**
BDAC1	17.583	17.679	35.263	0.096
BDAC2	18.124	18.88	37.004	0.756
BDAC3	18.376	18.185	36.562	−0.191
BDAC4	18.349	18.021	36.37	−0.328
BDAC5	18.007	18.03	36.036	0.023
BDAC6	17.468	18.418	35.886	0.949
BDAC7	17.41	18.375	35.785	0.966
BDAC8	16.288	18.425	34.713	2.137
BDAC9	19.34	18.608	37.948	−0.732
BDAC10	17.165	17.577	34.742	0.411
BDAC11	17.52	17.999	35.519	0.479
BDAC12	17.454	17.82	35.274	0.366
BDAC13	15.991	17.934	33.926	1.943
BDAC14	17.672	17.45	35.122	−0.221
BDAC15	17.784	17.789	35.573	0.005
BDAC16	17.586	15.292	32.878	−2.293
BDAC17	18.645	17.738	36.383	−0.906
BDAC18	19.523	18.073	37.596	−1.45
BDAC19	18.972	17.802	36.773	−1.17
BDAC20	19.048	18.209	37.257	−0.839

Figure 3 shows the model of significant relations where the values of (D + R) are placed on the horizontal axis and the values of (D − R) on the vertical axis. The coordinate system determines the position and interaction of each factor with a point in the coordinates (D + R, D − R).

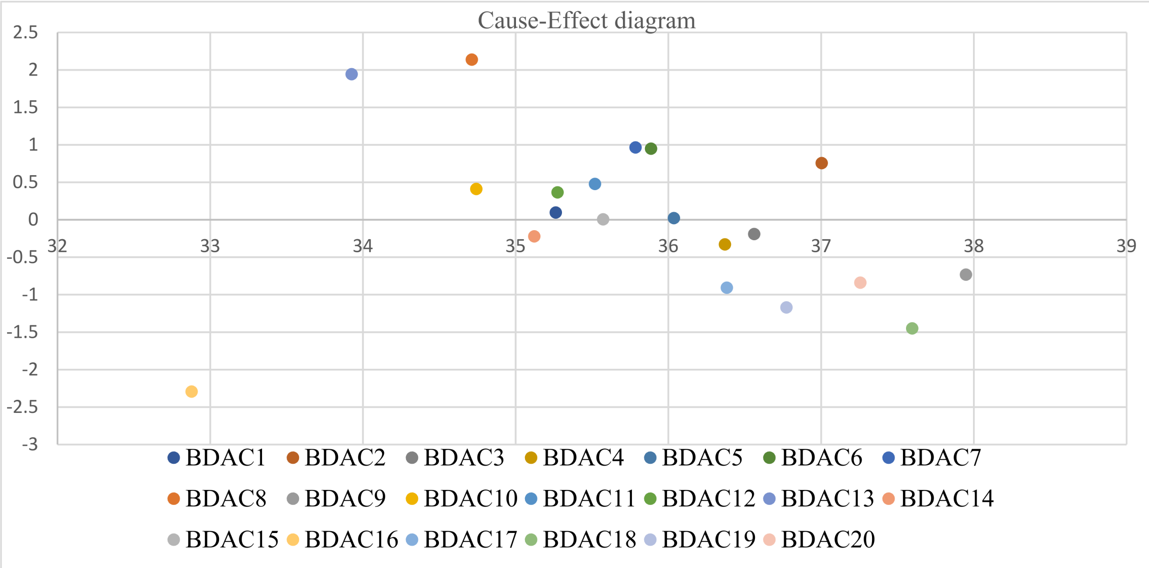

Figure 3. Cause–effect Diagram of Capabilities.

4. Results

4.1. The List of Key BDACs in Bangladesh's Health Sector

In the first stage of data collection, we identified 49 BDACs reported in the literature, as summarized in Table 1. Experts' opinions narrowed the capabilities down to twenty crucial capabilities relevant to our research context. In stage one, experts were requested to provide their opinion on three issues: (1) Which capabilities among the identified are near to similar, (2) which capabilities are most pertinent to the context of Bangladesh, and (3) which capabilities are either not suitable or not required in context to Bangladesh for building organization capabilities. The elimination of a massive number of factors occurred due to two reasons: (1) Similar capabilities were merged, and (2) the Bangladesh context was taken into consideration by the experts. The final list of capabilities combining the literature survey and experts' opinions is presented in Table 4.

While we have tried to present an exhaustive list of capabilities before our experts, it was crucial to understand the justification the expert provided in shortlisting the capabilities. Some capabilities were either unsuitable for our research context or already covered in another capability. For example, two capabilities ("Organization deploy dashboard applications/information to our managers' communication devices (e.g., smartphones, computers) [1,5,25,33]" and "Organization deploy dashboard applications/information to communication devices (e.g., smartphones, computers) [1,5,25,27,33,68]") are amalgamated to a single capability. This merge decision relies on the following consensus expert opinion: "if any organization uses dashboards, it is implied that managers will have easy access to it; therefore, dashboards are installed in managers' devices should not be a separate BDA core capability".

"Our big data analytics staff has the right skills to accomplish their jobs successfully [4,11,69,70]", "We hire new employees that already have the big data analytics skills [4,11,69,70]", "Our big data analytics staff has suitable education to fulfil their jobs [4,11,69,70]" and "Our big data analytics staff holds suitable work experience to accomplish their jobs successfully [4,70] " are all together referring to "Organization analytics workforce is highly capable in technology [4,8,11,18,37,69–72]". Experts suggested that if organizations only hire people who have data analytics skills, it is evident that all analytics personnel will possess the appropriate analytics skills (education as well, either formal or informal). Therefore, it is redundant to use "Our big data analytics staff has suitable education to fulfil their jobs [4,11,69,70]" and "Our big data analytics staff holds suitable work experience to accomplish their jobs successfully [4,70]" as different capabilities. Moreover, if analytics personnel have the right skills, "how they achieve it" is less critical irrespective of their educational background, as our experts opined.

Among the following three capabilities: "Organization's big data analytics managers understand and appreciate the business needs of other functional managers, suppliers, and customers [4,11,69,70]", " Organization's big data analytics managers can work with functional managers, suppliers, and customers to determine opportunities that big data might bring to our business [4,11,69,70]" and "Our big data analytics managers can coordinate big data-related activities in ways that support other functional managers, suppliers, and customers [4,11,69,70]", the majority of our experts advised keeping only the last one on the justification that coordination involves working with functional managers through understanding their needs. If a manager coordinates betters, it is needless to say that they work better with other functional units and understand their needs. So, "Coordination" is an umbrella capability for all three capabilities mentioned in the investigation [4,11,69,70].

Not all similar capabilities were combined and eliminated by the experts. For example, the "Organizations analytics personnel are very capable of interpreting business problems and developing appropriate solutions [9,18,71]" capability is similar to the "Organization analytics workforce is highly capable in technology such as programming, distributed computing, decision support systems, artificial intelligence, data management [4,8,11,18,37,69–72]" capability. However, experts decided to keep both capabilities because they thought the former is a specific knowledge for immediately responding to business change.

Table 4. BDAC capabilities from literature and subsequent expert opinion.

Code	Capability	Source
BDAC1	Organization uses advanced analytical techniques to improve decision making	[1,5,6,68]
BDAC2	Organization combines and integrates information from many data sources for use in our decision making	[1,4,5,8,25,42,68–70]
BDAC3	Organizations routinely use data visualization techniques to assist users or decision-makers in understanding complex information	[1,4,5,25,68–70]
BDAC4	Organization's dashboards facilitate decomposing information to help root cause analysis and continuous improvement	[1,5,25,68]
BDAC5	Our organization utilizes open systems network mechanisms to boost analytics connectivity.	[18,71]
BDAC6	All branches or units are connected to the central office for sharing analytics insights.	[8,9,18,71]
BDAC7	Software applications can be easily used across multiple analytics platforms	[18,37,71]
BDAC8	Organization's analytics workforce is highly capable in technology such as programming, distributed computing, decision support systems, artificial intelligence, and data management.	[4,8,11,18,37,69–72]
BDAC9	Organization has access to very large, unstructured, or fast-moving data for analysis	[4,8,42,69,70]
BDAC10	Organization's analytics personnel are very capable of interpreting business problems and developing appropriate solutions.	[9,18,71]
BDAC11	Organization has explored or adopted parallel computing approaches to big data processing	[4,37,69,70]
BDAC12	Organization has explored or adopted cloud-based services for processing data and performing analytics	[4,69,70]
BDAC13	Organization has explored or adopted open-source software for big data analytics	[4,69,70]
BDAC14	Organization's big data analytics projects are adequately funded	[4,70]
BDAC15	Organization's big data analytics projects are given enough time to achieve their objectives	[4,70]
BDAC16	Organization provides big data analytics training to employees	[4,11,69,70]

Table 4. *Cont.*

Code	Capability	Source
BDAC17	Organization's big data analytics managers can coordinate big data-related activities in ways that support other functional managers, suppliers, and customers	[4,11,69,70]
BDAC18	Organization's big data analytics managers can anticipate the future business needs of functional managers, suppliers, and customers	[4,11,69,70]
BDAC19	Organization's big data analytics managers have a good sense of where to apply big data	[4,11,69,70]
BDAC20	Organization relies on data rather than on instinct while making a decision	[4,11,37,69,70,72]

4.2. Highlighting Key BDAC

According to Figure 3 and Table 4, each BDAC can be assessed based on the following aspects:

- Horizontal vector (D + R) represents the degree of importance each factor plays in the entire system. In other words, (D + R) indicates both factor i's impact on the whole system and other system factors' impact on the factor. In terms of degree of importance, BDAC9 is ranked in first place and BDAC18, BDAC20, BDAC2, BDAC19, BDAC3, BDAC17, BDAC4, BDAC5, BDAC6, BDAC7, BDAC15, BDAC11, BDAC12, BDAC1, BDAC14, BDAC10, BDAC8, BDAC13 and BDAC16, are ranked in the next places.
- The vertical vector (D-R) represents the degree of a factor's influence on the system. In general, the positive value of D-R represents a causal variable, and the negative value of D-R represents an effect. In this study, BDAC1, BDAC2, BDAC5, BDAC6, BDAC7, BDAC8, BDAC10, BDAC11, BDAC12, BDAC13, and BDAC15 are considered to be causal variables, BDAC3, BDAC4, BDAC9, BDAC14, BDAC16, BDAC17, BDAC18, BDAC19, and BDAC20 are regarded as effects.

As shown in Table 5, the most crucial capabilities (positive D+R with positive D-R) are BDAC1, BDAC2, BDAC5, BDAC6, BDAC7, BDAC8, BDAC10, BDAC11, BDAC12, BDAC13, and BDAC15.

Table 5 underlines that the BDAC required for a developing economy context are relatively different from those demonstrated in the existing literature portrayed in Table 1. Capabilities related to reducing capital investments are more important in a developing economy context. The use of open-source software (BDAC13), the use of cloud-based services (BDAC12), and the compatibility of the software to use in different platforms (BDAC7) are all related to reducing organizational capital investment in technology infrastructure. Organizations often want quick results putting pressure on the implementation team [4,63]. This is more prominent in developing economies where financing is always a problem. Organizations justifiably prefer to invest limited resources in any projects with immediate return. However, implementing a highly tech-savvy BDA implementation requires ample time to bring results for an organization (BDAC15).

Overall, BDAC9 (access to a large volume of unstructured data) is identified as the most prominent (highest D + R prominence value) capability required for BDA adoption in healthcare in Bangladesh. Data are considered essential tangible assets for BDA implementation in any business [4]. Collecting and storing massive unstructured data from conventional and unconventional sources are challenging for a developing nation. A recent study reported that "Data and technological barriers" are the top challenges in BDA adoption in developing countries [54].

BDAC16 (providing analytics training to employees) holds the lowest importance in our study. Our experts probably considered it hard to create highly skilled analytics people in-house (BDAC8 and BDAC10) through internal training only, particularly with the limited training facilities available in Bangladesh. Instead, it is viewed as crucial to hire people with high analytical skills. Many studies [4,11,69,70] consider hiring new employees that already have big data analytics skills as a better way of forming organizational BDAC.

In the context of developing countries, it seems justified that hiring ready-to-use analytics skills is more suitable than developing in-house staff through training. In another recent study using DEMATEL to identify the most influential factors of sustainable supply chain implementation, the training indicator had the lowest priority [73].

Table 5. The most crucial capabilities are identified in the study.

Code	Capability	Source
BDAC1	Organization uses advanced analytical techniques to improve decision making	[1,5,6,68]
BDAC2	Organization combines and integrates information from many data sources for use in our decision making	[1,4,5,8,25,42,68–70]
BDAC5	Organization utilizes open systems network mechanisms to boost analytics connectivity.	[18,71]
BDAC6	All branches or units are connected to the central office for sharing analytics insights.	[8,9,18,71]
BDAC7	Software applications can be easily used across multiple analytics platforms	[18,37,71]
BDAC8	Organization analytics workforce is highly capable in technology such as programming, distributed computing, decision support systems, artificial intelligence, and data management.	[4,8,11,18,37,69–72]
BDAC10	Organization's analytics personnel are very capable of interpreting business problems and developing appropriate solutions.	[9,18,71]
BDAC11	Organization has explored or adopted parallel computing approaches to big data processing	[4,37,69,70]
BDAC12	Organization has explored or adopted cloud-based services for processing data and performing analytics	[4,69,70]
BDAC13	Organization has explored or adopted open-source software for big data analytics	[4,69,70]
BDAC15	Organization's big data analytics projects are given enough time to achieve their objectives	[4,70]

Cause indicators of DEMATEL results influence the entire system's performance and overall goal(s). So, special attention is required to make the (di − ri) values positive, which means the degree of influencing (di) must be greater than the degree of influenced impact (ri) [73]. The cause–effect score is negative even though access to a large volume of unstructured data (BDAC9) ranked first with the highest prominence score (di + ri). In the causal diagram, BDAC9 has less priority with fewer points. Therefore, the factor BDAC9 has a higher degree of being influenced than influencing others. Developing nations have a lack of ICT infrastructure to amass unstructured data. So, when the technological capability is improved, it will automatically enhance the organizational capacity to access a large volume of unstructured data. Therefore, our experts' opinion seems justified in the context of a developing country.

BDAC8 capability (the organization has competent skills in programming, artificial intelligence, technology, etc.) influences all other capabilities with the highest value. The major influence factors are BDAC8, BDAC13, and BDAC7, having values of 2.137, 1.943, and 0.966, respectively. Therefore, BADC8, BDAC13, and BDAC7 have a more significant influential impact (di) on all other factors, including the BDAC9 with the highest prominence value. The casual group factors (positive di+ri and di-ri value) must be prioritized over all other factors for making any profound decision. Additionally, the cause group factors are complicated to move. In contrast, the effect group factors can easily be moved [61]. Therefore, if we aim to yield superior performance in effect group factors, an organization must control adeptly and pay proper attention to the cause group factors (i.e., BDAC8, BDAC13, BDAC7) beforehand [61].

The top cause group factor BDAC8 is justifiably connected with some other salient findings of our empirical study. For example, "Train employees in-house (BDAC16)" had the lowest priority in the prominence table, which is well-connected with the finding that "having already highly skilled analytical personnel (BDAC8) greatly influences the whole system". If sourcing "having already highly analytical acumen (BDAC8)" is the causal factor with the highest value, it is implied that developing in-house technical talents should receive less priority.

In our findings, both "having high-end technical skills (BDAC8)" and "business skills (BDAC10)" were identified as the different critical skills for forming appropriate organizational BDAC. Previous studies reported these two as separate skills and emphasized having separate talent pools with business and technical acumen [18,40,74].

Many previous studies [4,9,18,40,72] reported BDAC evenly distributed into broad categories, i.e., management capability, infrastructure capability, tangible asset, intangible asset, etc. However, our study results show that capabilities related to lowering the organizational ICT capacity building cost (BDAC7, BDAC10, BDAC11, BDAC12) are critical in the developing economy context. Therefore, capital investment requirements must be kept at a minimum level in any BDA implementation projects in a developing economy context.

Our study revealed another important finding. Ref. [4] enumerated two BDACs, "Big data analytics projects are adequately funded" and "Big data analytics projects are given enough time to achieve their objectives (BDAC15 in our study)", as fundamental tangible assets under the "Basic resources" category. Our study confirmed that only the latter (BDAC15) is critical in the context of developing economies. As our research revealed, the former (adequately funded) is not crucial in developing countries. These findings are the opposite of researchers who often cited that adequate funding is vital for BDA implementation success [4,22,70,75,76]. The need for good funding in any project is beyond question. However, the underlining assumption for the developing economy context is that funds will be limited or insufficient for any project. Accordingly, finding alternative BDACs to offset funding shortcomings could be a game changer in successful BDA implementation.

5. Conclusions

This study was conducted to identify and establish a hierarchy of the BDAC in Bangladesh's health sector so that the decision makers can focus on specific capabilities rather than considering them jointly. According to the industry experts and applying the DEMATEL approach, the results show BDAC1, BDAC2, BDAC5, BDAC6, BDAC7, BDAC8, BDAC10, BDAC11, BDAC12, BDAC13, and BDAC15 are the eleven most crucial factors and should be prioritized at the planning stage to build organizational BDAC.

5.1. Implications for the Theory

This paper contributes to the big data and DEMATEL literature in three ways. Firstly, our study offers an empirical study of a developing country case to the literature. As per our limited knowledge and results from rigorous search in the three most receptive research outlets, Scopus, Google Scholars, and Web of Sciences, no research has been adopted to identify the most crucial BDACs in developing countries. BDA implementation factors in developing countries are significantly different from those of developed countries [54], and it is worth examining BDA implementation in different contexts [77]. Secondly, our study is one of the earliest studies using the DEMATEL hierarchical model and the cause–effect relationship among the BDAC in Bangladesh's health sector. DEMATEL provides a broader range of BDACs playing a role in BDA implementation. The DEMATEL method has been used since its inception in many sectors, such as ranking barriers [78], influential indicators [67,73], identifying determinants [79], and supplier selection [63], to name a few. Recently, a handful of researchers introduced the method into big data research to identify big data adoption barriers [53], influence [80], and modelling challenges [81]. Our study extends the DEMATEL model to the big data research field by identifying the key BDACs required to form an organization's BDACs in the hospital sector. Thirdly, the study reported a list of key BDACs that may act as the foundation of a knowledge base in BDA implementation, and which can serve as a checklist. The study narrows down the list to 11 capabilities that fit the context of the healthcare sector in Bangladesh. Besides identifying interrelationships among the key BDACs, the influence of each BDAC on others was quantified and tabulated in our study.

5.2. Implications for Practice

Our study points out key BDACs to industry practitioners and policymakers to show them the relative priority of the factors before undertaking any BDA adoption project. Findings from the study may assist healthcare industries in allocating the limited organizational resources in building the most important BDACs to optimize yield from the investment. In addition to industry, by adopting BDA, the government could focus on vital BDACs in a public hospital settings to improve healthcare quality. Although this study cannot be exhaustive in reviewing all BDACs, the criteria were shortlisted from a comprehensive list of BDACs available in the existing literature and two stages of scrutiny with experts' opinions. Thus, the empirically tested BDAC ranking could be used as a primary guide in framing different BDA implementation strategies in healthcare.

5.3. Limitations of the Study and Further Studies

This study has three key limitations. First, it is based in Bangladesh, making the generalizability of the results beyond the region problematic. Conducting similar studies in a similar context will help identify the extent of generalizability of our findings. Second, the study considered only the patient treatment facilities as study areas; however, the health sector comprises many sub-sectors. For example, the medical equipment and pharmaceutical industries also constitute a significant part of the healthcare supply chain. Researchers might conduct similar studies in the other health sector branches in the future. Third, the study relies on expert views, which entails possible biases. Identifying experts with superior knowledge in the field and taking opinions from as many experts as possible will minimize these potential biases [82].

Author Contributions: Conceptualization, M.A.U.M., D.C. and S.C.; Methodology, M.A.U.M.; Software, M.A.U.M.; Validation, M.A.U.M., D.C. and S.C.; Formal analysis, M.A.U.M.; Investigation, M.A.U.M., D.C. and S.C.; Original draft preparation, M.A.U.M.; Supervision, D.C. and S.C.; Review and editing, D.C. and S.C. All authors have read and agreed to the published version of the manuscripts.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Managerial Relevance Statement: The key BDAC identified in this paper allows managers to provide an empirically tested list of the most crucial BDAC in Bangladesh's healthcare sector. The study points out key BDAC to the industry practitioners and policymakers to show them the relative priority of the factors before commencing any big data analytics (BDA) adoption project. Findings from the study may assist healthcare organizations in allocating the limited organizational resources in building the most critical BDAC for optimum yield from the investment. Further, the findings might help government agencies to focus on the most vital BDAC when aiming to improve healthcare quality by adopting BDA in their public hospital settings. Although this study cannot be exhaustive in reviewing all BDAC, the criteria were shortlisted from a comprehensive list of BDAC available in the existing literature. Thus, policymakers can rely on the shortlisted BDAC criteria relevant to their countries' contexts.

Appendix A

Table A1. Direct Relationship Matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	2.6	3.6	3	2.8	3	3.4	3.2	2.6	3.6	2.2	3	3.4	3	3.4	3	3.2	3.4	3.6	3.8
C2	3.6	0	3.6	3.8	3.4	3.4	3.4	3	3.2	3.4	3	3.4	3.4	3	3.4	3	3.2	3.6	3.6	3.6
C3	3.8	3.2	0	3.2	3.6	3.2	3.4	3	3.2	3	2.4	3.4	3.2	3.2	3.2	3.4	3	3.4	3.2	3.6
C4	3.2	3.4	3.4	0	3.6	3.2	3	2.8	3.2	2.6	2.6	3.8	3.2	3.2	2.8	3.4	3.2	3.8	3	3.6
C5	3.4	4	2.8	3.4	0	3.2	3	3	3.6	3	3	3.4	2.6	3	2.8	3.4	3.2	3.4	3.4	3.4
C6	3.6	3.6	3.4	3.4	3.6	0	2.8	2.8	3.6	3	3	3.8	3	3	3.2	3.4	3	3.6	3.2	3.4
C7	3.6	3.4	3	3.6	2.8	2.6	0	2.8	4	3.6	3.4	3.2	2.8	3.2	3.4	2.8	3.6	3.4	3.6	3.4
C8	3.6	3.8	3.4	3.2	3	2.4	3	0	4	3.2	3.2	3.4	2.8	3	3.4	3.2	3.4	3.6	3.8	3
C9	3.6	3.2	3.6	3.8	3.8	3	3.4	2.6	0	3	4	3.2	2.8	3.2	3.4	2.6	3.6	3.6	3.4	3.2
C10	2.8	3.2	2.8	3.4	2.8	3.2	3	2.8	3.8	0	3.4	3	2.6	3	3.4	3.2	3.2	3.6	3	3.2
C11	2.4	3.6	3.4	3.2	3.4	3.2	3	2.8	4	3.4	0	2.8	2.8	2.8	3.2	2.8	3.4	3.4	3.6	3.6
C12	3.4	3.4	3.2	3.4	3	2.8	3	3	3.8	3	3.8	0	2.8	3	2.8	2.8	3.4	3.4	3	3.2
C13	2.8	3.4	3.6	3.4	3.4	2.8	3.4	2.8	3.4	3	3.2	3	0	2.8	3.2	2.8	3.4	3.6	3.4	3.2
C14	2.6	2.8	3.2	3.4	2.8	3.2	3.2	2.8	3.2	2.6	3.2	2.8	2.6	0	3.2	3.4	3.4	3.8	3.4	3.4
C15	3	2.2	3	3.2	3.2	3.2	3.2	3	3.6	3	3.4	3	2.8	3	0	3.2	3.6	3.6	3.6	3.4
C16	2	2.6	2.6	3	2.2	2.2	2.2	2	3.2	2.6	2.8	2.4	2	3.4	3	0	3.2	3.4	3.2	3.4
C17	3.4	3	3.2	2.8	3.4	3.6	3.2	2.8	3	3	3.2	2.8	2.8	3.2	3.2	3.2	0	3.4	3.4	3.4
C18	3	3.2	3.6	3.2	3.2	3.6	2.8	3	3.4	3.2	3.2	3.2	2.8	3.6	2.8	3.4	3.4	0	3.2	3.4
C19	3	3.2	3.2	2.8	3.6	3.4	3	3.2	3.4	3	3.2	2.6	2.8	3.4	3.2	3.2	3.4	3.2	0	3.4
C20	2.6	3.6	3.6	3	3.2	3.6	3.4	3.4	3.6	2.8	3	2.8	2.6	3.6	3.2	3.2	3.4	3.2	3.8	0

Table A2. The normalized direct-relation matrix (C1 refers to BDAC1 and so on).

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
C1	0	0.041	0.056	0.047	0.044	0.047	0.053	0.05	0.041	0.056	0.034	0.047	0.053	0.047	0.053	0.047	0.05	0.053	0.056	0.059
C2	0.056	0	0.056	0.059	0.053	0.053	0.053	0.047	0.05	0.053	0.047	0.053	0.053	0.047	0.053	0.047	0.05	0.056	0.056	0.056
C3	0.059	0.05	0	0.05	0.056	0.05	0.053	0.047	0.05	0.047	0.038	0.053	0.05	0.05	0.05	0.053	0.047	0.053	0.05	0.056
C4	0.05	0.053	0.053	0	0.056	0.05	0.047	0.044	0.05	0.041	0.041	0.059	0.05	0.05	0.044	0.053	0.05	0.059	0.047	0.056
C5	0.053	0.062	0.044	0.053	0	0.05	0.047	0.047	0.056	0.047	0.047	0.053	0.041	0.047	0.044	0.053	0.05	0.053	0.053	0.053
C6	0.056	0.056	0.053	0.053	0.056	0	0.044	0.044	0.056	0.047	0.047	0.059	0.047	0.047	0.05	0.053	0.047	0.056	0.05	0.053
C7	0.056	0.053	0.047	0.056	0.044	0.041	0	0.044	0.062	0.056	0.053	0.05	0.044	0.05	0.053	0.044	0.056	0.053	0.056	0.053
C8	0.056	0.059	0.053	0.05	0.047	0.038	0.047	0	0.062	0.05	0.05	0.053	0.044	0.047	0.053	0.05	0.053	0.056	0.059	0.047
C9	0.056	0.05	0.056	0.059	0.059	0.047	0.053	0.041	0	0.047	0.062	0.05	0.044	0.05	0.053	0.041	0.056	0.056	0.053	0.05
C10	0.044	0.05	0.044	0.053	0.044	0.05	0.047	0.044	0.059	0	0.053	0.047	0.041	0.047	0.053	0.05	0.05	0.056	0.047	0.05
C11	0.038	0.056	0.053	0.05	0.053	0.05	0.047	0.044	0.062	0.053	0	0.044	0.044	0.044	0.05	0.044	0.053	0.053	0.056	0.056
C12	0.053	0.053	0.05	0.053	0.047	0.044	0.047	0.047	0.059	0.047	0.059	0	0.044	0.047	0.044	0.044	0.053	0.053	0.047	0.05
C13	0.044	0.053	0.056	0.053	0.053	0.044	0.053	0.044	0.053	0.047	0.05	0.047	0	0.044	0.05	0.044	0.053	0.056	0.053	0.05
C14	0.041	0.044	0.05	0.053	0.044	0.05	0.05	0.044	0.05	0.041	0.05	0.044	0.041	0	0.05	0.053	0.053	0.059	0.053	0.053
C15	0.047	0.034	0.047	0.05	0.05	0.05	0.05	0.047	0.056	0.047	0.053	0.047	0.044	0.047	0	0.05	0.056	0.056	0.056	0.053
C16	0.031	0.041	0.041	0.047	0.034	0.034	0.034	0.031	0.05	0.041	0.044	0.038	0.031	0.053	0.047	0	0.05	0.053	0.05	0.053
C17	0.053	0.047	0.05	0.044	0.053	0.056	0.05	0.044	0.047	0.047	0.05	0.044	0.044	0.05	0.05	0.05	0	0.053	0.053	0.053
C18	0.047	0.05	0.056	0.05	0.05	0.056	0.044	0.047	0.053	0.05	0.05	0.05	0.044	0.056	0.044	0.053	0.053	0	0.05	0.053
C19	0.047	0.05	0.05	0.044	0.056	0.053	0.047	0.05	0.053	0.047	0.05	0.041	0.044	0.053	0.05	0.05	0.053	0.05	0	0.053
C20	0.041	0.056	0.056	0.047	0.05	0.056	0.053	0.053	0.056	0.044	0.047	0.044	0.041	0.056	0.05	0.05	0.053	0.05	0.059	0

Table A3. The total relation matrix (C1 refers to BDCA1 and so on).

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**
C1	0.824	0.888	0.914	0.904	0.886	0.863	0.866	0.811	0.945	0.858	0.854	0.863	0.8	0.873	0.884	0.869	0.921	0.965	0.942	0.949
C2	0.933	0.907	0.973	0.974	0.952	0.925	0.922	0.86	1.015	0.909	0.921	0.924	0.851	0.929	0.94	0.925	0.981	1.03	1.003	1.006
C3	0.904	0.921	0.886	0.932	0.921	0.89	0.89	0.83	0.98	0.872	0.881	0.892	0.818	0.899	0.905	0.898	0.943	0.991	0.962	0.971
C4	0.888	0.916	0.928	0.876	0.913	0.882	0.876	0.82	0.971	0.859	0.876	0.89	0.811	0.892	0.891	0.89	0.938	0.989	0.951	0.963
C5	0.891	0.925	0.92	0.927	0.86	0.882	0.877	0.823	0.977	0.865	0.882	0.885	0.803	0.889	0.892	0.891	0.939	0.983	0.957	0.961
C6	0.912	0.938	0.948	0.946	0.932	0.853	0.892	0.837	0.997	0.883	0.9	0.908	0.825	0.907	0.916	0.909	0.955	1.006	0.974	0.98
C7	0.91	0.933	0.94	0.947	0.919	0.89	0.848	0.835	1.001	0.889	0.904	0.898	0.821	0.908	0.917	0.898	0.961	1.001	0.977	0.978
C8	0.912	0.941	0.948	0.944	0.924	0.889	0.895	0.795	1.003	0.886	0.903	0.903	0.823	0.908	0.919	0.906	0.961	1.007	0.983	0.975
C9	0.921	0.942	0.96	0.961	0.944	0.907	0.909	0.843	0.954	0.891	0.923	0.909	0.831	0.919	0.927	0.906	0.973	1.016	0.986	0.987
C10	0.861	0.892	0.898	0.905	0.881	0.862	0.856	0.801	0.957	0.8	0.867	0.858	0.784	0.868	0.879	0.867	0.916	0.963	0.929	0.935
C11	0.875	0.918	0.927	0.923	0.91	0.881	0.875	0.819	0.982	0.869	0.836	0.875	0.805	0.885	0.896	0.881	0.94	0.982	0.958	0.962
C12	0.881	0.907	0.916	0.917	0.895	0.867	0.867	0.814	0.969	0.856	0.884	0.824	0.797	0.879	0.882	0.872	0.931	0.973	0.941	0.947
C13	0.878	0.912	0.927	0.923	0.907	0.872	0.878	0.816	0.97	0.861	0.88	0.875	0.76	0.882	0.893	0.878	0.937	0.981	0.952	0.953
C14	0.852	0.88	0.898	0.899	0.875	0.856	0.853	0.795	0.942	0.833	0.858	0.849	0.779	0.818	0.87	0.864	0.913	0.959	0.928	0.931
C15	0.874	0.888	0.911	0.913	0.897	0.871	0.868	0.813	0.965	0.854	0.877	0.868	0.796	0.878	0.838	0.877	0.932	0.974	0.948	0.948
C16	0.743	0.773	0.784	0.788	0.763	0.742	0.739	0.691	0.831	0.734	0.752	0.743	0.678	0.767	0.765	0.713	0.803	0.842	0.816	0.823
C17	0.877	0.897	0.912	0.905	0.897	0.875	0.866	0.808	0.954	0.852	0.871	0.862	0.794	0.879	0.884	0.874	0.876	0.968	0.942	0.946
C18	0.887	0.916	0.934	0.927	0.91	0.89	0.876	0.825	0.977	0.87	0.887	0.884	0.808	0.9	0.894	0.893	0.943	0.935	0.956	0.963
C19	0.874	0.903	0.915	0.908	0.903	0.875	0.866	0.816	0.963	0.855	0.874	0.863	0.796	0.884	0.887	0.877	0.93	0.969	0.895	0.949
C20	0.888	0.928	0.94	0.93	0.917	0.896	0.891	0.837	0.987	0.87	0.89	0.884	0.811	0.906	0.906	0.896	0.95	0.99	0.972	0.919

Table A4. The total- relationships matrix by considering the threshold value (C1 refers to BDCA1 and so on).

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**	**C17**	**C18**	**C19**	**C20**
C1	0	0	0.914	0.904	0	0	0	0	0.945	0	0	0	0	0	0	0	0.921	0.965	0.942	0.949
C2	0.933	0.907	0.973	0.974	0.952	0.925	0.922	0	1.015	0.909	0.921	0.924	0	0.929	0.94	0.925	0.981	1.03	1.003	1.006
C3	0.904	0.921	0	0.932	0.921	0	0	0	0.98	0	0	0	0	0.899	0.905	0.898	0.943	0.991	0.962	0.971
C4	0	0.916	0.928	0	0.913	0	0	0	0.971	0	0	0	0	0	0	0	0.938	0.989	0.951	0.963
C5	0	0.925	0.92	0.927	0	0	0	0	0.977	0	0	0	0	0	0	0	0.939	0.983	0.957	0.961
C6	0.912	0.938	0.948	0.946	0.932	0	0	0	0.997	0	0.9	0.908	0	0.907	0.916	0.909	0.955	1.006	0.974	0.98
C7	0.91	0.933	0.94	0.947	0.919	0	0	0	1.001	0	0.904	0.898	0	0.908	0.917	0.898	0.961	1.001	0.977	0.978
C8	0.912	0.941	0.948	0.944	0.924	0	0	0	1.003	0	0.903	0.903	0	0.908	0.919	0.906	0.961	1.007	0.983	0.975
C9	0.921	0.942	0.96	0.961	0.944	0.907	0.909	0	0.954	0	0.923	0.909	0	0.919	0.927	0.906	0.973	1.016	0.986	0.987
C10	0	0	0.898	0.905	0	0	0	0	0.957	0	0	0	0	0	0	0	0.916	0.963	0.929	0.935
C11	0	0.918	0.927	0.923	0.91	0	0	0	0.982	0	0	0	0	0	0.896	0	0.94	0.982	0.958	0.962
C12	0	0.907	0.916	0.917	0	0	0	0	0.969	0	0	0	0	0	0	0	0.931	0.973	0.941	0.947
C13	0	0.912	0.927	0.923	0.907	0	0	0	0.97	0	0	0	0	0	0	0	0.937	0.981	0.952	0.953
C14	0	0	0.898	0.899	0	0	0	0	0.942	0	0	0	0	0	0	0	0.913	0.959	0.928	0.931
C15	0	0	0.911	0.913	0.897	0	0	0	0.965	0	0	0	0	0	0	0	0.932	0.974	0.948	0.948
C16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
C17	0	0.897	0.912	0.905	0.897	0	0	0	0.954	0	0	0	0	0	0	0	0	0.968	0.942	0.946
C18	0	0.916	0.934	0.927	0.91	0	0	0	0.977	0	0	0	0	0.9	0	0	0.943	0.935	0.956	0.963
C19	0	0.903	0.915	0.908	0.903	0	0	0	0.963	0	0	0	0	0	0	0	0.93	0.969	0	0.949
C20	0	0.928	0.94	0.93	0.917	0.896	0	0	0.987	0	0	0	0	0.906	0.906	0.896	0.95	0.99	0.972	0.919

References

1. Srinivasan, R.; Swink, M. An Investigation of Visibility and Flexibility as Complements to Supply Chain Analytics: An Organizational Information Processing Theory Perspective. *Prod. Oper. Manag.* **2018**, *27*, 1849–1867. [CrossRef]
2. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Blome, C.; Papadopoulos, T. Big Data and Predictive Analytics and Manufacturing Performance: Integrating Institutional Theory, Resource-Based View and Big Data Culture. *Br. J. Manag.* **2019**, *30*, 341–361. [CrossRef]
3. Jha, A.K.; Agi, M.A.N.; Ngai, E.W.T. A note on big data analytics capability development in supply chain. *Decis. Support Syst.* **2020**, *138*, 113382. [CrossRef]
4. Gupta, M.; George, J.F. Toward the development of a big data analytics capability. *Inf. Manag.* **2016**, *53*, 1049–1064. [CrossRef]
5. Chen, C.-H.V.; Chen, Y.-C. Influence of intellectual capital and integration on operational performance: Big data analytical capability perspectives. *Chin. Manag. Stud.* **2021**, *16*, 551–570. [CrossRef]
6. Lin, C.; Kunnathur, A. Strategic orientations, developmental culture, and big data capability. *J. Bus. Res.* **2019**, *105*, 49–60. [CrossRef]
7. Akter, S.; Wamba, S.F.; Gunasekaran, A.; Dubey, R.; Childe, S.J. How to improve firm performance using big data analytics capability and business strategy alignment? *Int. J. Prod. Econ.* **2016**, *182*, 113–131. [CrossRef]
8. Shamim, S.; Zeng, J.; Khan, Z.; Zia, N.U. Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technol. Forecast. Soc. Change* **2020**, *161*, 120315. [CrossRef]
9. Yasmin, M.; Tatoglu, E.; Kilic, H.S.; Zaim, S.; Delen, D. Big data analytics capabilities and firm performance: An integrated MCDM approach. *J. Bus. Res.* **2020**, *114*, 1–15. [CrossRef]
10. Zhu, X.; Yang, Y. Big Data Analytics for Improving Financial Performance and Sustainability. *J. Syst. Sci. Inf.* **2021**, *9*, 175–191. [CrossRef]
11. Pitts, J.; Gopal, S.; Ma, Y.; Koch, M.; Boumans, R.M.; Kaufman, L. Leveraging Big Data and Analytics to Improve Food, Energy, and Water System Sustainability. *Front Big Data* **2020**, *3*, 13. [CrossRef]
12. Jeble, S.; Dubey, R.; Childe, S.J.; Papadopoulos, T.; Roubaud, D.; Prakash, A. Impact of big data and predictive analytics capability on supply chain sustainability. *Int. J. Logist. Manag.* **2018**, *29*, 513–538. [CrossRef]
13. Sivarajah, U.; Irani, Z.; Gupta, S.; Mahroof, K. Role of big data and social media analytics for business to business sustainability: A participatory web context. *Ind. Mark. Manag.* **2020**, *86*, 163–179. [CrossRef]
14. Mikalef, P.; Pappas, I.O.; Krogstie, J.; Giannakos, M. Big data analytics capabilities: A systematic literature review and research agenda. *Inf. Syst. E-Bus. Manag.* **2017**, *16*, 547–578. [CrossRef]
15. Cetindamar, D.; Shdifat, B.; Erfani, E. Understanding Big Data Analytics Capability and Sustainable Supply Chains. *Inf. Syst. Manag.* **2022**, *39*, 19–33. [CrossRef]
16. Wang, Y.; Kung, L.; Byrd, T.A. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technol. Forecast. Soc. Change* **2018**, *126*, 3–13. [CrossRef]
17. Korherr, P.; Kanbach, D. Human-related capabilities in big data analytics: A taxonomy of human factors with impact on firm performance. *Rev. Manag. Sci.* **2021**, 1–28. [CrossRef]
18. Wamba, S.F.; Gunasekaran, A.; Akter, S.; Ren, S.J.-F.; Dubey, R.; Childe, S.J. Big data analytics and firm performance: Effects of dynamic capabilities. *J. Bus. Res.* **2017**, *70*, 356–365. [CrossRef]
19. Wang, Y.; Hajli, N. Exploring the path to big data analytics success in healthcare. *J. Bus. Res.* **2017**, *70*, 287–299. [CrossRef]
20. Nations, U. *World Economic Situation and Prospects 2014*; United Nations: New York, NY, USA, 2014.
21. Song, M.; Zhang, H.; Heng, J. Creating Sustainable Innovativeness through Big Data and Big Data Analytics Capability: From the Perspective of the Information Processing Theory. *Sustainability* **2020**, *12*, 1984. [CrossRef]
22. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. The role of information governance in big data analytics driven innovation. *Inf. Manag.* **2020**, *57*, 103361. [CrossRef]
23. Arunachalam, D.; Kumar, N.; Kawalek, J.P. Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. *Transp. Res. Part E Logist. Transp. Rev.* **2018**, *114*, 416–436. [CrossRef]
24. Bag, S.; Wood, L.C.; Xu, L.; Dhamija, P.; Kayikci, Y. Big data analytics as an operational excellence approach to enhance sustainable supply chain performance. *Resour. Conserv. Recycl.* **2020**, *153*, 104559. [CrossRef]
25. Yu, W.; Wong, C.Y.; Chavez, R.; Jacobs, M.A. Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *Int. J. Prod. Econ.* **2021**, *236*, 108135. [CrossRef]
26. Kiron, D.; Prentice, P.K.; Ferguson, R.B. The Analytics Mandate. In *MITSloan Management Review*; MIT Sloan School of Management: Cambridge, MA, USA, 2014.
27. Dubey, R.; Gunasekaran, A.; Childe, S.J. Big data analytics capability in supply chain agility. *Manag. Decis.* **2019**, *57*, 2092–2112. [CrossRef]
28. Dubey, R.; Gunasekaran, A.; Childe, S.J.; Roubaud, D.; Wamba, S.F.; Giannakis, M.; Foropon, C. Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain. *Int. J. Prod. Econ.* **2019**, *210*, 120–136. [CrossRef]
29. Gupta, S.; Chen, H.; Hazen, B.T.; Kaur, S.; Gonzalez, E.D.R.S. Circular economy and big data analytics: A stakeholder perspective. *Technol. Forecast. Soc. Change* **2019**, *144*, 466–474. [CrossRef]

30. George, G.; Haas, M.R.; Pentland, A. Big Data and Management. *Acad. Manag. J.* **2014**, *57*, 321–326. [CrossRef]
31. Ramadan, M.; Shuqqo, H.; Qtaishat, L.; Asmar, H.; Salah, B. Sustainable Competitive Advantage Driven by Big Data Analytics and Innovation. *Appl. Sci.* **2020**, *10*, 6784. [CrossRef]
32. Gu, V.C.; Zhou, B.; Cao, Q.; Adams, J. Exploring the relationship between supplier development, big data analytics capability, and firm performance. *Ann. Oper. Res.* **2021**, *302*, 151–172. [CrossRef]
33. Yu, W.; Zhao, G.; Liu, Q.; Song, Y. Role of big data analytics capability in developing integrated hospital supply chains and operational flexibility: An organizational information processing theory perspective. *Technol. Forecast. Soc. Change* **2021**, *163*, 120417. [CrossRef]
34. Behl, A. Antecedents to firm performance and competitiveness using the lens of big data analytics: A cross-cultural study. *Manag. Decis.* **2020**, *60*, 368–398. [CrossRef]
35. Benzidia, S.; Makaoui, N.; Bentahar, O. The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technol. Forecast. Soc. Change* **2021**, *165*, 120557. [CrossRef]
36. Shamim, S.; Zeng, J.; Shariq, S.M.; Khan, Z. Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Inf. Manag.* **2019**, *56*, 103135. [CrossRef]
37. Raut, R.D.; Mangla, S.K.; Narwane, V.S.; Dora, M.; Liu, M. Big Data Analytics as a mediator in Lean, Agile, Resilient, and Green (LARG) practices effects on sustainable supply chains. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *145*, 102170. [CrossRef]
38. Belhadi, A.; Zkik, K.; Cherrafi, A.; Yusof, S.r.M.; El fezazi, S. Understanding Big Data Analytics for Manufacturing Processes: Insights from Literature Review and Multiple Case Studies. *Comput. Ind. Eng.* **2019**, *137*, 10609. [CrossRef]
39. Kim, G.; Shin, B.; Kwon, O. Investigating the Value of Sociomaterialism in Conceptualizing IT Capability of a Firm. *J. Manag. Inf. Syst.* **2014**, *29*, 327–362. [CrossRef]
40. Xiao, X.; Tian, Q.; Mao, H. How the Interaction of Big Data Analytics Capabilities and Digital Platform Capabilities Affects Service Innovation: A Dynamic Capabilities View. *IEEE Access* **2020**, *8*, 18778–18796. [CrossRef]
41. Upadhyay, P.; Kumar, A. The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *Int. J. Inf. Manag.* **2020**, *52*, 102100. [CrossRef]
42. Mikalef, P.; Boura, M.; Lekakos, G.; Krogstie, J. Big data analytics and firm performance: Findings from a mixed-method approach. *J. Bus. Res.* **2019**, *98*, 261–276. [CrossRef]
43. Anfer, O.; Wamba, S.F. Big Data Analytics and Strategic Marketing Capabilities: Impact on Firm Performance. In *New Knowledge in Information Systems and Technologies*; Springer: Berlin, Germany, 2019; pp. 633–640.
44. Arias-Pérez, J.; Coronado-Medina, A.; Perdomo-Charry, G. Big data analytics capability as a mediator in the impact of open innovation on firm performance. *J. Strategy Manag.* **2021**, *15*, 1–15. [CrossRef]
45. Ashrafi, A.; Zare Ravasan, A.; Trkman, P.; Afshari, S. The role of business analytics capabilities in bolstering firms' agility and performance. *Int. J. Inf. Manag.* **2019**, *47*, 1–15. [CrossRef]
46. Edwin Cheng, T.C.; Kamble, S.S.; Belhadi, A.; Ndubisi, N.O.; Lai, K.; Kharat, M.G. Linkages between big data analytics, circular economy, sustainable supply chain flexibility, and sustainable performance in manufacturing firms. *Int. J. Prod. Res.* **2021**, 1–15. [CrossRef]
47. Ferraris, A.; Mazzoleni, A.; Devalle, A.; Couturier, J. Big data analytics capabilities and knowledge management: Impact on firm performance. *Manag. Decis.* **2019**, *57*, 1923–1936. [CrossRef]
48. Khai Loon, L.; Cean Peing, L. Big Data and Predictive Analytics Capabilities: A Review of Literature on Its Impact on Firm's Financial Performance. *KnE Soc. Sci.* **2019**, 1057–1073. [CrossRef]
49. Liu, C.-H.; Mehandjiev, N. The Effect of Big Data Analytics Capability on Firm Performance: A Pilot Study in China. In *Information Systems*; Springer: Berlin, Germany, 2020; pp. 594–608.
50. Singh, S.K.; Del Giudice, M. Big data analytics, dynamic capabilities and firm performance. *Manag. Decis.* **2019**, *57*, 1729–1733. [CrossRef]
51. Suoniemi, S.; Meyer-Waarden, L.; Munzel, A.; Zablah, A.R.; Straub, D. Big data and firm performance: The roles of market-directed capabilities and business strategy. *Inf. Manag.* **2020**, *57*, 103365. [CrossRef]
52. Wang, C.; Zhang, Q.; Zhang, W. Corporate social responsibility, Green supply chain management and firm performance: The moderating role of big-data analytics capability. *Res. Transp. Bus. Manag.* **2020**, *37*, 100557. [CrossRef]
53. Raut, R.D.; Yadav, V.S.; Cheikhrouhou, N.; Narwane, V.S.; Narkhede, B.E. Big data analytics: Implementation challenges in Indian manufacturing supply chains. *Comput. Ind.* **2021**, *125*, 103368. [CrossRef]
54. Alalawneh, A.A.F.; Alkhatib, S.F. The barriers to big data adoption in developing economies. *Electron. J. Inf. Syst. Dev. Ctries.* **2020**, *87*, e12151. [CrossRef]
55. Delponte, L.; Grigolini, M.; Moroni, A.; Vignetti, S. *ICT in the Developing World*; European Parliament: Strasbourg, France, 2015.
56. Ahmed, S.M.; Alam, B.B.; Anwar, I.; Begum, T.; Huque, R.; Khan, J.A.; Nababan, H.; Osman, F.A. *Bangladesh Health System Review*; World Health Organization: Geneva, Switzerland, 2015.
57. Kraus, S.; Breier, M.; Dasí-Rodríguez, S. The art of crafting a systematic literature review in entrepreneurship research. *Int. Entrep. Manag. J.* **2020**, *16*, 1023–1042. [CrossRef]
58. Wu, W.-W. Segmenting critical factors for successful knowledge management implementation using the fuzzy DEMATEL method. *Appl. Soft Comput.* **2012**, *12*, 527–535. [CrossRef]

59. Kumar, A.; Dixit, G. An analysis of barriers affecting the implementation of e-waste management practices in India: A novel ISM-DEMATEL approach. *Sustain. Prod. Consum.* **2018**, *14*, 36–52. [CrossRef]
60. Büyüközkan, G.; Güleryüz, S. An integrated DEMATEL-ANP approach for renewable energy resources selection in Turkey. *Int. J. Prod. Econ.* **2016**, *182*, 435–448. [CrossRef]
61. Sharma, V.; Dixit, A.R.; Qadri, M.A. Empirical assessment of the causal relationships among lean criteria using DEMATEL method. *Benchmarking Int. J.* **2014**, *23*, 1834–1839. [CrossRef]
62. DeJonckheere, M.; Vaughn, L.M. Semistructured interviewing in primary care research: A balance of relationship and rigour. *Fam. Med. Community Health* **2019**, *7*, e000057. [CrossRef]
63. Chang, B.; Chang, C.-W.; Wu, C.-H. Fuzzy DEMATEL method for developing supplier selection criteria. *Expert Syst. Appl.* **2011**, *38*, 1850–1858. [CrossRef]
64. Huang, C.-Y.; Shyu, J.Z.; Tzeng, G.-H. Reconfiguring the innovation policy portfolios for Taiwan's SIP Mall industry. *Technovation* **2007**, *27*, 744–765. [CrossRef]
65. Shieh, J.-I.; Wu, H.-H.; Huang, K.-K. A DEMATEL method in identifying key success factors of hospital service quality. *Knowl.-Based Syst.* **2010**, *23*, 277–282. [CrossRef]
66. Tong, A.; Flemming, K.; Mclnnes, E.; Olvier, S.; Craig, J. Enhancing transparency in reporting the synthesis of qualitative research: ENTREQ. *BMC Med. Res. Methodolgy* **2012**, *12*, 181. [CrossRef]
67. Wang, L.; Cao, Q.; Zhou, L. Research on the influencing factors in coal mine production safety based on the combination of DEMATEL and ISM. *Saf. Sci.* **2018**, *103*, 51–61. [CrossRef]
68. Dubey, R.; Bryde, D.J.; Foropon, C.; Tiwari, M.; Dwivedi, Y.; Schiffling, S. An investigation of information alignment and collaboration as complements to supply chain agility in humanitarian supply chain. *Int. J. Prod. Res.* **2020**, *59*, 1586–1605. [CrossRef]
69. AlNuaimi, B.K.; Khan, M.; Ajmal, M.M. The role of big data analytics capabilities in greening e-procurement: A higher order PLS-SEM analysis. *Technol. Forecast. Soc. Change* **2021**, *169*, 120808. [CrossRef]
70. Henao-García, E.; Arias-Pérez, J.; Lozada, N. Fostering big data analytics capability through process innovation: Is management innovation the missing link? *Bus. Inf. Rev.* **2021**, *38*, 28–39. [CrossRef]
71. Aljumah, A.I.; Nuseir, M.T.; Alam, M.M. Organizational performance and capabilities to analyze big data: Do the ambidexterity and business value of big data analytics matter? *Bus. Process Manag. J.* **2021**, *27*, 1088–1107. [CrossRef]
72. Belhadi, A.; Kamble, S.S.; Zkik, K.; Cherrafi, A.; Touriki, F.E. The integrated effect of Big Data Analytics, Lean Six Sigma and Green Manufacturing on the environmental performance of manufacturing companies: The case of North Africa. *J. Clean. Prod.* **2020**, *252*, 119903. [CrossRef]
73. Li, Y.; Mathiyazhagan, K. Application of DEMATEL approach to identify the influential indicators towards sustainable supply chain adoption in the auto components manufacturing sector. *J. Clean. Prod.* **2018**, *172*, 2931–2941. [CrossRef]
74. Su, X.; Zeng, W.; Zheng, M.; Jiang, X.; Lin, W.; Xu, A. Big data analytics capabilities and organizational performance: The mediating effect of dual innovations. *Eur. J. Innov. Manag.* **2021**. *ahead of print*. [CrossRef]
75. Ciampi, F.; Demi, S.; Magrini, A.; Marzi, G.; Papa, A. Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *J. Bus. Res.* **2021**, *123*, 1–13. [CrossRef]
76. Grover, V.; Chiang, R.H.L.; Liang, T.; Zhang, D. Creating Strategic Business Value from Big Data Analytics: A Research Framework. *J. Manag. Inf. Syst.* **2018**, *35*, 388–423. [CrossRef]
77. Sun, S.; Cegielski, C.G.; Jia, L.; Hall, D.J. Understanding the Factors Affecting the Organizational Adoption of Big Data. *J. Comput. Inf. Syst.* **2016**, *58*, 193–203. [CrossRef]
78. Singh, R.; Bhanot, N. An integrated DEMATEL-MMDE-ISM based approach for analysing the barriers of IoT implementation in the manufacturing industry. *Int. J. Prod. Res.* **2019**, *58*, 2454–2476. [CrossRef]
79. Braga, I.F.B.; Ferreira, F.A.F.; Ferreira, J.J.M.; Correia, R.J.C.; Pereira, L.F.; Falcão, P.F. A DEMATEL analysis of smart city determinants. *Technol. Soc.* **2021**, *66*, 101687. [CrossRef]
80. Yadegaridehkordi, E.; Hourmand, M.; Nilashi, M.; Shuib, L.; Ahani, A.; Ibrahim, O. Influence of big data adoption on manufacturing companies' performance: An integrated DEMATEL-ANFIS approach. *Technol. Forecast. Soc. Change* **2018**, *137*, 199–210. [CrossRef]
81. Khan, M.I.; Khan, S.; Khan, U.; Haleem, A. Modeling the Big Data challenges in context of smart cities—An integrated fuzzy ISM-DEMATEL approach. *Int. J. Build. Pathol. Adapt.* **2021**. *ahead-of-print*. [CrossRef]
82. Chin, J.M.; Lutsky, M.; Dror, I.E. The Biases of Experts: An Empirical Analysis of Expert Witness Challenges. *Manit. Law J.* **2018**, *42*, 21.