

Decision support model to adopt big data analytics in higher education systems



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ABSTRACT

Data science or specifically data analytics systems have become an emerging trend in information technology and have attracted many organizations, including higher education. Higher Education Systems (HES) involve very active entities (students, faculty members, researchers, employers) who generate and require large volumes of data that go beyond the structured data stored in the house. The collection, analysis, and visualization of such big data present a huge challenge for HES. Big data analysis could be the solution to this challenge. However, the rationale and decision process for the adoption of big data analytics can be difficult. Such a knowledge-driven process requires a multitude of technical and organizational aspects that must be accounted for to ensure informed decisions are made. Existing research and development indicates that the decision to adopt, although systematic research with a theoretical background is rare and none of the existing studies have considered diffusion of innovation (DOI) theory. This paper aims to support HES, by providing a systematic analysis of the determinants for the decision to adopt big data analytics. An integrated framework referred to as the Technology Organization Environment (TOE) framework is proposed. The proposed framework is validated using structural equation modeling. Eleven determinants are confirmed that influence the TOE-driven framework for data analytics in HES. The result is expected to contribute to on-going research that attempts to address the complex and multidimensional challenge that relates to data science and analytics implementation in HES.

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1. Introduction

Competitiveness in the higher education sector has reached a peak (Bagley and Portnoi, 2014). Globalization and economic pressure are the main factors that have greatly encouraged this sector to enhance its performance (Oprea et al., 2017). Businesses and enterprises nowadays rely on data and the science behind it, thus enterprises are exploiting data and intelligence not only because they can but also because they should (Matsebula and Mnkandla, 2017). This has resulted in many universities and colleges seeking to innovate technologies in order to enhance their performance as well as increase their global ranking. In particular, there is a significant demand in the education sector

in taking advantage of the emerging Big Data technologies (Jha et al., 2018) that can help to improve students' learning, enhance teaching, reduce administrative workloads, support strategic planning, and improve collaboration.

Higher education institutions are amongst the largest data and information generators. This is due to the fact that they involve very active entities (students, teachers, researchers, employers). The huge volumes of data generated by these entities, as well as by other related parties, can be exploited by universities and colleges to identify important patterns, gain contextual insight, and enable informed decision-making about system or technology adoption. Big data analytics systems can support higher education in many areas. Through its prediction features, it can help determine the academic and non-academic performance of students (Saa et al., 2019).

For example, it can enable organizations to predict which students may be at risk of failing, and this can help universities to plan corrective measures for them during their studies. It can also

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help universities and colleges to improve students' teaching and learning experiences. Instructors and other educational experts can exploit a wide range of statistics and analytical models, and extract meaningful patterns from huge volumes of data and analytics which help them to evaluate student performance. Big data analytics helps organizations with the monitoring and evaluation of their activities, processes, and future strategic directions. It can improve students' admissions by providing the ability to admit a higher percentage of sound and aspiring students. Furthermore, it provides the ability to avoid admitting unqualified candidates and also reduces the rate of unsuitable admission practices in higher education organizations. It can also enhance collaboration with beneficiaries by analyzing large volumes of data concerning public opinions and views on the university.

As an emerging innovative technology, the adoption of big data analytics has received increasing attention in academia (Sivarajah et al., 2017). Existing research and development supports higher education systems (HES) that have implemented big data analytics, and many have explored the organizational benefits and challenges of so doing.

However, most existing big data analytics adoption studies are exploratory, descriptive, or case-based. The majority fail to use empirical data to identify the factors involved, and only a limited number have used a suitable theoretical framework to identify those influencing factors. A few studies have employed the Technology-organization-environment framework (TOE) (Matsebula and Mnkandla, 2016; Sam and Chatwin, 2018; Ijab et al., 2019), while Kumaran et al. (2015) have used TOC. However, none of the previous studies have employed the diffusion of innovation model (DOE) nor attempted integrated multiple models for identifying higher education readiness to implement big data analytics technologies. It has been argued that the integration of multiple theoretical perspectives will improve the take-up of innovative technologies (Fichman, 2004).

Overview and main contributions: This paper aims to address the deficiencies in the research on data analytics in the HSE context. It attempts to systematically cover all related variables surrounding the decision-making process. To achieve this, the results of the proposed study support the complementary use of two theoretical models for the adoption of innovation. The findings were also based on an analysis of the related literature and on empirical data that was collected during both the exploratory and evaluation phases. The proposed contributions of the work are listed as follows that are detailed in the remainder of the paper.

- Analysis and exploitation of big data and information-driven intelligence to support the decision-making process in the HES context.

- Exploring data-driven decisions to adopt data science in HES facilitated by secondary and primary data collection processes.
- A unique model that integrates the TOE and DOI models to ensure comprehensive coverage of the determinants.
- Identify the key determinants for the decision to adopt big data analytics in HES.
- Validation of the model using structural equation modeling for exploratory and confirmatory factor analysis based on data that is accumulated from practitioners and stakeholders of the HES.

Organization of the Paper: Section 2 highlights Background and Related Research. Section 3 presents Research Methodology. Section 4 presents an Analysis of the Structured Interviews. Section 5 highlights the Proposed Model and Hypothesis. Section 6 and Section 7 are dedicated to Model Evaluation and Hypothesis Testing. Section 8 presents a conclusive summary.

2. Background and related research

In this section, first, we present the background details in Section 2.1 and 2.2 that follows a critical review of the related studies. We introduce fundamental concepts and terminologies in this section that are used later throughout the paper.

2.1. Big data analytics

Almost all universities today utilize information technologies for their activities, especially for storing and managing student data. Currently, they face the challenge of managing sky-rocketing volumes of related data. Existing systems are usually not able to handle such data which means that universities miss important sources of information that can provide them with insights and facilitate more informed decisions and appropriate future strategic directions. Predictive analysis is considered as one of the critical business intelligence approaches. Many organizations in different industries have successfully implemented predictive analysis tools and techniques mainly to assess consumer behavior (Blazquez and Domenech, 2018). However, the application of predictive analytics extends far beyond business contexts which present a huge challenge. Big data analytics includes a multitude of solutions that include but are not limited to the statistical method, text mining, and multimedia analysis (Tsai et al., 2015).

The statistical analytics methods require both data mining and machine learning tools in order to examine current as well as historical processes and results that can be used to predict the future. In HES, predictive analytic tools are considered relatively innovative and needed for futuristic efforts (Hasan et al., 2020).

2.2. Organizational adoption of innovation

Big data analytics is an innovative and still emerging technology that many organizations are willing to adopt. This section, therefore, discusses the theoretical foundation for that adoption, and in particular, the TOE framework (Tornatzky et al., 1990) and DOI theories (Rogers, 2010). They have been widely used and discussed in the literature as important models for ensuring the successful implementation of innovative technologies, however, they usually require some degree of amendment depending on the innovation to be adopted which is also been arranged in this paper.

Technology Organization Environment (TOE) framework: The framework enables a holistic approach and guidance for the organization of the technology stack (Ramdani et al., 2013). It includes three main dimensions: technology, organization, and environment. They are considered to be the main contexts for the adoption of a particular technology. The framework can be used as a taxonomy to identify, classify, and prioritize the potential technologies to be adopted (Gangwar et al., 2015). It has been used in the context of adoption similar technology innovations, such as for cloud-based services, Internet of Things (IoTs), and mobile computing (McKinnie, 2016; Al-Hujran et al., 2018; Hsu and Yeh, 2017) and has also been used in the adoption of big data in HES (Matsebula and Mnkandla, 2016; Sam and Chatwin, 2018; Ijab et al., 2019).

However, it is worth mentioning that the implementation of this framework in this study is slightly different from its use in previous studies, where it was complemented and integrated with the DOI model which is discussed later in this section. The DOI model has not been used before for data analytics in HES.

2.3. Related research on the adoption of big data analytics in HES

This section presents a survey of previous studies and specifically Table 1 highlights the analysis of the related research on data science in HES. The lack of such analysis may hinder higher education institutions from using big data analytics or make the adoption difficult. In addition, it means that future research is not directed towards the challenging factors of adoption that need to be addressed in order to ease the use of big data analytics in higher educations.

The selected studies highlight the advantages of applying big data analytics and its impacts on higher education. The main advantages mentioned in multiple studies involve helping institutions with their future financial management, cost reduction, and students' performance prediction (Murumba and Micheni, 2017; Yusof et al., 2015; Salaki and Moge, 2020; Hoyle, 1995; Hair et al., 1998). However, in some researches such as Daniel (2015) and Segooa and Kalema (2018); costs are discussed

as an issue for the decision to adopt. The cultural shift in the decision-making process, toward more data-based decisions, is also highlighted in Hwang (2019), Murumba and Micheni (2017), Daniel (2015), and Rodzi et al. (2015) as the main factor that could improve the management of these organizations. Such a shift would increase the efficiency of management in higher education, fostering and providing more accurate business reporting in a timely manner with minimum effort (Murumba and Micheni, 2017). Further, improvements to the decision-making process would increase the satisfaction of beneficiaries, and finally, the improved quality of education is discussed in many previous studies as a major advantage of adopting big data analytics.

On the other hand, a number of challenges that may hinder uptake have also been discussed. This can be a marked hindrance to organizations as implementation can require quite high capital investment as well as ongoing costs. The shortage of relevant professional talent familiar with algorithmic and implementation-specific details is also discussed as a barrier to the decision to adopt as in Matsebula and Mnkandla (2016), Sam and Chatwin (2018), Daniel (2015), Yusof et al. (2015), and Huan and Bo (2018).

The availability of big data analytics cannot, on its own, ensure successful implementation. The critical factor to be considered is the quality of data in terms of its accuracy, relevance, and timing (Sam and Chatwin, 2018; Murumba and Micheni, 2017; Daniel, 2015; Daniel and Butson, 2014). A lack of policy for data collection and analysis may also increase the risks of breaching legal requirements (Yulianto and Kasahara, 2018; Attaran et al., 2018). The existing IT infrastructure in universities and colleges will play a major role in ensuring successful adoption (Ijab et al., 2019; Kumaran et al., 2015; Segooa and Kalema, 2018; Rodzi et al., 2015). Interpretability issues have also been discussed as obstacles to the implementation of big data analytics, as in Daniel (2015).

Conclusive Summary: The vast majority of the analyzed studies do not set out to identify the factors based on empirical data, but instead rely heavily upon previous studies. Furthermore, a limited number of studies have adopted a theoretical framework for the adoption of innovation that aims to identify the influencing factors. Studies of Matsebula and Mnkandla (2016), Sam and Chatwin (2018), Ijab et al. (2019), and Hasan et al. (2016) used the TOE framework while Kumaran et al. (2015) used Theory of Constraints (TOC).

However, none of the selected studies have made use of the DOE model or attempted integrated multiple models for identifying higher education readiness to employ big data analytics technologies. It has been argued that the integration of multiple theoretical perspectives could improve the adoption of innovative technologies (Fichman, 2004).

Table 1: Analysis of the research supporting big data analytics in HES

Proposed Approach	Theoretical Model	Factors Considered	Research Method	Type of Contribution
Big Data Analytics in the Context of HES (Hwang, 2019)	Not specified	Internal evaluation, External assessments, Relationships with students, Staff communications	Descriptive model	Design (conceptual model) Based on the three entities (institution, student, faculty)
Survey and Review of Big Data in HES (Murumba and Micheni, 2017)	Not specified	Cost reduction, lack of executive vision, Users or executives rooted in old technologies analytical tools, Data quality issues, simply	Evaluation Report	An exploration of the attributes and factors for the adoption
Factors for Business Intelligence in HES (Hasan et al., 2016)	TOE	Strategic alignment, IT infrastructure readiness, process engineering, data sources, changing process	Descriptive model	Organizations' readiness framework
Opportunities and Challenges for Big Data Systems in HES (Daniel, 2015)	Not used	Institutional factors, support student's learning needs, data governance structures, Data security, Staff acceptance, High cost, Interoperability issues, Data quality issues	Evaluation Report	Conceptual framework, emerging trends, and implementation challenges
Information Systems and Big Data Analytics in HES (Matsebula and Mnkandla, 2016)	TOE	Lack of top management support, cultural change, Compliance issues	Descriptive model	Conceptual framework
Business Intelligence and Implementations at Higher Education Institutes (Yusof et al., 2015)	Not Used	Business reporting, Beneficiaries satisfaction, Reduce Cost, Prediction features, Ease budget planning and management, the large amount of data, Cost needed	Evaluation Report	An Identification of the issues influencing the adoption decision
Big Data Adoption in Organizations (Sam and Chatwin, 2018)	TOE	Simplicity, Compatibility, Data security, Top management support, Infrastructure, Skills Environment	Descriptive model	Conceptual Framework
Big Data using TOE in HES (Ijeb et al., 2019)	TOE	Technology and skills Infrastructure, top leadership, Policy and legal framework, infrastructure, policies and procedures, Collaboration, Awareness	Descriptive model	Conceptual Framework
Application of TOC in HES (Kumaran et al., 2015)	Applying Theory of Constraints (TOC)	Top management support, Technology (data storage, data process, Reporting)	Descriptive model	business intelligence and decision support system
Big Data Intelligence in HES (Huan and Bo, 2018)	Mathematical models	Resources utilizations'	Analytical model	grey relational algorithm for decision-making
Foundations of Big Data and its Impact on HES (Daniel and Butson, 2014)	Not specified	Costs issues, algorithm for data mining, data quality	Descriptive model	An Identification of the issues influencing the adoption decision
IoT's and Big Data Analytics in Organizations (Moreira et al., 2017)	Not specified	Large volume of unstructured data	Descriptive model	An Identification of the issues influencing the adoption decision
Data Driven Intelligence in HES (Yulianto and Kasahara, 2018)	Not specified	Prediction features, data variety	Descriptive model	An Identification of the issues influencing the adoption decision
Big Data and Stakeholders' Decision Making in HES (Segooa and Kalema, 2018)	Not specified	Innovation, Organizational, and Environmental characteristics	Descriptive model	An Identification of the issues influencing the adoption decision
Conceptual Model for Opportunities and Challenges of Big Data (Attaran et al., 2018)	Not specified	Prediction features, Large volume of data, data governance	Descriptive model	Conceptualization model for implementation and execution
Big Data Integration and Analysis in HES (Rodzi et al., 2015)	Not specified	Strategic planning, variety of data	Descriptive model	A business intelligence implementation framework
Business Intelligence in HES (Salaki and Moge, 2020)	Not specified	Data governance	Descriptive model	Concept adoption framework

3. Research method

We now introduce the adopted research methods that are divided into three phases. Each of the phases is detailed as a subsection of this section.

3.1. Identify the needs and protocol for the study

As part of the research methodology, the first step in this study was to assess the need to identify the determinants, and this was achieved by analyzing related studies. The scope, needs, and justification for the exploratory study were discussed earlier (Section 2.3). This step resulted in the identification of some of the determinants for decision-making that are used in this study, which were then expanded upon and validated using two-stage surveys.

Initially, this step involved specifying the search string to be used with the different databases, which was as follows: Support OR Implement OR adopt OR diffuse AND big data analytics OR business intelligence AND higher education OR university OR college. On applying this string to different databases

(Scopus, Springer, ACM, and IEEE), a total of 480 studies were found. These studies were scanned to find only those that focused on identifying the determinants, challenges, and on higher education readiness to adopt big data analytics. At the end of the scanning phase, 21 studies remained. All factors identified in these studies were summarized in Table 1.

3.2. Collecting data for empirical analysis

Empirical data collection was undertaken to support the findings of the literature review. Fourteen semi-structured interviews were conducted. They included open-ended questions to allow spontaneous expression and free thoughts as expressed by the interviewees. The sample participants were selected based on their subject expertise. They were as follows: Vice-rectors of quality and development 3 Deans of Quality and development 5 Deans of IT and e-learning 3 stakeholders of big data analytics and business intelligence service providers.

3.3. Testing the hypotheses

For testifying the hypotheses, we used the Structural Equation Modelling (SEM) approach as per the guidelines in Hoyle (1995). SEM as a mathematical model provides a correlation between observed and latent variables including a structure-based measurement model. Specifically, measurement exhibits the correlation among two variables namely latent and observed variables to ensure formal analysis and reliability of the testing. The structural model helps to measure the path strength and direction of the relation. SEM is fundamental to ensure the reliability of the structure model before conducting any further tests.

4. Analysis of the exploratory phase for big data analytics adoption

Thematic analysis approach has been used for qualitative assessment of the data as per six phases analysis suggested by Chau and Tam (1997). The participants of the study highlighted that a number of factors positively impact the adoption of big data analytics in HES. They mostly agreed on performance efficiency (85.7%) and enhanced strategic planning (78.5%) followed by student performance and admission prediction (64.2%) and improved quality monitoring and timely reporting (42.8%) as positive drivers for the decision to adopt big data analytics. The findings from the interviews confirmed that the lack of experts with data science skills is a major challenge that may make adoption unsuccessful. This was raised by all IT Deans interviewed in the study. Further, they indicated cost management issues for the implementation of pay-per-use services.

The need for adaptation to the existing systems could make adoption difficult to accomplish because it would not be easy for universities and colleges to test big data analytics with their own systems prior to official implementation. Universities' and colleges' readiness in terms of the impact of the decision-making culture, staff, and lack of data governance and policy issues were pointed out by 64.2% as negative factors. Within the environment context, results for three main variables (information sources, regulation, and selection of service provider) negatively impact the decision to adopt big data analytics. The difficulty of accessing all relevant information, especially that from external sources, was pointed out by 57.1%, and concerns over data quality in terms of credibility, relevance, and timing were highlighted by half of the participants as negative factors for successful adoption. Furthermore, concerns over regulation were indicated by half of the participants (all IT deans) suggested a negative influence on the decision to adopt. Finally, the selection of service providers was indicated to have a negative influence at the stage of choice on the decision-making process by 42.8% of participants. Concerns within this variable included compatibility issues with existing systems and the

ability to change to another service provider. In summary, the interviews provided 13 variables for the DOI and TOE models of which 3 would motivate the decision to adopt big data analytics while the other 10 represent challenges that need to be addressed to support universities and colleges when making their decision whether to adopt as in Table 2.

5. Proposed model of decision support for the adoption of big data analytics

The proposed model for decision and criteria-driven adoption of big data analytics systems is illustrated in Fig. 1. It included the adoption variables based on four criteria (referred to as innovation characteristics, technology, organization and staff, and environment) which are considered in the DOI model and TOE frameworks. The TOE framework and DOI models are well-known and widely acknowledged mechanisms and used in the IT adoption of innovative technologies. The variables were selected from TOE and DOI models in a complementary way and are tailored for big data analytics adoption. The identification of these variables was based on the exploratory phase in this study (literature review and a semi-structured interview with practitioners). Then hypotheses were developed for the variables specified in the proposed model. The proposed model and the development of the hypotheses are discussed in the next subsections.

5.1. Innovation characteristics and technology contexts

5.1.1. Relative advantages

Realization of the benefits of adopting is critical to measure the trade-offs and cost-benefit analysis. This section discusses the perception of higher education institutions of the advantages of big data analytics that were identified from the related literature and expanded upon further by the interviews. Improving universities' performance, particularly their student services, was discussed as the main advantage of adopting big data analytics. This can be achieved through enhancements to the speed and accuracy of the decision-making process and by timely reporting.

Less human intervention is required which can enhance performance and also reduce dependence on and the need for employees as well as reducing costs. Another of the discussed advantages of adopting big data analytics was the ability to predict student performance. This is very important for universities as it enables them to predict the percentage of student dropouts and to provide unique support to students who are more likely to struggle, based on predicted outcomes. Early discovery of student issues provides universities with an opportunity to mitigate those issues, leading to fewer dropouts and higher levels of satisfaction. Based on this data, universities can review their

admission procedures and conditions in order to decrease the percentage of student dropouts.

Table 2: Finding for TOE framework and DOI model

Criteria	Evaluation	Key Findings	Impacts
Criteria for Innovation	Relative advantages (DOI)	Reporting quality, Improve decision-making process, Improve quality monitoring, Ease budget planning and management, Enhance monitoring and evaluation activities, Prediction for strategic management, Support accreditation requirements, Predict students performances	Positive
	Complexity (DOI)	IT Infrastructure capabilities, Experts with implementation skills, models and algorithms, Cost, The Engineering work needed to meet the specific requirements of different universities	Negative
	Triability (DOI) Risks (DOI)	Difficulty of testing, High capital investments Data security and privacy, Concerns about lock-in from vendors	Negative Negative
Adoption of Technology	Framework Compatibility (DOI)	Increasing volume and varieties of datasets, Impact on organizational culture, Mapping the analyzed data into decisions, interpretability issues, The wide ranging of systems may result and integration issues	Negative
	Size (TOE) Organization readiness (TOE)	The large volume of, Legacy data The Decision making culture needs to be changed toward data-driven decision making, Lack of Data Governance and policies Accessibility polices	Negative Negative
Organization	Internal social (TOE) External factor (DOI)	Need for adaptation, Successful adaption require disruption to current business processes, maturity of current IT infrastructure Collaboration, Improve provisioning of needed data to outsider beneficiaries, Beneficiaries satisfaction	Negative Positive
	Support from Top management (DOI) Information sources (TOE)	Competitiveness, Ensuring informed Decisions, Process monitoring, Timely KPIs, Higher information reliability Difficult access to information, Data quality	Positive Negative
Environment	Regulation (TOE) Selection of service provider (TOE)	Legal Implications, Service Level Agreements Selection of service providers is difficult, Configuration issues, Vendor lock-in	Negative Negative

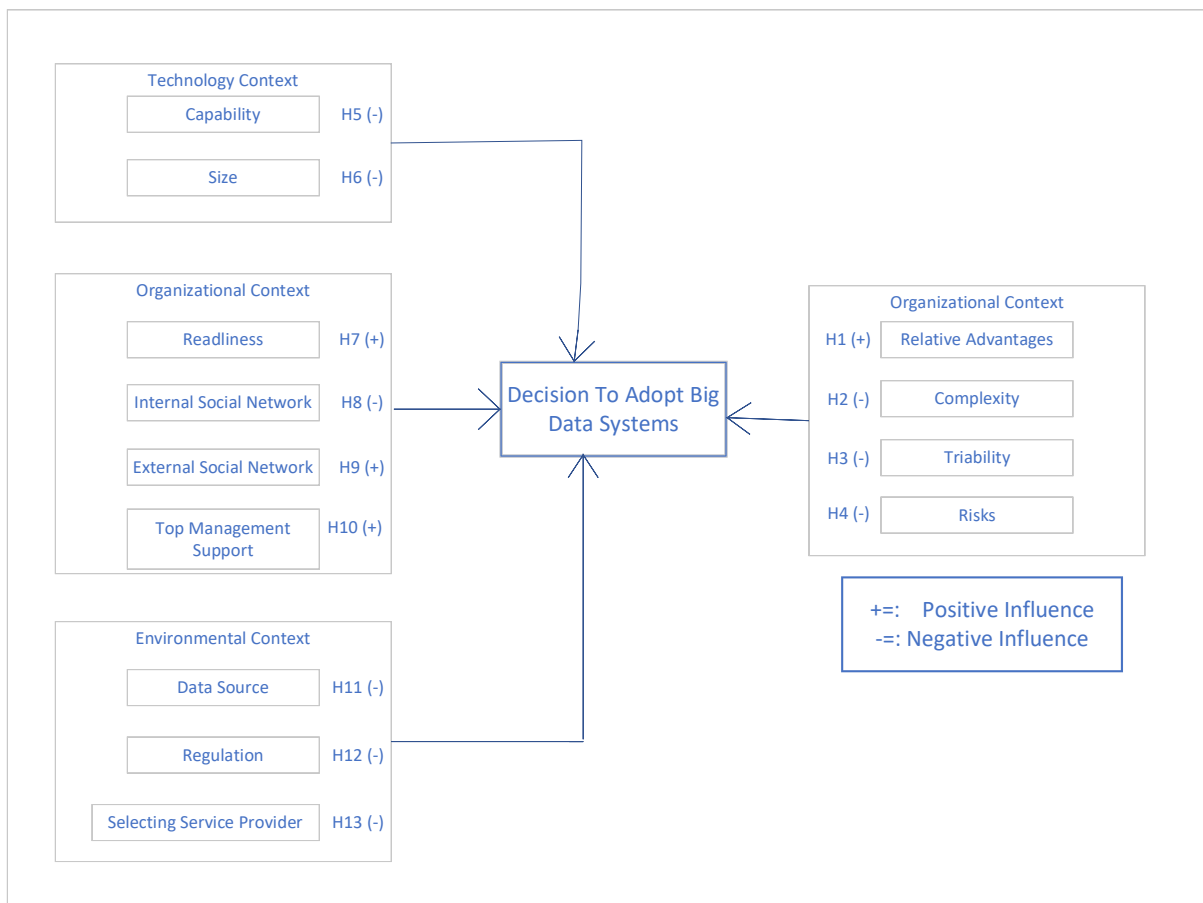


Fig. 1: Overview of the proposed model

In this study, other unique advantages were also discussed with the interviewees that had not been explicitly mentioned in previous related studies. First, big data analytics can provide universities, as they do other organizations, with better planning and management tools for budgeting as well as for

strategic planning. These analytics also enable universities and colleges to observe the progress they are making towards their goals through improved KPI measurements. The following is a statement from an interviewee: “As universities in Saudi Arabia are moving toward becoming

independent organizations, budget planning, management, and alignment with university strategy is becoming more important. It has been shown that big data analytics can be the solution for organizations to plan for their future expenditure." Second, accreditation has become a requirement for many universities and the accreditation process requires the collection and analysis of large volumes of data. This is a demanding job and inaccurate data analysis is likely if it is carried out in the traditional manner. Big data analytics were discussed by the interviewees as a key advantage for universities aiming to complete the accreditation process effectively because it improves the processes involved in monitoring and evaluating a university's activities. Third, many universities have established specific departments that follow-up the level of achievement of their strategies. Similar to the accreditation process, this is a demanding and time-consuming job, and big data analytics were discussed as a solution. Further, it enables to provide a prediction for universities' future positions, thus providing valuable information for their strategic planning. Fourth, timing, or more accurately, Key Performance Indicator (KPI) measurements. The performance of universities is currently measured through standardized KPIs for which universities need to provide values either annually or each semester. Currently, KPIs are measured in the traditional manner, but the measurements do not include all related data, such as that from social media platforms, because it is complex, error-prone, and time-consuming to analyses such data in the traditional way. Big data analytics could allow universities to improve the accuracy of their KPI measurements and ensure that all related data is included. The hypothesis is formulated as:

H-1: Universities' realizations of the relative advantages of big data analytics mean that they are likely to adopt them.

5.1.2. Complexity

The capital investment required by universities to implement big data analytics in their systems was discussed as the main barrier to adoption, and one that incurs ongoing costs that are usually annual in nature. Appropriate implementation and utilization of big data analytics also require data analytics experts which most universities do not have. Further, the lack of mapping the analyzed data with the decision-making process skills among different decision-makers in departments can also be challenging. Furthermore, universities and colleges have a wide range of automated services for which the collection and analysis of data require engineering work and raises security and privacy concerns.

H-2: Universities that consider big data systems as complex and difficult view their implementation and adoption negatively.

5.1.3. Trial-ability

The complexity involved in the process of implementing big data analytics within systems makes it difficult to provide universities with an opportunity to try big data analytics prior to official deployment. The main reason for this difficulty is the need for engineering work and adaptation to the specific systems of a given university.

H-3: The complexity to test and manage big data systems is perceived negatively for their adoption.

5.1.4. Risks

The integration of different automated services to feed the data analytics system may present some risks. One of the main concerns for the interviewees was data security and privacy where providing access to different services may result in breaches in those services. Universities were concerned that they may lose control of their systems if they were adapted for use with the big data analytics tool, meaning that it may not be easy to move to another service provider. Finally, the use of big data analytics provided by a third party raised concerns about data ownership and again the possibility that universities might lose control over their own data. This also would make it difficult for them to transition from one to another service provider.

H-4: Perception and degree of risk negatively impact the adoption of big data systems.

5.1.5. Compatibility

Implementation of big data analytics into university systems is not a straightforward task. It requires adaptations to the existing systems to enable automatic data transmission to the big data analytic tool. Universities usually have a large volume of datasets of a variety of types which can increase the difficulty of adoption, especially where the higher education systems involve subsystems that are incompatible with each other.

H-5: Perception about compatibility of big data systems with existing IT infrastructure negatively impacts the adoption of big data systems.

5.1.6. Size

The large volume of data generated by different stakeholders in a university can be challenging to collect, analyze, and visualize. This requires higher investment and more engineering work to provide the big data analytics that can accurately collect and analyze all relevant data. The different types of data involved with the active entities in higher education (students, faculty members, researchers) can also present challenges for big data analytics.

H-6: The volume and magnitude of data makes it complex for HES to adopt big data systems

5.2. Organization context

5.2.1. Organization readiness

A number of interviewees indicated that successful implementation of big data analytics is not sufficient to exploit the wide range of advantages it can provide. The decision-making culture, especially amongst top management, needs to change toward rationalized decision-making, and the skills of interpreting and mapping the visualized data into decisions are also required to ensure a successful utilization. Furthermore, a lack of data governance and data management policy can cause implementation problems. Accessibility policies for all stakeholders involved in the various systems need to be well defined for the smooth adoption of big data analytics.

H-7: Agility and innovation help organizations to readily adopt big data systems.

5.2.2. Internal social

In order to ensure successful implementation, there is a need for a shift in the organizational culture in terms of decision-making processes. However, interpreting the analyzed big data and mapping it to a decision can be challenging for higher education institutions. Furthermore, a successful adaption of big data analytics may require disruption to current business processes. This requires the development of business processes to ensure the successful adoption of big data.

H-8: The decision of stakeholders impacts the adoption of big data systems.

5.2.3. External social

The external social variable is one of the only three variables that positively impact the decision to adopt big data analytics in higher education. It can improve university collaborations with other organizations as related data can be automatically provided to all related parties in a timely manner. It can also improve the relationship with, and meet the data needs of, all beneficiaries, especially those outside the university, thus leading to a higher level of satisfaction with the university and its services.

H-9: The decision of customers impacts the adoption of big data systems.

5.2.4. Top management support

Realization of the advantages of big data analytics can encourage top management support of university and college investment in that area. This

is because these advantages can improve the strategic direction of the institution, including its competitiveness, the increased potential for making informed decisions, process monitoring, timely KPIs, and greater information reliability.

H-10: Support from higher management helps with the adoption of big data systems.

5.3. Environment context

5.3.1. Information sources

The automatic collection of all relevant data can be an issue for seamless adoption and integration of big data systems. This is mainly due to the huge volume and variety of educational data that is spread across different platforms. The quality of the data collected can present another problem. In order to ensure appropriate analysis of data, it must be of high quality in terms of its accuracy, relevance, timeliness, and completeness. Therefore, universities and colleges need to ensure access to all related data sources inside and outside their systems that include the data needed. It is also important to ensure that all data provided to the data analytics tool is of high quality to ensure that the results are credible.

H-11: Data integration and quality assurance concerns negatively impact the adoption of big data systems.

5.3.2. Regulation

Many organizations have to comply with organizational procedures and legal policies to adopt big data systems. Educational institutes need to review vendors' contracts and other regulatory issues before a final decision for adoption. Failure to comply with the regulations may lead to financial and legal consequences of big data adoption.

H-12: Data ownership and legal issues negatively impact the adoption of big data systems.

5.3.3. Selection of service provider

Big data analytics are usually provided by large companies involved in information systems and are charged on a pay-per-performance basis. Selecting the most appropriate service provider can be difficult. The selection requires managerial as well as technical skills to ensure that the most suitable option is chosen. This is an important aspect of ensuring the successful implementation of big data analytics because organizations need to adapt their systems to make them compatible with the requirements of the service provider. The adaptation and configuration may leave an organization in such a situation that it would be difficult to move their systems to another service provider (known as

vendor lock-in). Therefore, the absence of an automated tool that could help universities and colleges to assess the different service providers, and select the most appropriate, presents a challenge for organizations deciding whether to adopt big data analytics.

H-13: Service providers and their capability impact the decision of adoption of big data systems.

6. Hypothesis testing to evaluate the proposed model

Structural equation modelling (described in Section 3) has been used for statistical evaluation of the proposed research and to test the hypotheses. We focused on testing a total of 13 hypotheses to validate the theoretical framework (Section 4). Specifically, evaluating the exploratory and confirmatory factor guide the results that are discussed later in this section.

6.1. Exploratory factor analysis

Table 3, Table 4 highlight the measurement metrics in terms of validity, descriptive statistics, convergence, and reliability. Specifically, first of all, we needed to test the composite reliability of the study. Second, the reliability of the metrics from Table 3, Table 4 needs to be evaluated as per the

guidelines in Chau and Tam (1997). Cronbach's alpha (Hair et al., 1998) as a mathematical measure is considered as a reliable test for composite reliability. Cronbach's alpha values range between 0 and 1 to indicate the level of reliability. The guidelines in Fornell and Larcker (1981) suggested that composite reliability should be more than 0.70 to ensure the appropriate quality of research. The formulation for composite reliability is expressed as:

$(\sum \text{standardized loading})^2 / (\sum \text{standardized loading})^2 + \sum \epsilon$, where ϵ = error variance and \sum indicates summation.

Tables 4 shows the descriptive statistical analysis of the evaluated variables.

6.2. Confirmatory factor analysis

Furthermore, the principal component analysis was applied to factor analyze the scale to also validate the strength of correlation between variables to be tested. Values for the construct validity were also tested by applying Bartlett's Test of Sphericity and the Kaiser-Mayer-Olkin (KMO) test for measuring the adequacy of the sample (Beavers et al., 2013). The results of the Bartlett Test of Sphericity and the KMO value were 0.000 and 0.693 respectively (Table 3).

Table 3: Reliability and construct validity of statistical testing

Results of Bartlett's Testing		
Statistics for Reliability: Cronbach's Alpha=0.833; Total Items= 13		
	Measure of Sampling	0.693
		421.621
Bartlett's Test	Degree of variability freedom	79
	Sigma	0.00

Table 4: Descriptive statistical analysis

Variables	Minimum	Maximum	Median	Mean	Standard Deviation
I1 Higher performance	3.0	5.0	4.0	4.40	0.83
I1 Planning and management	2.0	5.0	4.0	4.15	0.76
I1 Accreditation requirements	3.0	5.0	4.0	4.06	0.93
I1 Timing analysis	3.0	5.0	4.0	4.29	0.69
I1 Average	2.75	5.0	4.0	4.22	0.80
I2 Cost management	2.0	5.0	4.0	4.03	0.68
I2 Lack of expertise	3.0	5.0	4.0	4.24	0.95
I2 Average	2.5	5.0	4.0	4.13	0.81
I3 Testing	1.0	4.0	4.0	3.03	0.91
I4 Security and data Privacy	2.0	5.0	4.0	4.23	0.89
I4 Loss of control	1.5	5.0	4.0	4.02	0.93
I4 Vendor lock in	1.6	5.0	4.0	3.95	0.79
I4 Average	1.6	5.0	4.3	4.12	0.87
T1 Adaptation requirements	1.0	5.0	5.0	3.49	0.98
T1 Variety of data	1.0	5.0	4.0	4.22	0.71
T1 Average	1.0	5.0	4.5	3.95	0.88
Size of T-2	1.0	5.0	4.0	3.59	0.83
O1 Decision-making culture	1.0	5.0	4.0	3.89	0.77
O1 Data governance	2.0	5.0	3.0	4.01	0.90
O1 Average	1.5	5.0	3.5	3.92	0.84
O2 Business processes requirements	1.0	5.0	4.0	3.78	1.03
O2 IT infrastructure	2.0	5.0	4.0	4.04	0.98
O2 Average	1.5	5.0	4.0	3.86	1.0
O3 Collaboration	2.0	5.0	4.0	4.14	0.84
O3 Benefactrices relationships	2.0	5.0	4.0	3.64	1.13
O3 Average	2.0	5.0	4.0	3.89	0.98
O4 Degree of support from Top management	1.0	5.0	4.0	4.17	0.91
E1 Data sources	1.0	5.0	4.0	3.69	0.74
E2 Compliance with regulation	2.0	5.0	4.0	4.22	0.78
E3 Selecting service provider	1.0	4.0	4.0	3.02	0.81

These results also demonstrate an appropriate level of adequacy for the sample. The correlation was then examined in order to measure the discriminant validity which is supported in this analysis. The overall results demonstrate reliability, convergent validity, and discriminant validity for testing.

7. Evaluation results

We now present results of the evaluation indicating that 11 out of the 13 variables identified (Table 5) have a significant impact on decision-making about adoption and integration of big data analytics in HES. The relative advantages factor followed perceived risks and regulation confirmed to be the highest influence from the analysis. While the factors selecting the service provider and trial-ability were confirmed as not significant. The descriptive statistical analysis (Table 4) shows a high rating for all factors within this Variable. The complexity of big

data analytics is also confirmed as a negative influence on the decision, it has a path coefficient of 0.10. Although testing an innovation is an essential variable in the DOI model is not validated during hypothesis testing. It only scored a path coefficient of 0.04. The perceived risks of the decision to adopt big data analytics were found to be a negative influence. It has a path coefficient of 0.17.

In the organizational context, the findings showed that it was important to consider all four variables when assessing the decision to adopt. Organizational decision making and top management significantly impact decision making with path coefficient reflecting the values: -0.16, 0.12, 0.15, and 0.14, respectively. In the environmental context, the information source and regulation factors negatively impact adoption, while selecting a service provider is not supported by this analysis. Table 5 highlight the key results of hypothesis testing.

Table 5: Statements, coefficient, and results of the hypothesis testing

ID	Hypotheses Statement	Coefficient	Result
H-1 (+)	Universities' realizations of the relative advantages of big data analytics mean that they are likely to adopt them	-0.19	(p<0.05)
H-2 (-)	Universities that consider big data systems as complex and difficult view their implementation and adoption negatively	0.10	(p<0.05)
H-3 (-)	The complexity to test and manage big data systems is perceived negatively for their adoption	0.04	Not supported
H-4 (-)	Perception and degree of risk negatively impacts the adoption of big data systems	0.17	(p<0.05)
H-5 (-)	Perception about compatibility of big data systems with existing IT infrastructure negatively impacts adoption of big data systems	-0.14	(p<0.05)
H-6 (-)	The volume and magnitude of data makes it complex for HES to adopt big data systems	0.10	(p<0.05)
H-7 (+)	Agility and innovation helps organizations to readily adopt big data systems	-0.16	(p<0.05)
H-8 (-)	The decision of stakeholder impacts the adoption of big data systems	0.12	(p<0.05)
H-9 (+)	The decision of customers impacts the adoption of big data systems	0.15	(p<0.05)
H-10 (+)	Support from higher management helps with adoption of big data systems	0.14	(p<0.05)
H-11 (-)	Data integration and quality assurance concerns negatively impact adoption of big data systems	-0.13	(p<0.05)
H-12 (-)	Data ownership and legal issues negatively impact the adoption of big data systems	-0.17	(p<0.05)
H-13 (-)	Service providers and their capability impacts the decision of adoption of big data systems	-0.03	Not Supported

8. Conclusive summary and needs for future research

Data science or specifically big data analytics has demonstrated a number of advantages to optimize the performance and efficiency of higher education organizations as well as overcome many existing challenges. However, the decision to intelligent and decision-driven systems in an ongoing HES can be complex and difficult. It requires the analysis of different aspects in order to ensure that successful adoption decisions are made. Therefore, this paper explored the factors influencing the decision to adopt big data analytics based upon a systematic analysis of the related studies. The findings of this stage were enhanced by conducting a number of interviews with decision-makers at universities in Saudi Arabia. The findings of the exploratory phase were classified using the theoretical model TOE and DOI. The model included five dimensions and eleven

factors that influence the decision to adopt and was then tested using exploratory and confirmatory factor analysis using primary data collected from practitioners in higher education systems. The analysis confirmed that, when assessing whether to adopt big data systems in HES, nine of the eleven factors identified in the DOI and TOE integrated model proposed in this study had a strong influence while the other two factors were less important.

The findings of this research contributed to the already on-going research which encourages higher education institutions to adopt big data analytics and then fully exploit their advantages. The methodology used for the exploration and identification of the determinants influencing the decision to adopt is unique and has not previously been used in this context. This improves the credibility of the findings of this research. However, the identification of the determinants alone is not sufficient to support the integration and seamless adoption of big data

analytics by higher education, and further research is needed to achieve this goal. Study results can be used as a basis for developing a suitable decision support system. Such systems need to address the criteria that negatively impact such an adoption.

Needs for future research and research limitation: Furthermore, there is a need to support higher education organizations in the assessment of their existing systems and how they could be used in conjunction with big data analytics. Also, since a successful implementation may require re-engineering of current business processes, future research is needed to help universities to improve those processes. Further, specific applications of big data analytics need to be examined, in order to ensure the successful adopting of big data analytics in HES.

The primary data for this study was collected from decision-makers and practitioners who work at universities in Saudi Arabia. This may limit the research findings from generalizing them to international institutions. Therefore, the proposed model needs to be used with data collected from universities in other countries in order to further verify the outcomes and to be able to generalize the findings.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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