Big Data Analytics Capability for Improved Performance of Higher Education Institutions in the Era of IR 4.0: A Proposed Conceptual Framework

Mohamed Azlan Ashaari[a], Azlan Amran[b], Karpal Singh Dara Singh[c*], [a,b,c]Graduate School of Business Universiti Sains Malaysia Penang, Malaysia, Email: [c*]kirpal005@yahoo.com,karpal@usm.my

Despite the growing interest towards big data within higher education institutions (HEI), research on big data analytics capability within the HEI context is rather limited. HEI's need to ensure that they have the right capabilities and resources to realise the actual benefits of big data. Underpinned by information processing theory and resource-based view, this paper reviews relevant literature. It proposes a conceptual framework which highlights the three capabilities (i.e. managerial, technological and human) that are instrumental in enabling big data analytics capability which can be leveraged to improve HEI's performance. In addition, the study also proposes continuous process innovation as a moderating factor that can affect the relationship between big data capability and HEI performance. A commitment to process innovation will further strengthen HEI's big data analytics capability for improved business performance. This study suggests that adequate big data capabilities are needed to enable HEI's to realise the value of their big data initiative. Accordingly, the study provides useful guidelines to HEI's about the important capabilities and resources that must be put into place to reap the benefits associated with big data implementations in the wake of IR 4.0.

Keywords: *Big Data Analytics Capabilities, Performance, Management Capabilities, People Capabilities, Technology Capabilities, Higher Education Institutions*

Introduction

In the age of big data, higher education institutions (HEI) must exploit the true value of big data to guide them in ways that are feasible within their capacity amidst fast-changing environmental conditions and resource constraints. With big data, HEIs can make informed decisions based on in-depth analysis of data for improved business performance and in the process of doing so become a data-driven organisation. Data from the information systems of HEIs provide a transparent analysis and means for a shared understanding of the institution's successes and challenges (Campbell, DeBlois, & Oblinger, 2007). To fully collect and utilise data, HEIs will need to not only create the right infrastructure for big data but also ensure that their employees and key decision-makers have high data literacy skills. This seems especially applicable for the top and middle management of HEIs in an era of increased accountability, reduced resources and shortage of experienced management teams. Additionally, the importance of developing people with high levels of data literacy and the ability to build a culture supportive of big data has been advocated by many scholars (Akter et al. 2016; Rahmat et al. 2016; Wamba et al. 2017).

Siemens and Long (2011) suggested that HEIs must infuse analytics into their information system infrastructure to meet the demands for improved productivity and business performance. This is because big data is the main thrust that can transform HEIs to fully utilise the mass data that is generated in their ecosystems (Juma, 2016). Quacquarelli Symonds (QS) best known for publishing the QS World University Rankings pointed out three HEIs including Purdue University (USA), London South Bank (UK) and Nottingham Trent University (UK) that have been leveraging on big data analytics to improve the student experience and reduce dropout rates which ultimately led to improved reputation and ranking performance. Research has also proven that smart universities such as Caltech University and Northwestern University, which are among the top universities in the world, have also endeavoured into the big data arena (Hayikader et al., 2015). The University of Cambridge, which ranks number two in the QS top universities ranking, uses big data, and they are still researching its potential and sharing their knowledge in what they call a "growing field" (Hayikader et al., 2015).

In Malaysia, HEIs are operating in a challenging environment. They are being put under intense strain to react towards national and global economic agendas, as well as political and social change (Hanapiyah et al., 2018). In addition, as reported by Yassin et al. (2011), the management of HEIs needs access to various data to oversee day-to-day activities and measure its performance. Huge amounts of data are generated regularly. By way of transforming such data into valuable information, HEIs can have the advantage of staying ahead of rivalry. By leveraging on big data, HEI's will be able to optimise their core processes, functions and roles in order to meet stakeholder demands, create competitive

advantages, manage risk, improve controls and, eventually strengthen organisational performance by converting information into intelligence (Lewis 2013).

Big data is reliant on technological capabilities and analytical models which uses algorithms and data analytics to make sense of data and realise its true value. According to Intezari and Gressel (2017), organisations can only benefit from big data's prominent characteristics with the support of the right technology and sufficient skills. In the same vein, Isik (2018) also highlighted that technological capabilities and organisational capabilities are instrumental drivers that can support big data analytics capability. The study of Wamba et al. (2017) highlighted that having the right technological, organisational, and people capabilities will allow organisations to realise big data analytic objectives and help improve their business performance. In addition, the study also investigates the role of continuous process innovation in compounding the effect of big data analytics capability on the performance of HEI.

The capabilities required for effective big data analytics have been largely under-examined, more so in the context of big data from the perspective of a developing country. Scholarly frameworks that integrate the use of big data and other management tools have not yet been resolved and continue to be the interest of many researchers (Dutta & Bose, 2014). According to Görnerup et al. (2013) investigations on big data in higher education, especially in developing countries, is insufficient. However, there are growing interests in exploring and unlocking the value of increasing data within a higher education environment. Conversely, it has been reported that there is no interactive data system that allows the top management of Malaysian HEIs to engage in effective decision-making and develop strategies that may have a strong bearing on business performance and ranking assessments (Abidin, Zaibidi and Karim, 2017). Addressing this gap may help elucidate how big data can be a leading actor in the complex nature of the higher education landscape. Organisation capabilities of big data analytics are becoming increasingly important for the effective management of HEI, but the current adoption of data-driven decision making at many HEIs is a slow process blocked by numerous challenges relating to the implementation of big data analytics. This is attributed to the inability of HEIs to develop and deploy resources and capabilities within their organisations for effective data-driven decision making. With the right capabilities, HEI's will be able to exploit big data analytics to respond quickly to the dynamic changes and uncertainties within the higher education landscape while sustaining their competitive advantage (Daniel, 2017).

Literature Reviews Relevant to the Conceptual Model
Underpinning Theories

Ultimately, big data is concerned with an emergent suite of technologies that can process mass volumes of data of various types at faster paces than ever before. Big data have been defined as high-volume, high-velocity and great variety information assets (also known as 3V's) which by their nature demand cost-effective, innovative systems of information processing that can empower greater insight and decision making (Daniel, 2014). Recently, the 3Vs has been extended to 5 V's which include value (extraction of benefits from big data) and veracity (data source quality) by Wamba et al. (2015) who defined big data as a holistic process to manage, process and analyse 5 Vs (i.e., volume, variety, velocity, veracity and value) to create practical and feasible insights for sustained competitive advantages within an organisation. Organisations of today simply cannot do without information, and the emergence of Organisational Information Processing Theory (OIPT) is attributed to the growing importance of information to organisations (Fairbank et al., 2006). The focus of OIPT is on information processing requirements and information processing capabilities (Premkumar et al., 2005) which is related to the present research as it deals with big data analytics capabilities for improved business performance. Given the context, OIPT is naturally connected to big data given its significance of processing data into information which actually presents itself as a valuable source of knowledge fueling the organisation's strategic decision-making abilities. OIPT have been deployed in various studies relating big data and data-driven decision-making studies (Premkumar et al., 2015; Fairbank et al., 2006, Cao et al., 2015, Isik, 2018).

On the other hand, the resources (management, technology and people) that are required to facilitate big data analytical capabilities also make the resource-based view (RBV) theory somewhat relevant to the current research endeavour (Mishra et al., 2018). In the context of developing big data, perhaps the core resource is data itself. For a data-driven organisation, data (that fulfils the 5V characteristics) is a unique resource that has been argued to be necessary for a firm to build competitive advantage (Kiron et al. 2014; Wamba et al. 2015). The attribute of resources is that they would not be able to produce any business value by themselves, yet demand effort to be leveraged effectively. Hence, a resource is something that a firm has access to, rather than something it can do. Notably, the studies of Wamba et al., (2017); Akter et al. (2016); Gupta and George, (2016) and Mikalef et al. (2018) approached big data from a resource-based perspective. Resources related to such IT initiatives can be divided into technological resources (e.g., infrastructure), management resources (e.g., management ability) and human skills (e.g., employees' knowledge and skills) (Kim et al. 2012). This classification has been predominantly used in big data literature (i.e. Wamba et al. 2017; Davenport et al. 2012; Kiron et al. 2012; McAfee & Brynjolfsson, 2012; Barton & Court, 2012).

Big Data Analytics Capabilities

Lamba and Dubey (2015) defined big data analytics as to the application of multiple analytic methods that address the diversity of big data to provide actionable descriptive, predictive and prescriptive results. Big data analytics capabilities, on the other hand, have been defined as the firm's ability to mobilise and deploy BDA resources effectively, utilise BDA resources, and align BDA planning with a firm strategy to gain competitive advantage and enhance firm performance (Kiron et al., 2014; Garmaki et al., 2016). From the perspective of RBV theory, there seems to be a consensus among researchers that big data analytics capabilities are fulfilled by sufficient resources (i.e. adequate and appropriate management, technological and people capabilities) without which big data analytics cannot be carried out effectively (Davenport et al., 2012; Mikalef et al., 2018; Kim et al., 2012). Organisations are required to have information systems architecture that is beyond the commonly used software tools to capture, sort, store and process data within a short period. This is so because big data usually deals with unstructured, semi-structured and structured data (Dedic & Stanier, 2017) with more attention given to unstructured data as it constitutes 95% of big data (Gandomi & Haider, 2015). The enormity and complexity of information coming from various sources call for the integration of a different set of technologies, techniques and resources to reveal useful insights (Ibrahim et al., 2015). Instead of relying on traditional database management systems and information management systems, big data processing tools have evolved (Katal, Wazid & Goudar, 2013). Big data breakthrough can be traced back to 2004 when Google introduced the MapReduce Framework, a programming paradigm made up of algorithms to process huge amounts of data. Its success and subsequent adaptation led to the creation of an open-source implementation of the MapReduce framework by Apache Software Foundation, which became known as Hadoop (Katal et al., 2013). The Hadoop system, which is written in Java can process high volumes of data of any structure and allow distributed storage and distributed processing of large data sets which otherwise cannot be handled by traditional data processing methods. Organisations need to ensure that they have efficient processes to process high volumes of diverse data into meaningful insights to drive decision making. According to Labrinidis & Jagadish (2012) the process of extracting insights is made up of 5 stages (i.e. i) acquisition and recording; ii) extraction cleaning and annotation; iii) integration, aggregation and representation; iv) modelling and analysis; and v) interpretation) which can be organised into two main sub-processes; data management and analytics (Gandomi & Haider, 2015).

Management Capabilities Supporting Big Data Analytics Capabilities

Management capabilities have been characterised as an intangible resource by Mikalef et al. (2018) which reflect ties, structures and roles established to manage big data-related resources. According to Sambamurthy and Zmud (1999), one of the terms that are frequently

referred to when managing data-driven mechanisms and IT resources is governance. Gross and Siegel (2014) argued that having a proper governance structure for big data analytics will enable organisations to extract business value in terms of making decisions that prioritise big data opportunities, obtain the required data and deploy analytical models. Given the enormity of information, Tallon et al. (2013) developed a framework entailing practices that can be used to govern such information assets which are made up of structural (assigning responsibilities, directing and planning); procedural (shaping user behaviours through value analysis, cost control and resource allocation); and relational (business-IT partnerships, idea exchange and conflict resolution). The relational aspect of governance has also been confirmed by Mishra et al. (2018), who found that business IT partnership and business-IT alignment was positively associated with big data analytics. The emphasis on big data and information governance is attributed mainly to the strategic importance that it holds in contemporary enterprises (Grossman and Siegel, 2014; Davenport et al., 2012). Likewise, numerous researchers note the importance of establishing governance schemes for big data (Cao & Duan 2014; Garmaki et al. 2016; Grossman and Siegel, 2014). Against this backdrop, the research postulates that management capability which is operationalised as governance by Tallon et al. (2013) comprising structural, procedural and relational dimensions are indeed important facilitators of big data analytics in HEI's.

Technological Capabilities supporting Big Data Analytics Capability

Big data analytics can only be realised with the presence of technological capabilities and infrastructure. At the operational level, technological capabilities will ensure that vast amounts of data can be stored, managed and transformed into value as per the extraction, transformation and loading (ETL) technologies needed for big data analytics (Suvarnamukhi & Seshashayee, 2018). Technological capabilities are made up of reliable technological architecture and data standards, sharable technical platforms, databases (Isik et al., 2013) and most importantly software and systems relevant to big data, i.e. MapReduce, Hadoop, etc. While the hardware and software aspects of technological capabilities can be secured through investments by organisations, the characteristics of effective technological capability needed for big data analytics capability is hinged on having the right IT architecture that fulfils the requirements of connectivity, compatibility and modularity based on the conceptualisations of Kim et al. (2012). Greater connectivity between different systems (i.e. customer relationship management, enterprise resource planning, databases and department/function specific systems, etc.) will enable organisations to extract data for big data analytics purposes. Compatibility is characterised by having an IT architecture that allows transparent data flows and sharing regardless of its technical base while modularity refers to the ease with which organisations are able to add, remove or modify any IT modules as and when needed in a cost-effective manner (Kim et al. 2012). Organisations that have the right technology architecture will have greater agility (Sambamurthy et al. 2013) and better IT

capabilities (Kim et al. 2012) and in the context of this research big data analytics capability. The research postulates that the right technological architecture (connectivity, compatibility and modularity) is a precursor to big data analytics capability of HEI's.

Human Capabilities supporting Big Data Analytics Capability

The capacity to utilise big data technologies and tools to make strategic decisions based on outcomes of big data analytics is highly dependent on the skills and knowledge of human resources. The lack of personnel with the appropriate skills has been noted in a few studies and constitutes a major constraint in realising the full potential of fast-evolving IS technologies (Tambe, 2014). Based on the systematic literature review by Adrian et al. (2018); Kiron et al. (2014); and Wamba et al. (2017), human capabilities for big data have been theorised to be a driver of big data analytics and business performance. According to Mohanty et al. (2013), data scientists are practitioners of the analytics models solving business problems. The core attributes of data scientists include having entrepreneurial and business domain knowledge, computer science skills, effective communication skills, the ability to create valuable and actionable insights, interest and curiosity, and knowledge of statistics and modelling (Chatfield et al. 2014). While the centre of attention has been placed on data scientists, primarily due to the novelty of the role, other skills and knowledge sets are necessary for employees of firms who are engaged in big data analytics. Of particular relevance are technical skills to able to acquire, store, cleanse and code data from multiple sources and of various formats (Mikalef et al. 2018). Similarly, big data architects accommodate such technical knowledge by being responsible for developing blueprint plans of data sources, as well as the appropriate technologies to leverage their potential. Due to the fusion of business and IT departments in organisations deploying big data, Akter et al. (2016) argued that there is a need of a liaison person who is capable of bringing different departments together and work collaboratively. According to Gross and Siegel (2014), employees involved in big data need three important knowledge sets which include knowledge about data and analytics, knowledge about tools and infrastructure and knowledge about business products, services and operations. In conceptualising personnel capabilities as a second-order construct making up IT capabilities of organisations (a third-order construct), Kim et al. (2012) empirically demonstrated that technical knowledge, technology management knowledge, business knowledge and human relations knowledge are important aspects of human capabilities required to support capabilities of IT initiatives in organisations.

Big Data Analytics Capability for Improved Performance of HEIs

Davenport et al. (2012) highlight that management, people and technology dimensions are interlinked in a big data environment to enable data-driven decision making for improved

firm performance. These dimensions of organisational resources and their relationships with big data analytics have been supported by Barton and Court (2012), and Kim et al. (2012) who highlight that management capability is imperative to optimise decision models. Technology capability is essential to explore and manage a variety of data; and finally, data science capability is essential to understand, develop and apply analytical models. Many organisations have paid attention to the potential use of big data to monitor, measure and manage performance and increase their competitiveness (Zhang et al., 2017). Top performing organisations are reliant on big data analytics five times more than low performing organisations (LaValle et al., 2011) on the premise that it can improve organisation's operations, business performance (Choi et al., 2017) and render competitive. Companies should build their data-driven decision-making processes based on performance management as an objective measurement criterion to monitor processes and outcomes. In this study, performance management capability refers to the ability to develop systematic and appropriate monitoring, evaluating and control approach to observe and measure business performance, and then guide managerial actions accordingly upon the outcome (Mithas et al., 2011).

In the context of HEI performance, the ranking assessments and evaluations have made Malaysian HEIs and their administrators far more conscious of the need to collect reliable data on a longitudinal basis. Several administrators said that they are collecting better data in response to ranking systems (Institute for Higher Education Policy, USA, 2009). Apart from being subjected to international ranking systems such as the QS and Times Higher Education world university rankings, domestically public universities are also subjected to the mandatory Malaysian University Research Assessment Instrument (MyRA), which is an assessment method used to evaluate the performance of Research Universities, as well as other public universities competing to become among the best. The amount of data to be organised is vast, and therefore an information system to aid data-driven decision making along the dimensions that are related to MyRA needs to be developed in order to organise data more efficiently (Abidin et al., 2017; Yassin et al., 2011). Given the context, the potential of big data analytics to offer tremendous opportunities for organisations (and in the case of this research HEIs) to improve their overall business operations and performance is undeniable (Raffoni et al., 2018; Kache and Seuring, 2017). Research has found that big data analytics can be used to understand customer intentions and behaviours (Srinivasan & Swink, 2017) and contribute to agile operations of organisations (Dubey et al., 2019). Notably, previous studies have demonstrated that big data analytics can bring about improvements in organisations operations and performance (Gunasekaran et al., 2017a; Gunasekaran et al., 2017b; Akter et al., 2016; Ren et al., 2017; Frank & Bannister, 2017; Wamba et al., 2017; Mishra et al., 2018).

The Moderating Effects of Continuous Process Innovation

Process innovation is regarded as an important approach that can spruce organisational efficiency, effectiveness and facilitate the achievement of competitive advantage (Harmon, 2010; Davenport, 2006; Bititci et al., 2010; Reichstein & Salter, 2006). Process innovation can be described as a unique invented feature into an organisation's day-to-day operations to reduce operational costs while upping product or service quality. The utilisation of process innovation has a positive influence on organisations financial and customers' performances (Kaplan et al., 1996; Gunday et al., 2011; Tuan et al., 2016). The outcomes on the implementation of innovation on organisation's performance have been a topic of major concern to economists and policymakers for many years (Hashi & Stojčić', 2012). Previous findings on innovation generally stated that there is a positive relationship between innovation and organisation's performance (Gunday et al., 2011). Although innovation is normally associated as a way of strengthening the organisation's effectiveness and performance, this association has not been reinforced clearly by experimental work (Hashi & Stojčić', 2012). Moreover, few research papers further deliberate the impact of innovation implementation within organisations, and those that do are limited in scope (Camisón & Villar-López, 2012). It is essential for HEI administrators to be interested in continuous process innovation by transforming their organisational culture so that it has a pro-innovative character. In this light, the study seeks to explore further the role played by continuous process innovation in the relationship between big data analytics capability and performance of HEIs in Malaysia.

Methodology

Our approach to develop and propose a conceptual framework of big data analytics capability in the context of higher education institutions consists of three phases: (1) reviews of relevant literature; (2) conceptual framework development and; (3) recommended data collection and analysis procedures. The literature review (in section 2) paid attention to studies relating to big data capabilities in relation to improved organisational performance. Since empirical studies drawing attention to big data analytics regarding performance of higher education institutions are scarce if not unavailable, the research reviewed literature of big data concerning business performance (Akter et al., 2016), agile business operations (Dubey, 2019) and improvement in organisational operations (Gunasekaran, 2017a; 2017b). The researchers relied on the Scopus database as the primary starting point to search for relevant big data articles. Majority of the research articles reviewed in this paper were obtained from high impact journals (i.e. International Journal of Production Economics, Journal of Management Information System, Information and Management, Journal of Business Research, MIT Sloan Management Review, MIS Quarterly, Management Decision, Information Systems and E Business Management to name a few). The key literature that

forms the cornerstone on which the proposed conceptual framework is developed has been summarised in the following table:-

Table 1: Key Literature Supporting the Proposed Conceptual Framework

No.	Dimensions	Attributes	Sources
1.	Big Data Analytics Capability (BDAC)	BDAC is the competence to provide business insights using data management, infrastructure (technology) and talent (personnel) capability to transform the business into a competitive force.	Kiron et al., (2014); Adrian et. al (2018)
2.	Big Data Analytics and Firm Performance	Big Data can enhance an organisations competitive advantage and help improve firm operations and performance.	Wamba et al., (2015); Wamba et al., (2017); Mishra et al., (2018); Dubey et al. (2019).
3.	The performance of HEIs	One of the most reliable instruments to measure the performance of HEI in Malaysia is the Malaysian Research Assessment (MyRA. It is a comprehensive assessment system that is used to assess the research capacity and performance of all public and private universities in Malaysia.	Abidin et al. (2017); MyRA Glossary USM (2018); Yassin et al. (2011)

| 4.	Big Data Analytics Capabilities Inclusive of three (3) main dimensions as follows; • Technology Capabilities • Management Capabilities • People Capabilities	Management, people and technology dimensions are important big data resources to enhance broader firm performance. Driven by RBV these studies proposed the need for organisations to develop the following resources:- - Technology Infrastructure. - Processes and practices. - Leadership. - Culture and behaviours. Skills and values	Davenport et al., (2012); Mikalef et al., (2017); Adrian et al., (2018); Kim et al., (2012); Wamba et al. (2015)
5.	Management Capability	Management's responsibility in developing and maintaining a governance structure for the effective and efficient deployment and use of big data analytics to support data driven decision making for improved firm performance.	Davenport et al. (2012); Grossman & Siegel, (2014); Mishra et al., (2018); Tallon et al. (2013
6.	People Capabilities • Sufficient number of big data analytics expertise.	A critical mass of data scientists. The need for an analytics group to include a mixture of data scientists, some of whom are generalists and others who are specialists.	Grossman & Siegel, (2014), Adrian et al. (2018)

Table 1: (Continued)

No.	Dimensions	Attributes	Sources
7.	People Capabilities • Knowledge and skillsets	Professional skills, knowledge and ability to undertake big data analytics related tasks. The knowledge set required are as follows:- • Technical knowledge (knowledge about technical elements). • Technology management knowledge	Barton and Court (2012); Davenport and Patil (2012); Kim et al. (2012); Kiron et al. (2014);

		(big data resource management knowledge that is necessary to support business goals). • Business knowledge (understanding of various business functions and the business environment). • Relational knowledge (ability to communicate and work with people across different business functions).	
8.	Technology Capabilities • Connectivity • Compatibility • Modularity	BDA infrastructure (e.g., applications, hardware, data, and networks) to enable the BDA staff to quickly develop and deploy necessary system components for a firm as follows; • Connectivity among different business/Section/Department in sourcing and analysing a variety of data from different functions. • Compatibility enables continuous flows of information for real-time decisions. It also helps to synchronise and merge overlapping data and to fix missing information. • Modularity embodies flexible platform development which allows the addition, modification or removal of features to improve performance.	Barton and Court (2012); Davenport, (2006); Davenport and Harris, (2007); Kim et al. (2012); Wamba et.al (2015); Wamba et al. (2017), Adrian et. al (2018)
9.	Continuous Process Innovation	An effort to infuse innovative process improvements into organisations day-to-day operations with the intention of reducing operational costs. The utilisation of process innovation has been proven to influence positive organisational performance.	Kaplan et al., (1996); Gunday et al., (2011); Tuan et al. (2016).

Proposed Conceptual Framework

The proposed conceptual framework will be further fine-tuned following semi-structured interviews with big data experts from academia and industry who are primarily responsible for big data projects and implementations. The purpose is to understand organisational resources and requirements that are required for the effective deployment of big data analytics in the HEI context. Based on the review of relevant literature the following conceptual framework is proposed:-

Figure 1. Proposed Conceptual Framework
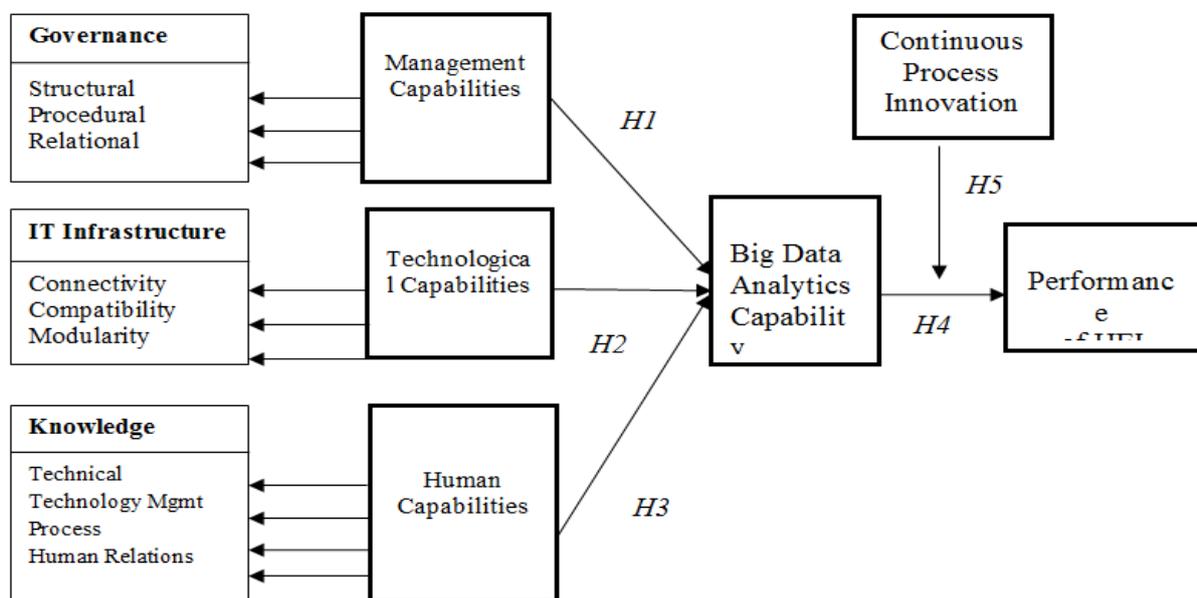
Sampling, Data Collection and Data Analysis

In order to have a significant comparison of the performance of HEIs, the study intends to select one key informant such the head or leader of HEIs responsible for the preparation of MyRA evaluations in their respective HEIs. Based on MyRA list, there are 102 HEIs involved in MyRA assessments. For a population size of 102 HEIs, the minimum sample size for the study is 80 based on Krejcie and Morgan's (1970) table of determining the sample size of a given population. Purposive sampling technique is proposed to be used as the sample would be selected on the basis of characteristics, relationships and expertise regarding the research subject (Freedman et al., 2007). For this study, two inclusion criteria will be utilised for selecting the appropriate HEIs which are as follows;

i.   HEIs that are involved in MyRA and;
ii. HEIs which offers postgraduate programs with a research component.

The required data for this study will be collected through a questionnaire that will be distributed to the chosen sample. The instrument will measure the constructs using items derived from validated instruments used in prior research where possible. The questionnaire will be anchored on a 5 point Likert scale ranging from 1 strong disagree to 5 strongly agree. Data will be analysed by using Structural Equation Modeling (SEM) through the Partial Least Squares (PLS) Software 3.0. PLS can be used in analysing the measurement model and the structural model. PLS path modelling is a variance-based structural equation modelling technique that is widely applied in business and social sciences. PLS path modelling results are suitable for confirmatory and exploratory research and provide guidelines for assessing the fit of the overall model, the validity and reliability of the measurement model, and the relationships between constructs (Henseler, 2017).

Implications and Future Research

This study is considered a work in progress and is being conducted with the hope that it may contribute to the emerging literature supporting the business case for big data analytics investments to aid data-driven decision making (Gupta & George, 2016; Mikalef et al., 2017; Wamba et al., 2017, Mishra et al. 2018), particularly within the HEI industry where big data adoption is slowly but surely catching up. These studies provide evidence that when all the big data resources are in place and are being managed well, it can transform the way HEI carries out its operations and provision of educational programmes. While early literature has been focused on big data analytics capability as a technical capability, this paper demonstrates with supporting literature that the combination of managerial, technological and human aspects are all important part big data analytics capability that can aid strategic decision making and improve an organisation's performance. This conceptual model can be replicated or extended by future researchers to different industries and different countries more so in emerging markets such as China, India and South Africa that have benefited tremendously from the use of big data. Future researchers can also explore environmental factors that may impede or enhance big data analytics capabilities. Given the fact that different types of decisions are made by different organisations, future studies may consider adopting other moderating variables such as decision environment or organisational culture to understand better the different circumstances affecting big data initiatives to render its full potential to organisations. As the developments of IR4.0 is exerting pressure on HEI's to be innovative in the delivery of academic programmes and the way in which it operates, future research could look at the outcomes associated with big data adoption by HEI's in terms of the use of big data in meeting the demands of IR.40.

In terms of practical implications, the study enhances the understanding amongst administrators and regulators of HEIs about processes and core resources they should focus on when planning to delve into a big data analytics project (van de Wetering et al., 2017)

specifically for improved data-driven decision making. It gives insight not only on the main issues that should be taken into account but also on the possible options that are available. It is necessary for organisations to have the right big data capabilities to effectively pursue big data analytics and be mindful of the need and ability to manage such capabilities as organisations' use of big data grows and matures over time. The proposed conceptual model can be used as a guideline for HEIs to formulate governance policies and deploy resources and strategies to overcome potential obstacles which can jeopardise HEI's quest to embrace big data so as to realise the ideals of an organisation that is committed to data-driven decision making instead of being reliant on intuition. In the era of IR 4.0, HEIs in Malaysia must leverage on big data as a new enabler for developing unique, vibrant and dynamic competitive advantages in line with the RBV theory. Therefore, HEIs must identify, source, develop and continuously sustain their big data capabilities in order to fully realise the true potential of big data in enhancing organisational performance. In keeping with the developments and demands of IR4.0, big data deployment may support HEI's in numerous ways such as; i) enabling impactful research and publications amongst faculty thereby increasing the intellectual contribution of the university as a whole; ii) blended learning and personalised adaptive learning; iii) digital, experiential learning for enhanced student experience; iv) re-imagined assessment strategies; v) marketing analytics for better digital marketing solutions to attract potential students and etc. The use of data analytics to aid teaching, learning, assessments and in particular to monitor progress and effectiveness of the education programme as a whole will become the mainstay of IR4.0 within the HEI context. All these outcomes are closely tied to MyRA measurement standards and QS global university ranking measurement exercises which are compelling reasons as to why HEI should adopt big data. The adoption big data will not only enable HEI's to fulfil the IR4.0 imperative, i.e. produce graduates who are industry-ready but may also create various opportunities for HEI to be innovative, effective and efficient in their operations.

In conclusion, this paper outlined the key capabilities (management, technological and people) that are required by HEI's to enable big data analytics. As informed by the RBV theory, these capabilities are essential resources that are required by HEI's in their quest of embracing big data initiatives, which is effectively managed and leveraged upon can lead to competitive advantage. Conversely, from the lens of OIPT theory, this paper also highlighted the information processing requirements and capabilities (i.e. big data analytics capabilities) that will help HEI's to transform raw data into data that meets the 5 V characteristics to enable data-driven decision making for improved performance of HEI as a whole.

REFERENCES

Abidin, N.Z., Zaibidi, &. Karim, K.N. (2017). Strategic planning for MyRA performance: A causal loop diagram approach". In *AIP Conference Proceedings*, vol. 1891 (1), 020151. AIP Publishing.

Adrian, C., Abdullah, R., Atan, R. & Jusoh, Y.Y. (2018). Conceptual model development of big data analytics implementation assessment effect on decision-making. *Journal of Interactive Multimedia and Artificial Intelligence, 5*(1), 101-106.

Akter, S., Fosso Wamba, S., Gunasekaran, A., Dubey, R. & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment?. *International Journal of Production Economics, 182,* 113-131.

Barton, D. & Court, D. (2012). Making advanced analytics work for you. *Harvard Business Review, 90*(10), 78-83.

Bititci, U., Ackermann, F., Ates, A., Davies, J., Gibb, S., MacBryde, J., Mackay, D., Maguire, C., van der Meer, R., Shafti, F. & Bourne, M. (2010). Managerial processes: an operations management perspective towards dynamic capabilities. *Production Planning & Control, 22*(2), pp. 157 – 173.

Calantonea, R.J., Cavusgila, S.T. & Zhao, Y. (2002). Learning orientation, firm innovation capability, and firm performance. *Industrial Marketing Management, 31*(6), 515-524.

Camisón, C., Villar-López, A. (2014). Organizational innovation as an enabler of technological innovation capabilities and firm performance, *Journal of Business Research, 67*(1), 2891–2902

Campbell, J.P., De Blois, B. P., Oblinger, D.G. (2007). Academic Analytics: A New Tool for a New Era. *Educause Review, 42(*4). 40–57.

Cao, G. & Duan, Y. (2014). Gaining competitive advantage from analytics through the mediation of decision-making effectiveness: an empirical study of UK manufacturing companies. In: *Proceedings of the Pacific Asia conference on information systems (PACIS),* 377.

Cao, G., Duan Y., & Li, G. (2015). Linking Business Analytics to Decision Making Effectiveness: A Path Model Analysis. *Transactions on Engineering Management, 62*(3), 384-395.

Chatfield, A.T., Shlemoon, V.N., Redublado, W. & Rahman, F. (2014). Data scientists as game changers in big data environments. In: *Proceedings of the 25th Australasian conference on information systems (ACIS).*

Chen, H., Chiang, R.H.L. & Storey, V.C. (2012). Business intelligence and analytics: from big data to big impact. *MIS Quarterly, 36*(4), 1165-1188.

Choi, T.M., Wallace, S.W. & Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, Special Issue on Big Data in Supply Chain Management, 27 (10),1868-1883.

Clarke, J., Nelson, K., & Stoodley, I. (2013). The place of higher education institutions in assessing student engagement, success and retention. In Proceedings of the Higher Education Research and Development Society of Australasia Conference, Auckland, New Zealand.

Damanpour, F. & Schneider, M. (2006) Phases of the adoption of innovationin organization: Effects of environment, organization and top managers. British Journal of Management, 17(3), 215-236.

Daniel, B. (2014). Big data and analytics in higher education: opportunities and challenges. *British Journal of Educational Technology, 46*(5), 1-17.

Daniel, B.K. (2017). Big data in higher education: The big picture. In Big data and learning analytics in higher education. Springer, 19-28.

Davenport, T.H., Barth, P. & Bean., R. (2012). How 'big data'is different. *MIT Sloan Management Review, 54(1)*, 43–46.

Davenport, T.H. (2006). Competing on analytics, *Harvard Business Review, 84*, (1), 98–107.

Davenport, T.H. and Harris, J.G. (2007). *Competing on Analytics: The New Science of Winning*, Harvard Business School Press.

Davenport, T.H. and Patil, D.J. (2012). Data scientist: the sexiest job of the 21st Century – a new breed of professional holds the key to capitalizing on big data opportunities, *Harvard Business Review*, *90* (10), 70-76.

Dedic, N. & Stanier, C. (2017). *Towards differentiating business intelligence, big data, data analytics and knowledge discovery.* Springer International Publishing, Berlin, Heidelberg, 114-122.

Dubey, R., Gunasekaran, A. and Childe, S.J. (2019). Big data analytics capability in supply chain agility: the moderating effect of organizational flexibility, *Management Decision*, *57*(8), 2091 – 2112.

Dutta, D. & Bose, L., (2014). Managing a big data project: The case of Ramco Cements Limited. *International Journal of Production Economics*, *165*, 293-306.

Fairbank, J.F., Labianca, G., Steensma, H.K. & Metters, R.D (2006). Information Processing Design Choices, Strategy and Risk Management Performance. *Journal of Management Information Systems, 23*(1), 293-319.

Fritsch, M. & Meschede, M. (2001). Product innovation, process innovation, and size. *Review of Industrial Organization, 19*(3), 335-350.

Freedman, David, Pisani, Robert, Purves, Roger, (2007). *Statistics,* Fourth edition, New York, W. W. Norton & Company Inc., 346.

Gandomi, A. & Haider, M. (2015). Beyond the hype: Big data concepts, methods, and analytics. *International Journal of Information Management*, *35*(2), 137–144.

Garmaki, M., Boughzala, I. & Wamba., S.F. (2016). The effect of big data analytics capability on firm performance. In: Proceedings of 20th Pacific Asia conference on information systems (PACIS).

Görnerup, O., Gillblad, D., Holst, A., & Bjurling, B. (2013). Big Data Analytics: A Research and Innovation Agenda for Sweden. The Swedish Big Data Analytics Network.*In: ICT SS*, editor. (Online). Accessed on the 2nd of February 2020: http://www.vinnova.se/PageFiles/0/BigDataAnalytics.pdf

Grosssmen, R.L. & Siegel, K.P. (2014). Organization Models for Big Data Anakytic. *Journal of Organization Design, 3(*1), 20-25.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S.F., Childe, S.J., Hazen, B. & Akter, S. (2017a). Big data and predictive analytics for supply chain and organizational performance. Journal of Business Research, 70, 308-317.

Gunasekaran, A., Yusuf, Y.Y., Adeleye, E.O. and Papadopoulos, T. (2017b). Agile manufacturing practices: the role of big data and business analytics with multiple case studies. *International Journal of Production Research, 56*(1-20),1-13.

Gunday, G., Ulusoy, G., Kilic, K. & Alpkan, L. (2011). Effects of innovation types on firm performance. *International Journal of Production Economics, 133*(2), 662-676.

Gupta, M. & George, J.F. (2016). Toward the development of a big data analytics capability. *Journal Information & Management*, *53*(8), 1049-1064.

Hanapiyah, Z.M., Hanafi, W.N.W., & Daud, S. (2018). Issues, Challenges and Opportunities of Big Data Management in Higher Education Institutions in Malaysia. *Indian Journal of Science and Technology, 11*(4),1 – 6.

Harmon, P. (2010). *Scope and evolution of business process management. Handbook on Business Process Management*, International Handbooks Information System, Part I, Vol. 1, Springer, Warren, MI, 37-81.

Hashi and Stojcic., N. (2013). The Impact of Innovation Activities on Firm Performance Using a Multi-Stage Model: Evidence from the Community Innovation Survey 4. *Research Policy, 42*(2), 353.

Hayikader, S., Khan, M.N., Khan, M.T., & Ahmad Dahlan, A.R. (2015). Big data and a smarter university: a literature review. *International Journal of Scientific and Research Publication, 5*(5), 1-4.

Huergo, E. & Jaumandreu, J. (2004). Firm's age, process innovation and productivity growth. *International Journal of Industrial Organization*, *22*(4), 541-559.

Ibrahim, A.T.H., Ibrar, Y., Anuar, N.B., Mokhtar, S. Gani, A. & Khan, S.U. (2015). Big data on cloud computing: Review and open research issues. *Information Systems, 47*, 98-115.

Institute of Higher Education Policy.(2009). Impact of college ranking on institutional decision making: Four Country Case Study. Accessed on 13th July 2019: http://www.ihep.org/sites/default/files/uploads/docs/pubs/impactofcollegerankings.pdf

Intezari, A. & Gressel, S.(2017). Information and reformation in KM systems: Big data and strategic decision-making. *Journal of Knowledge Management, 21*(1), 71–91.

Isik, O. (2018). Big Data Capabilities: An Organizational Information Processing Perspective. In A. V. Deokar, A. Gupta, L. S. Iyer, & M. C. Jones (Eds.), Analytics and Data Science, 29–40, Springer Nature, Switzerland AG.

Işık, O., Jones, M.C. & Sidorova, A. (2013). Business intelligence success: The roles of BI capabilities and decision environments. *Information & Management*, *50*(1), 13–23.

Henseler, J. (2017). Bridging Design and Behavioral Research With Variance-Based Structural Equation *Modeling, Journal of Advertising 46* (1), 178-192.

Juma, C. (2016). How can Africa master the digital revolution?. Retrieved July 20, 2019, from World Economic Forum:https://www.weforum.org/agenda/2016/04/how-africa-can-master-the-digital-revolution/

Katal, A. Wazid, M. & Goudar, R.H. (2013). Big data: Issues, challenges, tools and Good practices. Sixth International Conference on Contemporary Computing (IC3), 404–409.

Kim, G., Shin, B. & Kwon., O. (2012). Investigating the value of sociomaterialism in conceptualizing IT capability of a firm. *Journal of Management Information Systems 29 (3)*, 327–362.

Kiron, D., Prentice, P. K. & Ferguson, R. B. (2012). Innovating With Analytics. (cover story). *MIT Sloan Management Review, 54(1)*, 47-52.

Kiron, D., Prentice, P. K., & Ferguson, R. B. (2014). 'The analytics mandate'. *MIT Sloan Management Review*, Vol. 55, No. 4, pp.1–25

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and psychological measurement*, *30*(3), 607-610.

Labrinidis, A. and Jagadish, H.V. (2012). Challenges and opportunities with big data. *Proceedings of the VLDB Endowment, 5*(12), 2032–2033.

Lamba, H.S. & Dubey, S.K. (2015). Analysis of requirements for big data adoption to maximize IT business value in reliability. In: 4th International conference on infocom technologies and optimization (ICRITO): Trends and Future Directions. IEEE,1–6.

LaValle, S. Lesser, E., Shockley, R. Hopkins, M.S. & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT Sloan Management Review, 52*(2), 21-32.

Lewis, A. and Portalatin M. (2013). Tips for successful use of FM Technology: From Strategy to implementation. Facility Engineers Association Magazine.

Macfadyen , L.P. & Dawson, S. (2012). Numbers are not enough: Why e–learning analytics failed to inform an institutional strategic plan. *Educational Technology & Society, 15*(3), 149–163.

McAfee, A. & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review, 90*(10),60-68.

Mikalef, P., Pappas, I.O., Krogstie, J. & Giannakos, M. (2017). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management*,1-32.

Mikalef, P., Pappas, I.O., Krogstie, J. and Giannakos, M. (2018). Big data analytics capabilities: a systematic literature review and research agenda, *Information Systems and e-Business Management, 16*, 547 – 578

Mishra, D., Luo, Z., Hazen, B., Hasini, E. & Foropon, C. (2018). Organizational capabilities that enable big data and predictive analytics diffusion and organizational performance: A resource-based perspective. *Managemnt Decision.* Ahead of Print.

Mithas, S. & Ramasubbu, N. (2011). How information management capability influences firm performance. *MIS Quarterly, 35*(1), 237–256.

Mohanty, S., Jagadeesh, M. & Srivatsa, H. (2013). *Big data imperatives: enterprise "Big Data" warehouse, BI implementations and analytics.* Apress, New York.

MyRA Glossary USM (2018), Universiti Sains Malaysia. Accessed on the 5th of August 2019: https://rdmusm.files.wordpress.com/2019/12/glosari-myra-ii-pindaan-2018-final-6.12.2019.pdf

Premkumar, G., Ramamurthy, K., & Saunders, C.S. (2005). Information Processing View of Organizations: An Exploratory Examination of Fit in the Context of Interorganizational Relationships. *Journal of Management Information Systems, 22*(1), 257-294.

Raffoni, A., Visani, F. M. Bartolini and R. Silvi. (2018). Business performance analytics: exploring the potential for performance management systems. *Production Planning & Control, 29*(1), 51-67.

Rahmat, A.R., Ahmad, A. & Ta'a, A. (2016). Business Intelligence Readiness for Higher Learning Institution (IHL): Preliminary Study and Research Model. *British Journal of Applied Science & Technology, 15*(5), 1 – 10.

Reichstein, T. & Salter, A., (2006). 'Investigation the source of process innovation among UK manufacturing firms', *Industrial and Corporate Chan*ge, *15(*4), 653-682.

Ren, S.J., Wamba, S.F. Akter, S. Dubey, R. & Childe, S.J. (2017). Modelling quality dynamics, business value and firm performance in a big data analytics environment. *International Journal of Production Research, 55*(17), 5011-5026.

Sambamurthy, V. & Zmud, R.W.(1999). Arrangements for information technology governance: a theory of multiple contingencies. *MIS Quarterly, 23*(2), 261-290.

Sambamurthy, V., Bharadwaj, A. & Grover, V. (2003). Shaping agility through digital options: reconceptualizing the role of information technology in contemporary firms. *MIS Quarterly, 27*(2), 237–263.

Siemens, G., & Long, P. (2011). Penetrating the Fog: Analytics in learning and education. *Educause Review, 46*(5), 30.

Srinivasan, R. & Swink, M. (2018). An investigation of visibility and flexibility as complementsto supply chain analytics: an organizational information processing theory perspective. *Production and Operations Management, 27(*1), pp. 1849 – 1867.

Suvarnamukhi, B. & Seshashayee, M. (2018). Big Data Concepts and Techniques in Data Processing. *International Journal of Computer Sciences and Engineering, 6*(10), 712–714.

Tallon, P.P., Ramirez, R.V., & Short, J.E. (2013). The information artifact in IT governance: toward a theory of information governance. *Journal of Management Information System, 30*(3), 141–178.

Tambe, P. (2014). Big Data Investment, Skills, and Firm Value. *Management Science, 60*(6), 1452–1469.

Tuan, N., Nhan N., Giang, P. & Ngoc, N. (2016). The effects of innovation on firm performance of supporting industries in Hanoi, Vietnam. *Journal of Industrial Engineering and Management, 9*(2), 413-431.

van de Wetering, R., Mikalef, P. & Pateli, A. (2017). A Strategic Alignment Model for It Flexibility and Dynamic Capabilities: Towards an Assessment Tool. *The 25th European Conference on Information Systems (ECIS):* Association for Information Systems.

Wamba, S.F., Akter, S., Edwards, A., Chopin, G., & Gnanzou, D. (2015). How 'big data'can make big impact: Findings from a systematic review and a longitudinal case study. *International Journal of Production Economics,165*, 234-246.

Wamba, S.F., Gunasekaran, A., Akter, S., Ren, S.J.F., Dubey, R. & Childe, S.J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 70,* 356-365.

Yassin, I.M., Zabidi A., Johari, M.A., Hijaz, F., Izzudin, A.Y., Tahir, N.M., & A .A. (2011). Entity-Relationship analysis for development of Malaysian University Research Assessment Instrument (MyRA) information system. In 2011 IEEE International Conference on System Engineering and Technology (ICSET), 219-224.

Zhang, Y. Ren, S., Liu, Y. & Si, S. (2017). A big data analytics architecture for cleaner manufacturing and maintenance processes of complex products. *Journal of Cleaner Production, 142*, 626-6