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Original Research

Analytical Study on Building a Comprehensive Big Data Management Maturity Framework

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Abstract

Harnessing big data in organizations today realizes benefits for competitive advantage. Generated profound insights are reflected in informed decision making, creating better business plans, and improved service delivery. Yet, organizations are still not recognizing how mature their big data management capabilities are. However, there is no structured approach to assess and build necessary capabilities for valuable big data utilizing, which draws a clear improvement pathway. Existing solutions lack a consistent perception of big data management capabilities, a reliable assessment, and a rigid improvement scheme. This paper contributes in building an analytical study on existing key works in assessing and building big data management capabilities. Drawing upon the results and gaps revealed from this analytical study, the main requirements for building a comprehensive big data management maturity framework are defined. This framework will enable organizations to assess and improve their current capabilities towards effective big data management.

Keywords: Big Data Management Maturity, Big Data Management Capabilities, Big Data Capabilities, Big Data Capabilities Construct, Big Data Maturity Model.

Introduction

Big data has aroused tremendous attention to gain valuable data wealth for organizations. There is an exponential growth of data nowadays from diverse data sources. For example, data generated from daily administrative processes, business transactions, analytical reports, social media, the internet of things, and many others. Big data today does not only concern with the massive amounts of data, but also looks out the benefits of leveraging, exploiting and processing all available digital data generated humans and machines (Bhuiyan, Ali, Zulkiflin&

Kumarasamy, 2020). The value of such generated data lies in the actionable insights derived from a broader spectrum of big data analytics (Gunther et al., 2017; Predescu, 2019; Yaqoob et al., 2016). Analytical models offer the ability to build behavioral scenarios based on forecasting mechanisms that help extract powerful data indicators (Grossman, 2018; Madhlangobe & Wang, 2019; Naik, 2017). The matter that is considered a promising innovation and has a transformative effect for data-driven organizations and that advances informed decision-making and performance optimization (Alzaghal & El-Omari, 2017; Dremel, Overhage, Schlauderer & Wulf, 2017; Janssen, van der Voort, Van Der & Wahyudi, 2016; Roden, Nucciarelli, Li & Graham, 2017; Shi, Ai & Cao, 2017). So, with the course of time, it is noteworthy to strive in leveraging the value of big data across different industries to gain competitive advantage in the highly global environment.

Possessing the right capabilities to manage and analyze big data is an essential enabler for organizations to hold the power of such data (Gong & Janssen, 2020; Isik, 2018). Capabilities are the coordinating processes that facilitate the organization's resources to achieve objectives (Mikalef, Krogstie, Pappas & Pavlou, 2020). The emergence of big data has required a change in existing capabilities in managing such data (Henderson, Earley, Sebastian-Coleman, Sykora & Smith, 2017; Fleckenstein & Fellows, 2018; Siddiqa et al., 2016). The changing business environment requires that organizations should enhance their adaptability to get an opportunity to gain value from big data (Grover, Chiang, Liang & Zhang, 2018; Haddad, Ameen & Mukred, 2018; Sheng et al., 2017). Furthermore, Big data has brought opportunities to create the fourth industrial revolution (IR4.0). Big data provides further advancement in Industry 4.0 and plays a significant and potential role in its successful adoption (Bhuiyan, et al., 2020). Yet, the availability of appropriate resources and optimized processes for leveraging big data challenges its value delivery (Rajnai & Kocsis, 2018). The winners will be those who can change, adapt, embrace new resources and technologies and respond to new demands to gain an edge through leveraging big data, and they will succeed to survive in the new industrial environment 4.0.

While some organizations have massive amounts of data, they are still behind figuring appropriate capabilities to realize the underlying potential benefits of big data (Fleckenstein & Fellows, 2018; Grover *et al.*, 2018; Gong & Janssen, 2020; Haddad, et al., 2018; Klievink, Romijn, Cunningham & de Bruijn, 2016; Sheng, Amankwah-Amoah & Wang, 2017; Siddiqa et al., 2016). They may still be uncertain whether they have the tools to fully engage in utilizing such data (Klievink et al., 2017). Meanwhile, organizations are now trying to underpin their technological competencies for processing and analyzing big data, while ignoring other necessary data management capabilities areas that support effective big data analytics (Austin, 2018; Ferraris, Mazzoleni, Devalle & Couturier, 2019; Ghasemaghaei, 2019; Gong & Janssen, 2020; Mandal, 2019; McAfee & Brynjolfsson, 2012).

Big data technical investments alone are not enough to deliver the opportunistic value of big data (Ferraris et al., 2019; Ghasemaghaei, 2019; Mandal, 2019; McAfee & Brynjolfsson, 2012). Other supporting organizational aspects should exist such as strategies, policies, organization's culture, human skills, and processes that deliver, control, and enhance the value of big data assets throughout their lifecycle for successful value delivery (Henderson et al., 2017; Gandomi and Haider, 2015; Isik, 2018; Elgendy N. & Elragal, 2014; Popovič Hackney, Coelho & Jaklič, 2012; Portela, Lima and Santos, 2016). Nevertheless, organizations are still uncertain about how mature their big data management capabilities are and what improvements are needed (Ghasemaghaei, 2019; Klievink et al., 2017).

So, capabilities maturity assessment and building in big data management are crucial for organizations to assess, build, and improve their big data management capabilities and draw upon an improvement pathway (Corea, 2019; Farzaneh, Mozaffari, Ameli, Karami, Mohamadian & Arianyan, 2018; Lasrado, 2018; Saltz & Shamshurin, 2016). Assessing maturity of big data management helps organizations in addressing existing problems and challenges in a structured way. This type of assessment is not just related to the degree of big data enactment, but it represents an indicator of how well existing capabilities can gain an advantage of big data (Austin, 2018; Klievink et al., 2017). It can be viewed as a measure to assess the capabilities across an evolutionary growth scale (Arunachalam, Kumar & Kawalek, 2018; Comuzzi & Patel, 2016; Di. Proença & Borbinha, 2018; J. Saltz, 2017). Organizations that periodically assess and undertake improvements advance in performance compared to their competitors (Austin, 2018; F. Lasrado, 2018; Portela et al., 2016).

Although some existing capabilities maturity assessment and development solutions for effective big data utilization have been proposed, they are still unstructured, simplistic, and do not provide a holistic and concrete visualization of big data management capabilities. They provide a general assessment for organizations' readiness towards big data adoption but do not assess specific process areas within each capability. Besides, little attention is given to building a consistent big data management capabilities' architecture to fully exploit the potential of big data analytics (Philip Chen & Zhang, 2014; Shams & Solima, 2019; Siddiqa et al., 2016). In addition, emerging researches in IR 4.0 have also focused mainly on the technical aspects of adoption (Liao, Deschamps, Loures & Ramos, 2017), and rarely addressed the organizational requirements. With such challenging issues, there is a necessity to develop a comprehensive big data management maturity framework that helps organizations assess, build, and improve their capabilities to utilize big data better.

So, the contribution of this article is threefold:

- Conducting an analytical study to explore and evaluate existing capabilities' building and maturity assessment key work efforts in big data management to reveal their strengths and weaknesses,
- Based on that analytical study, a set of essential requirements are concluded, which could be used as a roadmap for building a comprehensive big data management maturity framework, and that could be used for research and development in this direction,
- A comprehensive big data management maturity framework is proposed based on the requirements revealed in that analytical study.

This article is structured into six sections. The first section introduces the entire article, followed by the second section of the research methodology. The third section covers a literature review on prominent key capabilities building and maturity assessment efforts in big data management. Then followed by presenting the importance of big data in the fourth industrial revolution (IR4.0). Then the discussion section provides a comparative analysis and reveals the strengths and weaknesses of the reviewed key works. Then followed by a section that identifies a set of Requirements For Building A Comprehensive Big Data Management Maturity Framework. Finally, the last section highlights the Conclusion and Future Work.

Research Methodology

This article is qualitative research that adopted the critical literature review method to study existing key works in big data management capabilities maturity. The research methodology had run into four phases. The first phase screened the existing related articles through significant search engines such as Google Scholar, Emerald, IEEE Xplore Digital Library, ProQuest, Science Direct, Taylor &Francis, Scopus, and Web of Science. The screening phase used a keyword-based search on the terms “big data maturity models”, “big data management maturity”, “big data analytics capabilities”, “big data capabilities”, “big data capabilities constructs”, “big data capabilities assessment”, “Fourth Industrial Revolution challenges”. The second phase had focused on filtering the collected articles for choosing the major key works that would be reviewed and analyzed. All relevant articles were categorized according to their origin, whether scientific or practice-oriented, and according to the publication site, whether in journals, conference proceedings, industry associations publications, or by software vendors. The third phase was building a descriptive-analytical study on the corpus of the filtered works to reveal their strengths and weaknesses in big data capabilities maturity assessment, encountering the fourth industrial revolution, and identifying its challenges and requirements for effective implementation. Besides, a comparative analysis had been conducted to compare existing works using a set of evaluation criteria adopted from the existing literature. Finally, the fourth phase had drawn the conclusions form the analytical study which led to drawing a proposed solution for existing challenges.

Background

Most of the existing work efforts in the area of capabilities assessment for big data utilization have used the terms “Big Data Capabilities” such as (Anwar, Khan & Shah, 2018; Hassna & Lowry, 2016; Marfo, 2017), and some studies used the term “Big Data Analytics Capabilities (BDAC)” like the ones in Akter, Wamba, Gunasekaran, Dubey & Childe (2016), Gupta and George (2016), Singh and Del Giudice (2019), and others used the term “Big Data Management Capabilities” like the studies of (Mandal, 2019; Shamim, Zeng, Shafi Choksy, et al., 2019; Shamim, Zeng, Shariq, et al., 2019) to express the capabilities needed to extract value from big data (Anwar et al., 2018). These terms were used interchangeably in the reviewed literature. The authors of this article tackled the term big data management exclusively into a more depth view by considering all required organizational and technical capabilities as supporting areas in big data utilization, which are vital for successful enterprise-wide big data leveraging.

Capabilities assessment runs over a set of definite capabilities in a functional domain to assess and improve existing performance to achieve specified goals (Chaudhary & Chopra, 2017). Applying to big data management, such assessment involves investigating two main complementary research areas as addressed in the literature; assessment of big data adoption capabilities and building big data management capabilities constructs. These are discussed in the following sub-sections.

Assessment of Big Data Adoption Capabilities

In the reviewed literature, big data adoption capabilities had been assessed through two approaches; maturity-based assessment approaches and capabilities fulfillment assessment approaches. These are discussed in the following sub-sections.

Maturity–based Assessment Approaches

Maturity assessment can be viewed as evaluating multiple process areas inside a set of capabilities through an evolutionary growth scale (Chaudhary & Chopra, 2017). This scale consists of a set of maturity levels, which draws a path that ensures organizations can improve a group of specified successive process areas in an incremental manner (Chaudhary & Chopra, 2017). Each maturity level consists of a set of processes, which, when implemented together, will help to attain a specified maturity state (Chaudhary & Chopra, 2017). Maturity is commonly known to be measured through maturity models (Arunachalam et al., 2018; Comuzzi & Patel, 2016; Di. Proença & Borbinha, 2018). Maturity models help recognize an existing state to achieve specified tasks and goals in a functional domain and draw upon incrementally necessary improvements (Saltz & Shamshurin, 2016; Wendler, 2012). Several studies have encouraged the development of maturity models to facilitate the assessment of big data adoption capabilities inside organizations as tools for capacity development and process innovation (Moore, 2014; Saltz, 2017).

Accordingly, some models were developed, such as the Big Data Maturity Model (BDMM) by Comuzzi and Patel (2016). In this model, some organizational and technical capabilities for effective big data adoption were described implicitly across progressive maturity stages. The assessment relied only on diagnosing an “As-is” state and recommending an implicit “To-be state” for improvement. No independent assessment tool was developed that could include measurement indicators for each capability. The model also lacked encountering a big data life cycle process and did not define areas of big data integration and cloud computing deployments. Similarly, the International Data Corporation (IDC) developed a big data and analytics maturity scape framework to enable organizations to assess their big data analytics competency (Vesset, Olofson, Brien & Woodward, 2015). In this framework, capabilities were also implicitly described across maturity stages. The framework guided a progressive transition for capabilities improvement. However, that framework needed to be more comprehensive in covering more big data management capabilities, where it acted as a general readiness assessment mechanism. It also lacked detailed tangible, and actionable practices inside each capability for implementation.

Besides, Sulaiman, Cob and Ali (2015) developed a big data maturity model to assess the readiness of governmental Zakat (almsgiving) institutions to benefit from big data efficiently. The model relied only on providing a structured set of maturity stages that included an implicit description of some big data management dimensions; business goals, big data enablers, people, processes, and technology. The assessment process relied on checking the fulfillment of the capabilities defined across each maturity stage. Also, Olszak and Mach-Król (2018) developed the Temporal Big Data Maturity Model (TBDMM) to assess an organization’s level of maturity in temporal big data analytics. The model accommodated the time factor across temporal maturity levels. It assessed four capabilities areas: data/knowledge, IT solutions, the functionalities of solutions, and sustainable development using a qualitative questionnaire. The model lacked a quantitative assessment tool and encountering the processes of big data life cycle.

Hausladen and Schosser, 2020 developed a maturity model to assess big data adoption readiness in airline network planning and management. The model extracted its development phases from Becker’s methodology (Becker, 2009). Capabilities were assessed through a self-assessment questionnaire. The model lacked defining areas such as big data quality, business intelligence, big data analytics, and performance measurement, and no improvement measures were defined upon the assessment process. Also the Data Warehousing Institute (TDWI) developed a big data maturity model (Halper & Krishnan, 2014) to help organizations develop a roadmap for advanced big data analytics. The model served for benchmarking purposes. It covered broad areas of big data management. Still, some capabilities descriptions needed to be more consolidated in one maturity stage for more practicality instead of expanding them on several stages. More refinement was needed on the developed assessment questionnaire to cover all process areas in the addressed capabilities. Peña, Bonet, Lochmuller, Tabares, Piedrahita & Sánchez (2018) developed a fuzzy model to assess the maturity of big data management inside organizations. The associated capabilities were assessed using a qualitative decision matrix that allowed the modeling of a series of proposals to show the occurrence of a maturity level (Peña et al., 2018). The model relied on the TDWI big data maturity model in selecting the assessment criteria. However, the model needed to automate the assessment process to hide the complexity of the fuzzy logic from the model users during implementation.

Corea (2019) proposed a Data Stage Development Structure (DS2), a maturity model to help organizations build impactful big data strategies and enhance their capabilities. The assessment process relied on identifying the maturity extent in which capabilities descriptions were achieved. No quantitative assessment indicators were defined. The model also lacked addressing significant big data management areas such as data quality, data integration, and cloud technologies. The work in (Cheon & Baek, 2016) provided a reference model and an assessment system for big data adoption capabilities maturity. The assessment process relied on checking the maturity extent of achieving each capability. That model was very simplistic in its maturity description of capabilities, and no development methodology was adopted. In addition to the previous works, some other models were developed by practitioners such as (El-Darwiche, Koch, Meer, Shehadi & Tohme, 2014), and other maturity models were developed (Klievink et al., 2017; Yurievna, 2016) to address big data adoption in the public sector.

Capabilities Fulfillment Assessment Approaches

Capabilities fulfillment assessment measures the achievement extent of individual process areas across incremental capability levels (Chaudhary & Chopra, 2017). By adopting such type of assessment in the area of big data management,, the work in (Zschech, Heinrich, Pfitzner & Hilbert, 2017) proposed a Big Data Capability Assessment Model (BDCAM) represented in a two-space matrix: dimensions space which includes: skills, organization, strategy, technology, processes and big data management space which includes: Data Management, Data Analytics, and Governance. The assessment relied on measuring the fulfillment of the two spaces against each other using a set of closed qualitative questions. However, this model did not express a detailed maturity state of each assessed area to clarify concrete improvements due to its assessment simplicity. It did not cover a broad set of big data management areas, such as big data quality, big data integration, big data security and privacy, metadata management, business intelligence, and cloud deployments.

Besides, Ngo, Hwang & Zhang (2020) developed a big data and predictive analytics capability assessment tool. A set of capabilities that impact big data analytics was assessed across three levels; low, medium, and high. Some big data management areas were lacked such as, data security, quality, integration, and governance. The assessment questionnaire was so generic that it lacked an in-depth assessment of existing capabilities process areas. Also, the study in (Barham & Daim, 2020) introduced a readiness assessment model for capabilities that could affect successful big data projects. Hierarchical decision modeling and expert judgment quantification techniques were adopted to categorize capabilities (ibid). The model used value curves as a quantitative scale to represent an iterative assessment to better understand the dynamics of capabilities. Although it provided a measurable assessment approach, no improvement utility was provided.

The work presented in this article will rely on a maturity-based assessment approach. Still, it will be distinguished by assessing the coherency between related capabilities process areas and setting a goal for each area to measure progress towards valuable big data management. It will be developed using the prescriptive design principles (Pöppelbuß & Röglinger, 2011) to provide detailed best practices and improvement measures.

Building Big Data Management Capabilities Constructs

Building big data management/analytics capabilities constructs have been intensively addressed in the literature. Those constructs help organizations identify necessary capabilities for effective big data utilization (Anwar et al., 2018; Gupta & George, 2016). These capabilities interact through deploying data, technology, and human resources across organization-wide processes, roles, and structures (Gupta & George, 2016). Several studies have pointed out the importance of building such constructs and their impact on achieving business objectives (Dubey, Gunasekaran & Childe, 2019; Garmaki, Boughzala, and Wamba, 2016; Mneney and Van Belle, 2016; Ngo et al. 2020; Singh & Del Giudice, 2019; Wang, Kung & Byrd, 2018). The developed constructs in this literature built their theoretical foundation based on different standpoints; either on the Resource-Based Theory (RBT) (Madhani, 2010); or the Dynamic Capabilities Theory (DCT); or empirically-tested models. These are discussed in the following sub-sections.

Resource-Based Capabilities' Constructs

The RBT considers an organization a bundle of resources and capabilities (Barney, Ketchen & Wright, 2011; Mweru, Maina, Mweru & Tirus Muya, 2015). It classifies resources into tangible, intangible, and human resources. Tangible resources considered in RBT are data, technology, and other basic resources such as time and investment. Intangible resources in RBT are data-driven culture and organizational learning. Human resources involve managerial and technical skills. These resources, when operationally combined, allow an organization to gain a competitive advantage (Barney et al., 2011; Shabbir & Gardezi, 2020).

Drawing upon RBT, Gupta and George (2016), developed a formative multi-dimensional big data analytics capabilities' construct, with its dimensions being the organization's resources defined by RBT. That construct was empirically assessed to clarify the impact of those resources on a firm's performance. In a similar context and relying on RBT, Akter et al. (2016) proposed a hierarchical big data analytics capabilities model. They pointed to the necessary relationship between resources and capabilities for improving performance. The model included three primary dimensions of capabilities: management (organizational) capability, big data talent capability, and big data technology capability. That study recommended that equal attention be paid to all the encountered capabilities for successful big data deployment. Besides, the work in (Lozada, Arias-Pérez & Perdomo-Charry, 2019) analyzed the relationship between the three resources: tangible, human, and intangible in building big data analytics capabilities. The authors also tested the role of such capabilities in the co-innovation process, which resulted in positive influencing. This work lacked addressing the importance of aligning big data adoption with the organization's strategy and the financial allocation of big data investments. It is noted that all the previous RBT-based constructs that focused on the aspects of the resources lacked addressing a view on capabilities of big data management such as data modeling, data architecture, data governance, data security, data quality, data science, data risk management, etc., and which are aligned with the big data life cycle.

From a broader perspective and drawing on RBT and The Information Systems Success Model (ISSM) (DeLone & McLean, 2003), Adrian, Abdullah, Atan and Jusoh (2018) proposed a conceptual model for big data analytics implementation. However, the model lacked addressing significant big data management areas such as data security and privacy, modeling, architecture, data risk management, data science, and business intelligence. The authors argued that the model needed validation to test big data analytics capabilities' effectiveness on decision making.

Dynamic Capabilities-based Capabilities' Constructs

The dynamic capabilities theory is a comprehensive approach to RBT (Wang & Ahmed, 2007; Shams & Solima, 2019). Most studies argue that RBT has not adequately explained how and why specific organizations have a competitive advantage in situations of rapid and unpredictable change (de Camargo Fiorini, Seles, Jabbour, Mariano & de Sousa Jabbour, 2018). The DCT argues that having the organization's resources is not the main aim to create value. Effective management of resources is more important (Mikalef & Pateli, 2017; Shamim, Zeng, Shariq, et al., 2019). Firms need to reconfigure existing capabilities and practices to respond to rapid changes in market demands (Anwar et al., 2018; Gong & Janssen, 2020). As big data has a dynamic nature due to the changing business requirements for such data utilization, this matter encouraged using dynamic capabilities as they could adapt to environmental changes (Mikalef et al., 2020; Mishra et al., 2019).

Accordingly, Mikalef, Pappas, Krogstie and Giannakos (2018) and Mikalef, Krogstie, Pappas and Pavlou (2020) combined both theories, RBT and DCT, to build a holistic, big data capabilities construct that could provide a competitive advantage to organizations. In that construct, a set of operational capabilities, marketing, and technological capabilities were addressed in conjunction with the resources defined by RBT. Besides, Shdifat, Cetindamar and Erfani (2019) study defined a proposed construct of big data analytics capabilities that could influence organizations' sustainability performance in supply chains. The authors considered capabilities as assessment factors to be measured, categorized into human capabilities and non-human capabilities. However, both constructs of Shdifat, Cetindamar and Erfani (2019) and Mikalef, Pappas, Krogstie and Giannakos (2018) and Mikalef, Krogstie, Pappas and Pavlou (2020) did not define the crucial big data management processes areas aligned to a big data life cycle.

Another DCT-based work is in Marfo (2017). Big data capabilities were classified in a hierarchical construct into three first-order core capability dimensions; technological capabilities, human skills capabilities, and organizational capabilities. Resources were included as zero-order capabilities. The work lacked covering capabilities areas of big data governance, big data quality, and big data integration.. Besides, the work in (Hassna & Lowry, 2016) proposed a higher-level construct of big data capabilities for improving firms' performance and customer agility. The construct was built of three dimensions; big data infrastructure capability, big data management capability, and big data science capability. The authors suggested that building capabilities consider organization resources as a basic layer. However, this work lacked to address organizational capabilities such as strategy alignment and financial investments in big data leveraging.

Capabilities Constructs Based on Empirically-tested Models

Some authors relied on building their capabilities constructs on previous empirically-tested models of big data adoption. For example, Kalema and Motau (2017)'s study represented big data capabilities as the influencing factors on developing countries' organizations' readiness for big data adoption. Those capabilities were conceptualized in people, technological, organizational, and environmental capabilities. This study was rooted in previously developed big data maturity models, but it lacked addressing data quality and modeling and needed more investigation in technological capabilities. Similarly, Mneney and Van Belle (Mneney & Van Belle, 2016) built a model of big data capabilities with a theoretical foundation of two models: The Technology, Organization, and Environmental (TOE) framework (Nam, Kang & Kim, 2015; Oliveira & Martins, 2011) and the Task Technology Fit (TTF) model (D'Ambra, Wilson & Akter, 2013; Mneney & Van Belle, 2016). Four categories of capabilities were addressed in the model: technology, organization, environment, and task technology fit. The model lacked significant big data management areas such as big data architecture, big data quality, and big data security.

Moreover, the study in (Pedro, Brown & Hart, 2019) identified the capabilities for successful big data analytics initiatives. The study was based on Business Analytics Capability Maturity Model (BACMM) (Cosic, Shanks & Maynard, 2012), combined with some requirements for successful big data analytics in (Watson, 2014), which are: alignment to strategy, committed sponsorship; fact-based decision-making culture; analytical skills; infrastructure; analytical tools; and legal compliance for data protection. But this model lacked addressing some capabilities areas such as data quality and data architecture. The work presented in this article will extract its theoretical foundation of big data management capabilities based on the DAMA-DMBOK framework (Henderson et al., 2017) according to its illustrations of data management knowledge areas and the surrounding organizational factors with the addition of a rigorous content analysis on big data management process areas.

Big Data in the Fourth Industrial Revolution (IR 4)

The digital revolution of data has tackled the Fourth Industrial Revolution 4.0 (IR 4.0). The fourth industrial revolution introduced the adoption and integration of disruptive technologies such as the Internet of things, big data, cloud computing, advanced robotics, and artificial intelligence (Bhuiyan et al., 2020). The main challenging phenomena in the fourth industrial revolution are big data, the internet of things, cloud computing, advanced robotics, and artificial intelligence (Bhuiyan et al., 2020). Big data is considered one of the main pillars driving IR 4. Barriers of big data management and analytics in the era of IR 4 include lack of intelligent big data sources, lack of scalable real-time analytics capabilities, the availability of sufficient network resources for running applications, the concerns about data privacy and information security regulations, the problems with data integration and fragmented data and lack of availability of cost-effective storage subsystem of high performance (Ram, Zhang & Koronios, 2016). Other barriers exist towards effective IR 4 outcomes, and these are Economic/Financial issues such as high investments and lack of clearly defined economic benefits; cultural issues such as lack of support by top management; competencies/resources issues such as lack of skilled employees, lack of technical knowledge, and complexity of the Industry 4.0 implementation; legal issues such as data security concerns; technical issues such as lack of standards, uncertainty about the reliability of the systems, weak IT infrastructure, difficult interoperability/compatibility, and technology immaturity; implementation process issues such as the need for new business models, lack of systematic approach for implementation, and high co-ordination efforts. However, existing research has focused mainly on technical aspects of IR 4 (Liao et al., 2017), and rarely addressed the organizational requirements. Despite the considerable number of studies published on IR 4, no focus has been on developing IR 4 implementation models through methodological approaches (Liao et al., 2017).

Some approaches were developed to help the existing business environment decide on the most appropriate roadmap for assessing organizations' readiness towards encountering IR 4. Hajoary & Akhilesh (2021) proposed a conceptual framework to assess an organization's maturity for IR 4 through eight dimensions: strategy, organization, business model, employee, manufacturing and operations, supply chain, production system, and products and services. Similarly, Schumacher, Erol and Sihn (2016) proposed a maturity model for assessing readiness. Products, Customers, Operations, and Technology were addressed to be assessed as the basic enablers. Additionally, the dimensions of strategy, leadership, governance, culture, and people were encountered. The model had been transformed into a practical tool and was tested in several companies. Despite the existence of some assessment approaches, they did not provide the implementation plan that should be conducted upon a concluded state of assessment.

Big Data Management Reskilling and Upskilling

One of the significant dimensions for effective big data management in IR 4 is building organizational workforce skills. The challenge of lacking appropriate workforce skills has prevented the progress of IR 4, where organizations need to overcome this barrier to progress in the adoption of digital technologies (Shirani, 2019). Some organizations are starting to refocus on reskilling and upskilling their workforce to respond to the increasing demand for newer skills (Bag et al., 2021), where upskilling is the process of upgrading the current skill set of the employees to become more valuable in their current roles. Reskilling equips employees with the essential skills to fit into a new role (Meena & Parimalarani, 2020). One challenge that organizations face in reskilling and upskilling is that they need to document what skills each employee currently possesses, specify the skills that the organization needs now and in the future, and plan training programs to fill the existing skills gap. Besides, it is necessary to translate the organization’s goals to the skills and competencies needed to achieve these goals and develop a strategy for training and upskilling, along with necessary resources and incentives for the employees. Some countries have strengthened the workforce by retraining unskilled workers and upskilling trainers (Hassan & Ismail, 2018). Other countries implemented various internship and apprenticeship programs, including an upskilling program, where training providers and industry players provide training for fresh graduates to achieve the IR 4.0 transformation.

Some approaches were proposed for reskilling and upskilling an organization workforce by building models of the required skills. For example, Acosta (2018) proposed a general taxonomy of working skills, including professional skills, such as problem-solving skills, teamwork skills, business thinking, and technological skills literacy. Vrchota, Maříková, Řehoř, Rolínek & Toušek (2020) proposed architecture of two categories of skills: personal skills such as time management, adaptability to change, social teamwork skills, communication skills, and knowledge management; and technical skills such as the ability to process and analyze data, knowledge of statistics, ability to use the latest devices, and awareness of data protection and IT security. In addition, Koshal, Natarajarathinam & Johnson (2019) surveyed to determine the future needs of personnel through surveying the ability to perform current duties, ability to navigate future technological advances in the medium term without additional training, ability to use data analysis tools, and ability to interact with and maintain smart devices and objects that collect and share data.

In addition, Flores, Xu and Lu (2020) proposed a human-focused perspective for companies beneath the new Industrial Revolution. This model aimed to draw future competencies by exploring how each competence might support IR 4 activities, giving the most required skills by dividing the competencies into five distinct categories: soft skills, hard skills, cognitive workforce skills, emotional intelligence workforce skills, and digital workforce skills. Gan and Yusof (2019) proposed a set of six practices for encountering IR 4, which are: knowledge management that could lift employees' innovation and the ease of learning, human resources policy-making, training, recruiting, building a reward system to retain and develop existing workers and to attract talented new workers, and job design. Bongomin, Gilibrays Ocen, Oyondi Nganyi, Musinguzi & Omara (2020) proposed some required skills for IR 4, which were divided into theory and expertise skills, technical and hardware skills, software and algorithms skills (digital skills), and personal (soft) skills. Akyazi, Goti, Oyarbide, Alberdi and Bayon, (2020) also generated an automated database of current and future professions, competencies, and skills.

Shevyakova, Munsh, Arystan & Petrenko (2021) proposed an implementation roadmap for competence development in IR 4, consisting of skills classified into three categories: technology/databases, processes/ customers, and infrastructure/organization. Chaka (2020) also proposed skills that involve information and communication technologies, innovation management, organizational learning such as encouraging participation, and environment skills such as creativity in designing strategies. Hecklau, Galeitzke, Flachs and Kohl (2016) developed a competence model, where three main functional areas of human resources development were defined: personal development (competencies), team development (collaboration), and organizational development (structure and processes). The model was also designed to assess individual employees since the given competencies are too specific to generalize to an entire workforce. Qasem, Abdullah, Atan and Jusoh (2019) proposed a type of cloud-based education as a service for flexible training and built a model which involved four educational dimensions; learning, teaching, service, and research, each having its associated education methods. Fitsilis, Tsoutsa & Gerogiannis, (2018) proposed a framework that employed six different dimensions to define the educational needs for IR4, namely technology, industry sector, software lifecycles, transversal skills, proficiency, and job profiles. The model was based on measuring skills proficiency across five graded maturity levels.

Adopting a Production Environment for Reskilling and Upskilling

While organizations conduct traditional big data analytics training programs, this type of training relies too heavily on theory versus practice and fails to show a return on investment (Illanes, Lund, Mourshed, Rutherford & Tyreman, 2018). Accordingly, some authors adopted the working environment techniques for reskilling and upskilling the workforce. Aini Abdullah, Humaidi & Shahrom (2020) studied the importance of the Learning Factory (LF) approaches. These approaches provide a reality-conform production environment. Through learning paths, trainees can discover and test or conduct experiments in this environment on technological and organizational industry-related issues. LF approaches appear as highly complex learning environments that allow the development of high quality and autonomous competences, which are linked to training, education and research including the IR 4 (Baena, Guarin, Mora, Sauza & Retat, 2017).

Besides, Amiron Latib and Subari (2019) proposed adoption of the concept of Technical and Vocational Education and Training (TVET). The study aimed to identify the skills required in an IR 4 working environment. Although, current literature shows that there has not yet been defined a clear-cut set of IR 4 generic skills and enablers to be included in TVET curriculum (ibid). Karacay (2018) suggested adopting Science, Technology, Engineering, and Mathematics (STEM) competencies, where employees would have core skills built on these basic sciences required for technology-based innovations. STEM competencies have become critical for economic competitiveness due to their positive influence on innovation, technological growth, and economic development. Likewise, Hashim and Hussein (2020) proposed using Operator Training Simulator (OTS) systems to prepare the operating personnel with adequate capabilities to handle planned and unplanned process conditions. An OTS system is divided into two types: Emulated system (partial stimulation) and Direct Connect (full stimulation), where the trainees simulate the actual working environment. Adopting learning approaches through a working environment or simulating a business case could be more powerful and productive since trainers could visualize the resulting outcomes and investigate how this impacts their business. But those learning approaches still need further validation to test their reliability in different business domains.

It is noted that the above reskilling and upskilling workforce approaches were built as preliminary approaches. They acted as initial efforts that help organizations draw a roadmap towards identifying the necessary skills for encountering IR 4. Those approaches generally proposed skills that could be acquired through training and were supposed to fit in all business domains, regardless of organization size, which is a significant factor to address. There is a need that each organization should build its plan to identify the appropriate skills needed. Besides, the existing approaches did not identify the pre-requisites and the specifications of the existing workforce for reskilling or upskilling and did not recognize the necessary organizational resources needed for implementation. The significant point is that the approaches did not mention the return-on-investment of IR 4 to an organization after acquiring the proposed skills and how to monitor the impact on a business environment. They did not also identify whether the organization has the corresponding job roles that will benefit from reskilling or upskilling.

It is concluded that, IR 4 will open horizons of new jobs of cognitive abilities, technically skilled, complex problem solving, resource management skills, content, process, and social skills, etc. New skills and forms of jobs will replace many traditional jobs. Many tiresome and repetitive tasks will transform from manual labor to automation (Bhuiyan et al., 2020), which requires rigorous reskilling. So, the public and private sectors, academia, and training institutes should increase investment in human capital and skills to claim industrial transformation for upskilling, reskilling, and long-term training and capabilities-building to meet the demand of the fourth industrial revolution and to bridge the gap between education and industry.

Discussion

This section investigates the strengths and weaknesses of the above-reviewed capabilities assessment approaches and capabilities' constructs in big data management.Table 1 compares the capability/maturity assessment approaches using a set of detailed evaluating criteria that were identified from the literature. These are as follows:

1. Purpose: identifies whether the model is comparative, or descriptive, or prescriptive,
2. Composition: identifies whether the model is built as a maturity grid, a Likert-like questionnaire, or as a CMMI-like model,
3. Capabilities consistency: identifies the extent of coverage of big data management capabilities,
4. Capability Description: identifies whether capabilities are described implicitly or explicitly,
5. Design approach: identifies whether a development methodology is adopted,
6. Assessment method: identifies whether the assessment is done manually or automated,
7. Improvement utility: identifies whether the improvement practices are defined,
8. Validity and reliability identify whether the work is empirically validated.

Table 1
Comparison between existing big data capability/maturity assessment works

Works / Criteria	Purpose	Composition	Capabilities consistency	Capability description	Design approach	Assessment method	Improvement utility	Validity / reliability
(Comuzzi and Patel, 2016)	Prescriptive (Implicit-to-levels)	Maturity grid	Partially covered	Implicit	Iterative development	Manual questionnaire	To-be state	Validated
(Sulaiman, Cob and Ali, 2015)	Descriptive	Textual document	Partially covered	Implicit	No design approach	Capability achievement	None	Need more validation
(Olszak and Mach-krol, 2018)	Descriptive	Maturity grid	Partially covered	Implicit	No design approach	Manual questionnaire	None	Need more validation
(Hausladen and Schosser, 2020)	Descriptive	Maturity grid	Partially covered	Implicit	Iterative development	Online questionnaire	None	Validated
(Halper and Krishnan, 2014)	Comparative	Likert-Like questionnaire	Covered	Implicit	Iterative development	Online questionnaire	Checklist reports	Validated
(Vesset et al., 2015)	Prescriptive (Implicit-to-levels)	Maturity grid	Covered	Implicit	No design approach	Online questionnaire	Guidelines	Validated
(Peña et al., 2018)	Comparative	Maturity grid	Covered	Implicit	No design approach	Scoring technique	None	Validated
(Corea, 2019)	Descriptive	Maturity grid	Partially covered	Implicit	No design approach	Maturity verification	None	Need more validation
(Cheon and Baek, 2016)	Descriptive	Maturity grid	Covered	Implicit	No design approach	Maturity level achievement	None	Need more validation
(Ngo et al. 2020)	Comparative	Likert-Like questionnaire	Partially covered	Implicit	No design approach	Automated tool	None	Validated
(Zschech et al., 2017)	Comparative	Likert-Like questionnaire	Covered	Implicit	Becker methodology	Manual Questionnaire	None	Need more validation
(Barham and Daim, 2020)	Comparative	Likert-Like questionnaire	Partially covered	Implicit	Hierarchical modelling	Manual Questionnaire	None	Validated

From Table 1, it is noted that most of the existing big data capabilities assessment models had been designed for comparative and descriptive purposes; few of them tried to act as prescriptive. Existing descriptive models were used only to diagnose “As-is” states of big data adoption capabilities, without defining explicit actionable improvement practices to those states. Those that tend to be prescriptive such as Comuzzi and Patel (2016) and Vesset et al. (2015), only described the maturity of capabilities implicitly-to-levels and provided “To-be” improvement states as general guidelines, but not in the sense of detailed best practices for each capability. Many models, today, don’t describe how to perform practices, the issue known as the “Knowing-doing gap” (Mettler, 2009). It is valuable that models should first be descriptive to draw an in-depth understanding of an existing state. They should evolve to serve for prescriptive issues for indicating improvement practices and how to implement them, and finally, they could serve as comparative models for benchmarking among organizations (de Bruin, Rosemann, Freeze & Kaulkarni, 2005; Pöppelbuß & Röglinger, 2011).

Furthermore, big data capability/maturity assessment models were built either as a maturity grid or a Likert-like questionnaire. None of those models was designed as a CMM-like model, which is commonly known to be a more formal and comprehensive approach in building maturity models (Mettler, 2012). A CMM-like model specifies a set of goals and key practices and uses a process-view concept of maturity to reach a predefined level of elaboration (Mettler, 2011), which represents a powerful assessment and improvement approach. To reach successful big data leveraging, setting goals in each process area will help organizations draw the right path to maturity and evaluate their progress towards achieving that goal.

Moreover, the characterization of capabilities was generally identified in the existing models. A more detailed breakdown of capabilities must be visualized across a set of related process areas. Being in such decomposition helps organizations build a holistic perception of the necessary capabilities required for valuable big data utilization. Also, some models partially covered big data management capabilities. As mentioned in the above section, some significant capabilities, such as big data security, big data quality, and big data integration, were lacking. A rigorous theoretical foundation should be adopted when conceptualizing such capabilities which was not clear in the reviewed models. Besides, the “process” dimension addressed in some existing models did not focus on the big data management capabilities needed to handle, control, and process big data. Instead, it focused on the general processes needed to measure an organization’s readiness to big data adoption. Existing models also lacked incorporating key performance indicators (KPIs) inside each capability to measure its efficacy. KPIs are essential to measuring big data business impact and its alignment to organizational objectives.

The most significant issue is that most of the reviewed capability/maturity assessment models were not developed according to a clear and systematic development methodology. Few models used simple iterative development techniques to adapt to changes after the implementation. But, those techniques usually lack a full initial specification of development requirements and general maintenance costs for change in each iterative. It is also noted that newly developed big data maturity assessment models are usually developed upon the previous ones without considering the appropriateness of the design decisions in the studied domain (Okuyucu & Yavuz, 2020). Besides, the design process of the model components was also unclear. A common issue among several existing maturity models impresses that the identified design elements seem subjective (Frick, 2012; Frick, Küttner & Schuber, 2013). Despite the existence of different capability/maturity models’ development methodologies (Lasrado, Vatrapu & Mukkamala, 2017; Mettler, 2012; van Hillegersberg, 2019), very few models have adopted them in a clear and systematic process (Mettler, 2011). The matter that hardens understanding and maintains the model.

Using a defined and systematic methodology enables a stable state of model development and facilitates incremental improvements to be made over time (de Bruin et al., 2005; Lacerda & von Wangenheim, 2018). Besides, the design process of those artifacts has to be documented and communicated understandably for model users. Existed maturity assessment models also lacked adopting the common design principles of maturity models proposed by Pöppelbuß & Röglinger (2011). These principles help to reveal to what extent a maturity model provided the intended usage target. Such design principles also benefit in evaluating capability/maturity models.

Besides, the existing models adopted a simple self-assessment technique. Such technique does not provide an in-depth assessment due to: lack of specialized experts in the emerging area of a big data adoption (Frick et al., 2013), or the assessment was usually performed Ad-hoc by the internal staff of the organization, or there was no identification of the target respondents for assessment. Rigorous and concrete assessments help to provide clear strengths and weaknesses improvement areas. Furthermore, no assessment methodology was used that outlined how the assessment procedure should be conducted. Such methodology helps to offer a procedure model to guide users through the assessment (Pöppelbuß & Röglinger, 2011).

Moreover, most models provided manual assessment tools, few of them provided automated ones with a scoring technique. Most models did not guide implementing the model and conducting a smooth assessment. They also needed more validation cases.

Capability/maturity assessment in big data management should measure what barriers exist in moving from a maturity state to a higher one to reveal an organization maturation potential. Besides, assessments should state how to adapt or configure the improvement measures according to different situational characteristics in different domains (Becker, Niehaves, Poeppelbuss & Simons, 2010; Pöppelbuß & Röglinger, 2011).

So, it is concluded that existing maturity/capability assessment models acted as preliminary approaches for a general and straightforward assessment process on big data adoption readiness, not on the specific capabilities process areas required for big data management. Too simple assessments may lack the necessary aspects of capabilities maturity, which is reflected in identifying accurate improvement areas. Big data adoption assessment in organizations should point out important issues: how significant a successful big data initiative is to organizations, what big data value is expected, how possible the development of capabilities is, and the degree of maturity of the existing capabilities (Nda, Tasmin & Hamid, 2020).

Regarding the big data/management/analytics capabilities constructs, Table 2 shows a comparison between existing capabilities constructs. A significant drawback in those constructs is that they had diversity in their capabilities' constitution due to the independence in their development. They did not adopt a strong theoretical basis that conceptualizes big data management capabilities. To date, studies on big data have lacked a clear understanding of the key components of big data utilization capabilities (Hansmann & Niemeyer, 2014). These capabilities were covered implicitly in most of all the reviewed constructs and need more investigation. Some models lacked a full view of organizational capabilities that are significant in supporting big data leveraging inside organizations (Hassna & Lowry, 2016; Lozada et al., 2019). Furthermore, most models lacked addressing necessary big data life cycle management processes areas in (Henderson et al., 2017) that to be adopted for matured data management activities. They did not also tackle the processes of the life cycle from planning, designing, operating, and analysing big data.

Another drawback is that some of those works relied only on RBT in identifying big data utilization requirements without addressing the necessary capabilities to exploit resources for improved performance. The study of Braganza, Brooks, Nepelski, Ali and Moro (2016) and de Camargo et al., 2018) criticized using the RBT in a big data environment, where big data wears down the theory's assumptions of valuable, rare, inimitable, and non-substitutable resources described by RBT (Braganza et al., 2016). First, big data is not rare since it can be obtained from many different data providers (ibid). Second, physical resources such as hardware and software for big data utilization are neither rare nor imperfectly inimitable.

Table 2
Comparison between big data management/analytics capabilities constructs

Construct	Big Data Management Capabilities			
	Organization	Human	Technology	Big data utilization
(Kalema & Motau, 2017)	√	√	Implicitly covered	X
(Cetindamar, Shdifat & Erfani, 2020)	√	√	Implicitly covered	X
(Marfo, 2017)	√	√	Implicitly covered	Partially covered
(Hassna & Lowry, 2016)	X	Implicitly covered	√	√
(Mneney & Van Belle, 2016)	√	√	Implicitly covered	Partially covered
(Mikalef et al., 2018)	√	√	√	X
(Adrian et al., 2018)	√	√	Implicitly covered	Partially covered
(Gupta & George, 2016)	√	√	√	X

Construct	Big Data Management Capabilities			
	Organization	Human	Technology	Big data utilization
(Akter et al., 2016)	√	√	√	X
(Lozada et al., 2019)	Partially covered	√	Implicitly covered	X
(Pedro et al., 2019)	√	√	Implicitly covered	Partially covered

Most existing studies addressed technical skills but did not focus on managerial skills and organizational culture, which are considered a major factor influencing the success of Industry 4.0 (Mohelska & Sokolova, 2018). Implementing the Industry 4.0 concept requires continuous innovation inside organizations, and a collaborative, explorative, and entrepreneurial mindset is considered a success factor for the employees (Tortorella, Vergara, Garza-Reyes & Sawhney, 2020) . There is a need for approaches that increase innovation by improving problem-solving capability, creativity, and systems thinking capability (Abele et al., 2015). Existing studies also lack further details on how the skills in the proposed models affect the workforce in the Industry 4.0 context. Moreover, existing approaches lack continuous emerging important competencies, such as business intelligence and data science.

As revealed from the previous discussion, there is a necessity to develop a comprehensive framework that indicates a roadmap for big data management maturity assessment and process improvement. The following section will draw on the results of the conducted comparative analysis in the above-discussed key works by introducing the requirements for building such a comprehensive framework.

Requirements For Building A Comprehensive Big Data Management Maturity Framework

Based on the findings of the comparative analysis presented in Table 1 and

Table 2, a set of conceptual and technical requirements are defined for building a comprehensive big data management maturity framework. These are as follows:

Req.1: Big Data Management Maturity Reference

This is a holistic reference that is comprised of a set of big data management capabilities and three associated types of practices; a set of achievement practices that exist in each capability level of a single process area, the corresponding improvement practices, and the improvement measures on how to implement those practices. It acts as a guide for capabilities building and improvement. The reference is built up of some components as follows:

Req.1.1: Big Data Management Capabilities Construct

This construct provides the architecture of big data management capabilities process areas categorized according to their coherency. Table 3 shows the classification of big data management capabilities encountered in the construct. The architecture is drawn upon a content analysis on process areas of big data management and the DAMA-DMBOK framework (Henderson et al., 2017) and the environmental factors affecting big data utilization, such as Human Resources and Organizational aspects.

Req.1.2: Maturity Scale

The maturity scale consists of five levels that measure each set's achievement extent of coherent capabilities' process areas. This scale represents a pathway that organizations use to incrementally assess and improve their capabilities. The staged representation approach is adopted (Chaudhary & Chopra, 2017), where a set of related process areas are assessed together across a maturity scale. Quantitative weights and a scoring scheme are associated with each maturity level. The maturity levels are as follows:

<u>Level 1-</u> *Ad-hoc: No existence of a big data leveraging strategy, narrow knowledge on big data and its business impact, lack of skills, individual efforts on big data analytics, and rely on existing technologies,*

<u>Level 2-</u> *Managed: worth thinking in recognizing business values of big data, no or little enterprise support, some analytical skills exist, small pilot projects of big data utilization are created in siloes,*

<u>Level 3-</u> *Defined: big data initiatives are carried out through a business unit level strategy and handle both structured and unstructured data,*

<u>Level 4-</u> *Measured: there is enterprise-wide support and budget for leveraging big data in business, performance measurement tools exist, evaluating the quality of big data, and a broad set of skills exist.*

<u>Level 5-</u> *Optimized: ensures continuous big data utilization process improvement and value realization, experts in big data analytics are innovating prediction models and data-driven decisions.*

<u>Req.1.3: Capabilities' Goals Scheme</u>

Each capability process area defined in the construct will be assigned a measurable goal through an underlying set of improvement practices. Goals act as indicators of progress, and they are assessed to check their magnitude of fulfillment.

Table 3

Proposed Classification Big Data Management Capabilities

Capabilities Category	Capabilities Process Areas
Human Resources	Analytical/ Managerial skills, Training, Collaboration
Organization	Big Data Value, Big Data Leveraging Strategy, Top Management Support, Big Data Culture, Alignment between IT and Business, Communications, Big Data Budgeting Strategy, Big Data Business Case, Big Data resources requirements
Big Data Governance	Big Data Governance Functions (Policies and Procedures), Stewardship, Business Glossary, Compliance Monitoring
Big Data Management Big Data Architecture	Big Data Architecture Standards, Big Data Modelling, Big Data Integration
Big Data Content	Big Data Content Management, Historical Data and Archiving
Big Data Processing	Big Data characteristics handling, Big Data Life Cycle Management
Big Master Data	Big Master data management, Big Master Data awareness
Big Data Security	Big Data Privacy, Big Data Access
Big Metadata	Big Metadata management, Big Metadata structure
Big Data Quality	Big Data Quality Strategy, Big Data quality management, Big Data Trustiness, Big Data Completeness, Big Data Timeliness, Big Data Cleansing
Big Data Interoperability	Big Data Sharing

Big Data Analytics	Big Data Business Analytics, Big Data Analytical tools
Big Data Technology	IT Strategy, Infrastructure
Processes Management	Big Data process management quality
Risk Management	Big Data Risk Management Plan.

<u>Req.1.4: Big Data Management Improvement Practices and Improvement Measures</u>

Each capability process area is associated with a set of improvement practices across an incremental path. Those practices are used to enhance an existing state and move it to a higher state of maturity. The proposed framework in this article is developed as a prescriptive model. Hence, improvement measures are defined to structure how the improvement practices are implemented through an organization. The improvement measures are defined explicitly in each maturity level.

<u>Req.2: Big Data Management Gap Analysis</u>

The gap analysis technique is used to identify gaps in big data management in a specified organization that needs specified improvements to attain the assigned capabilities' goals. This technique will help recognize the challenging issues of leveraging big data inside the assessed organizations, whether managerial, technical or other. The process of gap analysis is composed of two main phases as follows:

<u>Req.2.1: Quantitative Maturity Assessment</u>

This type of assessment aims to identify the existing state of big data management capabilities inside an entity. The assessment runs across the whole organization's hierarchy to draw a holistic maturity state. It uses the Goal-Question-Metric (GQM) paradigm (Aljedaibi & Alsulami, 2017; Sommerville, 2011). GQM enables a goal-based assessment, and it is driven by the assigned goals in the capabilities construct. In GQM, a set of questions is defined to reflect the extent of goals' achievement using a set of quantitative metrics that measure performance efficiency. An automated assessment tool will be developed to implement the assessment process and report results.

<u>Req.2.2: Capabilities' Gaps Identification</u>

The results will be analyzed upon the maturity assessment to identify strengths and improvement areas inside big data management capabilities. Gaps could be a missing or a shortcoming in some capabilities' practices or a need to strengthen some process areas for better performance. The maturity state of an assessed organization will be given a maturity report generated from the assessment tool.

<u>Req.3: Staged Improvement Roadmap</u>

Once gaps are identified, an improvement roadmap should be drawn to decide the necessary improvement actions. According to the maturity results, each set of related capabilities will be improved through a staged roadmap in two steps: The first is to carry out the improvements practices defined in the concluded maturity level by using the improvement measures, and the second is to move to a higher level of maturity through implementing the associated improvement practices in this level. An organization should study the required antecedents of the improvement roadmap, such as compliance rules and regulations, roles, and responsibilities.

It is crucial to think about how a big data initiative will help solve a business problem while implementing the roadmap.

Req.4: Monitoring and sustaining plan

Monitoring the affected improvement areas is significant to check whether the running improvements are effective. Performance metrics inside each capability helps to measure effectiveness, accuracy, and timeliness factors during implementation. Iterative assessments should be conducted regularly to sustain the best maturity state in big data utilization.

A structured development methodology will be designed to build the proposed big data management maturity framework components. Hevner, March, Park & Ram's (2004) design guidelines will formulate specific design requirements in the methodology. A top-down design approach will be adopted; the big data maturity levels and capabilities are first defined, then the assessment scheme will be developed. All the above-entailed requirements will be used to construct the proposed big data management maturity framework that will enable organizations to perform a rigorous capabilities maturity assessment to quantitively assess their running practices, identify the set of capabilities for effective big data utilization and value delivery, and consequently draw the necessary improvement roadmap of best practices

- for better big data utilization.

Figure *1* shows the components of the proposed big data management maturity framework.

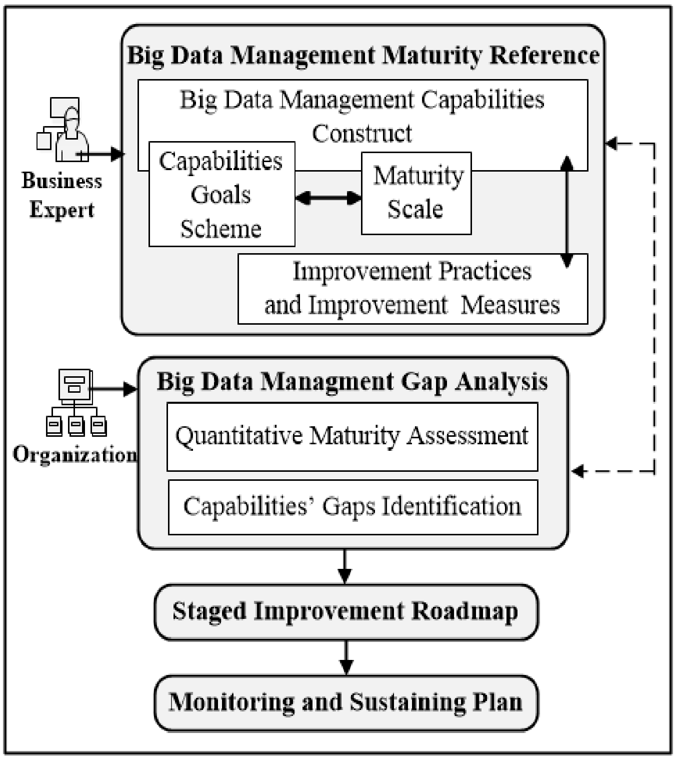

Figure 1: Comprehensive Big Data Management Maturity Framework

Conclusion and Future Work

With the emergence of big data, organizations are accelerating to gain the potential value of such data to their business. Being a data-driven business organization is significant today in the rapidly changing environment and the fourth industrial revolution. Through big data management capabilities' maturity assessment and building, organizations will be able to identify their readiness towards effective big data utilization and improve their existing capabilities. This article provided an analytical study on prominent work efforts on big data management capabilities construction and maturity assessment, revealing the strengths and weaknesses. Accordingly, it is indicated that there is a necessity to develop a comprehensive big data management maturity framework to provide a rigorous capabilities maturity assessment and a consistent improvement roadmap. Then, a set of conceptual requirements were defined in a proposed comprehensive big data management maturity framework. Currently, the framework is being built using appropriate techniques and tools according to a systematic development methodology. The future work will be the validation of the framework through real-life use cases. By implementing such a framework, organizations will be able to perceive the necessary capabilities for effective big data management and draw their roadmap of process improvement towards unlocking the value of big data to their business.

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