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An Integrated DOI-TOE Model for the Adoption of Big-Data Analytics in Higher Education Systems

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Abstract: *Big data analytics 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 house. The collection, analysis, and visualization of such big data presents a huge challenge for HES. Big data analysis could be the solution to this challenge. However, the decision-making surrounding the adoption of big data analytics can be difficult. It requires the consideration and evaluation of a wide range of technical and organizational aspects that need to be taken into account to ensure informed decisions are made. Many previous studies have been conducted to explore the factors that influence 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 model based on the DOI and the technology-organization-environment (TOE) framework is proposed. The model is then evaluated using structural equation modeling. The statistical analysis shows the level of impact of the identified variables on the decision to adopt big data analytics. Eleven determinants are confirmed to have influence on the decision to adopt big data analytics in HES. The result is expected to contribute on-going research that attempts to address the complex and multidimensional challenge of big data analytics implementation in HES.*

Keywords: Big data, Big data analytics, Innovation adoption, DOI, TOE, Decision-making, Higher education, Decision support

1 Introduction

Competitiveness in the higher education sector has reached a peak [1]. Globalization and economic pressure are main factors that have greatly encouraged this sector to enhance its performance [2]. Business nowadays is awash with data and its crunchers, thus organizations are competing in analytics not only because they can but also because they should [3]. This has resulted in many universities and colleges seeking innovate technologies in order to enhance their performance as well as increase their global ranking. In particular, there has been growing interest amongst the higher education sector in taking advantage of the emerging Big Data technologies [4] 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 be universities and colleges to identify important patterns, gain contextual insight, and enable informed decision-making. The acquisition of these benefits requires particular analytics, known as big data analytics, which can be defined as "the extensive use of large volumes of data, statistical and quantitative analysis, explanatory and predictive models and facts-based management to drive decisions and actions" [5]. Big data analytics can support higher education in many areas. Through its prediction features, it can help determine the academic and non-academic performance of students [6]. 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 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 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 [7]. A number of studies have been conducted to support 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, for example [8][9][10], have employed the Technology-organization-environment framework (TOE), while [11] have used TOC. However, none of the previous studies have employed the diffusion of innovation model (DOE) nor attempted an integrated multiple model

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 [12].
This paper aims to address the deficiencies in the research concerning the adoption of big data analytics in higher education. It attempts to systematically cover all related variables surrounding the decision-making process. To achieve this, the findings of the study were developed based on 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 contributions of this paper can be summarized as follows and will be discussed in detail in the following sections. It provides:

- An analysis of the level of support for the use of big data analytics in the decision-making process in higher education
- An exploration of the determinants for the decision to adopt big data analytics in higher education 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
- Validation of the model using structural equation modeling for exploratory and confirmatory factor analysis based on primary data collection from practitioners

The reminder of the paper is organized as follows. The background and related research are presented in Section 2. The research methodology is detailed in Section 3. Section 4 discusses the analysis of the interviews. The proposed model and hypothesis are explained in Section 5. Model evaluation and hypothesis-testing results are discussed in Sections 6 and 7. The conclusions and future work directions are presented in Section 8.

2 Background and related studies

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. Big data analytics is growing and has the potential to provide such advantages for higher education systems, as well as to predict future outcomes. Essentially, it can be said that the role of big data in higher education is to manage big data which are difficult to manage using existing IT systems [7]. Further, the continuous improvement in information technology has made many existing systems obsolete. Therefore, the shift towards use and pay based on performance have emerged as an important strategy in higher education organizations [13]. There are a variety of analytical techniques available for interpreting higher education data, which can then be used to ensure the provision of high quality services. The diverse origins and forms of big data in higher education systems make it challenging to develop methods for data processing. There is a great demand for techniques that combine important data sources [14]. A number of conceptual approaches can be employed to recognize irregularities in vast amounts of data from different datasets that include predictive analytics and machine learning.
Predictive analysis has been widely recognized and used as one of the major business intelligence approaches. Many organizations in different industries have successfully implemented predictive analysis tools and techniques mainly to assess consumer behavior [14]. However, the application of predictive analytics extends far beyond business contexts which present a huge challenge. Big data analytics includes various methods, including statistical, text, and multimedia analytics [15]. The statistical analytics methods require both data mining and machine learning tools in order to examine current as well as historical processes and results can be used to predict the future. In higher education, the application of predictive analytical tools is relatively new and still emerging. They are used for knowledge discovery and the identification of important patterns, using models and algorithms. This can be particularly useful for universities that are engaged in data-intense projects such as: monitoring the learning of students and the effectiveness of teaching; early warning systems and interventions to increase students' academic success; predictive student performance; managing financial performance; enhancing the learning experience of students; and improving the allocation of resources [16].

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 and DOI theories developed by Tornatzky and Fleischer [17] and Rogers [18] respectively. They have been widely used and discussed in the literature as

important models for ensuring 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.

2.2.1 The Technology-organization-environment framework

The TOE is argued to be an integrative framework that provides a holistic approach and guidance [19]. It includes three main dimensions: technology, organization and environment. They are considered to be the main contexts that influence the process by which innovations are adopted. The framework can be used as a taxonomy for the determinants that facilitate or prevent adoption of technology innovations [20]. It has been used in the context of adoption similar technology innovations, such as for cloud-based services, Internet of Things (IOT), and mobile computing (see for example [21, 22, 23]) and has also been used in the adoption of big data analytics in higher education, which is the context of this study (see for example [8, 9, 10]). However, it is worth mentioning that the implementation of this framework in this study is slightly different to 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 in the context of big data analytics in higher education.

The three main contexts of the TOE framework that influence a decision to adopt an innovation. The technological dimension relates to the maturity level of an organization in terms of its use of technology and how the innovation would interact with its current technology implementation. This helps an organization to focus on how the innovative technology would influences the adoption process. The organizational context looks at the structure and the processes in an organization that constrain or facilitate the adoption and implementation of innovations. The importance of the environmental context is also supported by Tornatzky and Fleischer [17], and it includes aspects such as the industry, its competitors, regulations and relationship with government, all of which are considered to be important to the analysis.

2.2.2 The diffusion of innovation model

Subsequent to the TOE model, research on adoption of innovation continued in order to provide richer and possibly more explanatory models [24]. A major contribution in this regard was the development of the Diffusion of Innovation model, and it has been widely used in the context of IT innovation adoption. The model is concerned with the way that a new technological innovation progresses from creation to utilization. It describes the patterns of adoption and the mechanisms for diffusion, and also helps to predict whether and how a new invention will be successful. It has three main categories of factors that influence the decision whether to adopt an innovation: Innovation Characteristics, Organizational Characteristics, and Individual Characteristics. The innovation characteristics comprise the perceived attributes of the innovation that either encourage or hinder. Rogers [18] indicated that the five attributes of an innovation are: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage refers to the level to which an advantage is perceived as better than the current system. Compatibility is the degree to which an innovation is perceived as being consistent with the existing values, past experiences and needs of potential adopters. Complexity relates to the perceived difficulty of understanding and using the innovation while trialability refers to the degree to which the innovation can be easily tried and tested over time. Finally, observability refers to the level to which the results of an innovation are visible to the technology adopter [18].

2.3 Analysis of the research supporting the adoption of big data analytics in HES

The evolution and increase in popularity of data analytics and data mining techniques have led to a significant rise in awareness amongst industrialists and academics of the support required when making adoption decisions. Thus, a significant amount of research has been devoted to studying the uptake of big data analytics by higher education. This section presents a survey of previous studies on determinants that affect the adoption of big data analytics in higher education. Table (1) shows the analysis of the related research in adopting big data analytics in higher education. Section 3 discusses the systematic method used to identify the related studies.

Although, there has been a significant amount of research on the adoption of big data analytics in higher education, limited attention has been paid to systematic analysis of the determinants of, and challenges to, that adoption. 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 in higher education. The main advantages mentioned in multiple studies involve helping institutions with their future financial management, cost reduction, and students' performance predication (see [26, 29, 37, 38, 40]). However, in some researches such as [28] and [34] 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 [25, 26, 28, 36] as a 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 [26]. 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. The failure of top management to realize the importance of data in the decision-making process can be a significant challenge to the adoption of big data analytics as in [8, 9, 10, 11]. This can be a marked hindrance to organizations as implementation can require a quite high capital investment as well as ongoing costs. The shortage of relevant professional talent familiar with algorithms, data mining, machine learning, and data visualization is also discussed as a barrier to the decision to adopt as in [8, 9, 28, 29, 30]. The availability of big data analytics cannot, on its own, ensure successful implementation. An important factor that needs to be considered is the quality of data in terms of its accuracy, relevance, and timing [9, 26, 28, 31]. A lack of policy for data collection and analysis may also increase risks of breaching legal requirements [33, 35]. The existing IT infrastructure in universities and colleges will play a major role in ensuring successful adoption [10, 11, 34, 36]. Interpretability issues have also been discussed as obstacles to the implementation of big data analytics, as in [28].

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

Proposed approach	Theoretical model	Factors taken into account	Research method	Type of contribution
Adoption of Big Data in Higher Education for Better Institutional Effectiveness [25]	Not specified	Internal evaluation, External assessments, Relationships with students, Staff communications	Descriptive model	Design (conceptual model) Based on the three entities (institution, student, faculty)
Big Data Analytics in Higher Education: A Review [26]	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
Business intelligence readiness factors for higher education institution [27]	TOE	Strategic alignment, IT infrastructure readiness, process engineering, data sources, changing process	Descriptive model	Organizations' readiness framework
Big Data and analytics in higher education: Opportunities and challenges [28]	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 innovation adoption in higher education: Big data and analytics [8]	TOE	Lack of top management support, cultural change, Experts with data visualization, interpretation, analysis, predictive analytics skills, Compliance issues	Descriptive model	Conceptual framework
Implementation issues affecting the business intelligence adoption in public universities [29]	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

Understanding adoption of Big Data analytics in China: from organizational users Perspective [9]	TOE	Simplicity, Compatibility, Data security, Top management support, Infrastructure, Skills Environment	Descriptive model	Conceptual Framework
Investigating Big Data Analytics Readiness in Higher Education Using the Technology-Organisation-Environment (TOE) Framework [10]	TOE	Technology and skills Infrastructure, top leadership, Policy and legal framework, infrastructure, policies and procedures, Collaboration, Awareness	Descriptive model	Conceptual Framework
Applying Theory of Constraints (TOC) in business intelligence of higher education : A case study of postgraduates by research program [11]	Applying Theory of Constraints (TOC)	Top management support, Technology (data storage, data process, Reporting)	Descriptive model	business intelligence architecture with decision making process
Application of the big data grey relational decision-making algorithm to the evaluation of resource utilization in higher education [30]	Mathematical models	Resources utilizations'	Analytical model	grey relational algorithm for decision-making
Foundations of Big Data and Analytics in Higher Education [31]	Not specified	Costs issues, algorithm for data mining, data quality	Descriptive model	An Identification of the issues influencing the adoption decision
Higher Education Disruption Through IoT and Big Data: A Conceptual Approach [32]	Not specified	Large volume of unstructured data	Descriptive model	An Identification of the issues influencing the adoption decision
Implementation of Business Intelligence With Improved Data-Driven Decision-Making Approach Case Study on Student's Single Tuition Fee in a State University in Indonesia [33]	Not specified	Prediction features, data variety	Descriptive model	An Identification of the issues influencing the adoption decision
Leveraging big data analytics to improve decision making in South African public universities [34]	Not specified	Innovation, Organizational, and Environmental characteristics	Descriptive model	An Identification of the issues influencing the adoption decision
Opportunities and challenges for big data analytics in US higher education: A conceptual model for implementation [35]	Not specified	Prediction features, Large volume of data, data governance	Descriptive model	: A conceptual model for implementation
Significance of data integration and ETL in business intelligence framework for higher education [36]	Not specified	Strategic planning, variety of data	Descriptive model	A business intelligence implementation framework
Agile analytics: Adoption framework for business intelligence in higher education [37]	Not specified	Data governance	Descriptive model	Conceptional adoption framework

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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 [8, 9, 10, 27] used the TOE framework while [11] used Theory of Constraints (TOC). However, none of the selected studies have made use of the DOE model or attempted an integrated multiple model 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 [12].

The review of the related studies shows that the vast majority do not support the assessment process that is required prior to implementation of big data analytics. Also, despite the large volume of research outcomes, there is a shortage of a Decision Support System (DSS) for universities to use when considering big data analytics. The evaluation of service providers and their appropriate selection are critical. Further, making an informed decision to adopt big data analytics requires the analysis of a wide range of factors at the initial stages of a decision process. Universities need to develop a suitable understanding of big data analytics and their capabilities, regulation, potential and challenges, before coming to a decision. The literature still lacks comprehensive support for HES that considers all related factors. Furthermore, the majority of the existing studies are either evaluation reports or conceptual in nature. Therefore, the provision of established DSS that include relevant information could substantially aid the decision-making process.

3 Research method

The nature of the investigation in this research topic is exploratory. It a comparatively new research area and it is still evolving. The study focuses on the identification of the determinants of the decision-making process employed when deciding whether to use big data analytics. Therefore, a sequential exploratory strategy was found to be the most appropriate way to gather the data needed to answer the research questions. This strategy was tested using a two-stage survey that firstly gathered qualitative and then quantitative data to validate the research findings. The author began by collecting and analyzing related literature. A number of determinants and characteristics that either support the decision to adopt, or increase the complexity of decisions with regard to adopting, big data analytics were identified. The findings of the literature were supplemented by data gathered from semi-structured interviews with practitioners.

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 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 diffus 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, as shown in Table 1.

Empirical data collection was undertaken to support the findings of the literature review. Fourteen semi-structured interviews were conducted. They included open-ended questions that were employed to ensure consistency, whilst still allowing a degree of freedom and adaptability when obtaining information from the interviewees. The interviews were conducted using video conferencing tools (Zoom and WebEx applications) between April 16 to 28, each lasting on average about 45 minutes. 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), and big data analytics and business intelligence service providers (3). The choice of interview technique was based on the belief that real life practitioners, in particular service providers, can offer a richer understanding of the benefits and challenges of adopting big data analytics due to their related experience. The interviews were carried out to gain greater insight into the factors, issues, and concerns about adoption decisions, as well as to develop a foundation for further analysis. This phase resulted in identification of the research hypotheses, based on the recommendations of the TOE and DOI models.

Structural Equation Modelling (SEM) [38] was used to test the research hypotheses. SEM is a statistical approach for exploring the relationships between observed variables and latent variables. It includes two main components: the measurement model and the structural model. The measurement model shows relationships between latent variables and observed variables. It aims to provide reliability and validity, based on these variables. The structural model measures path strength and the direction of the relationships among the variables. It is first necessary to test the measurement model and ensure that it has a satisfactory level of reliability and validity before exploring the significance of the relationships in the structural model.

In order to test the hypotheses, the stage 2 survey was implemented using an online survey questionnaire. It targeted: decisions-makers in higher education and faculty members in the subject area of computer science and management. The questions were based on the findings from Stage 1 (see Table 2) and on the analysis of the related literature. Zikmund [39] suggested that the target population is the entire group of subjects of interest who are defined by the research objectives. However, there is usually a considerable difference between the population that a researcher is attempting to study and their availability for sampling [40]. The sample population in this study consisted of targeted professionals and users with experience in related disciplines. The sampling method used was convenience sampling in which the researcher attempted, as far as possible, to find participants from the target audience by distributing the questionnaire using various methods. The target audience were mainly invited by e-mail through personal contacts. The questionnaire was sent to 293 decision makers and faculty members. A total of 137 responses were received, of which 29 responses were either incomplete or completed in less than 7 minutes, therefore they were eliminated from the analysis leaving 108 usable responses. This was 36.8% of the total population and consistent with what could be expected for a survey of this kind.

The data was imported from the survey tool (survey Monkey) into an IBM SPSS sheet. The reliability of the questionnaire was calculated which was followed by exploratory factor analysis and confirmatory factor analysis. The constructs (relative advantages, complexities, testing, probable risks, compatibility, da volume, organizational readiness, impact on internal network, external network, top management support, information sources, regulatory, and selecting service providers) were measured using a five-point Likert scale on an interval level ranging from 1 (very low importance) to 5 (very high importance). The lower scores indicate low influence of variables on the decision to adopt.

4 Analysis of the exploratory phase

Thematic analysis was used to analyze the qualitative data which was applied in six phases as suggested by [41]. The qualitative analysis enabled insights into challenges, issues, and factors that influence the decision-making process with regard to the adoption of big data analytics. To further specify these factors, the DOI and TOE frameworks were applied to the data. This resulted in findings within the following contexts: innovation characteristics, technology, organization, and environment, as shown in Table 2. The innovation characteristics were divided into four categories: relative advantages, compatibility, trialability, and probable risks. Participants indicated a number of advantages that can positively influence the decision to adopt big data analytics. 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.

Interviewees reported a number of factors that increase risks and complexity (see Table 2). The findings from the interviews confirmed that the lack of experts with data visualization, interpretation, analysis, and predictive analytics 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. Additionally, they indicated that there was a high level of concern for privacy and confidentiality regarding the sharing of highly confidential data with a third party to feed the big data analytics tools.

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. In the technology context, interviewees highlighted issues with compatibility, and the difficulties of integrating large-volumes of legacy data, as negative factors. The organizational context was divided into four variables (see Table 2) in which two were viewed as negative (universities' readiness and internal sources) and the other two were viewed as positive (external sources and top management support). 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. The disruption to current business processes was considered a negative internal factor by 50% of the interviewees. Collaboration and top management support were considered by 64.2% of the participants to be positive influences supporting the decision to adopt. Within the environment context, results for three main variables (information sources, regulation, selection of service provider) were found to have a negative effect on 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) to have 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. Table 2 shows the main findings of Stage1 in the context of the DOI and TOE.

Table 2: The findings of stage 1 in the context of DOI and TOE

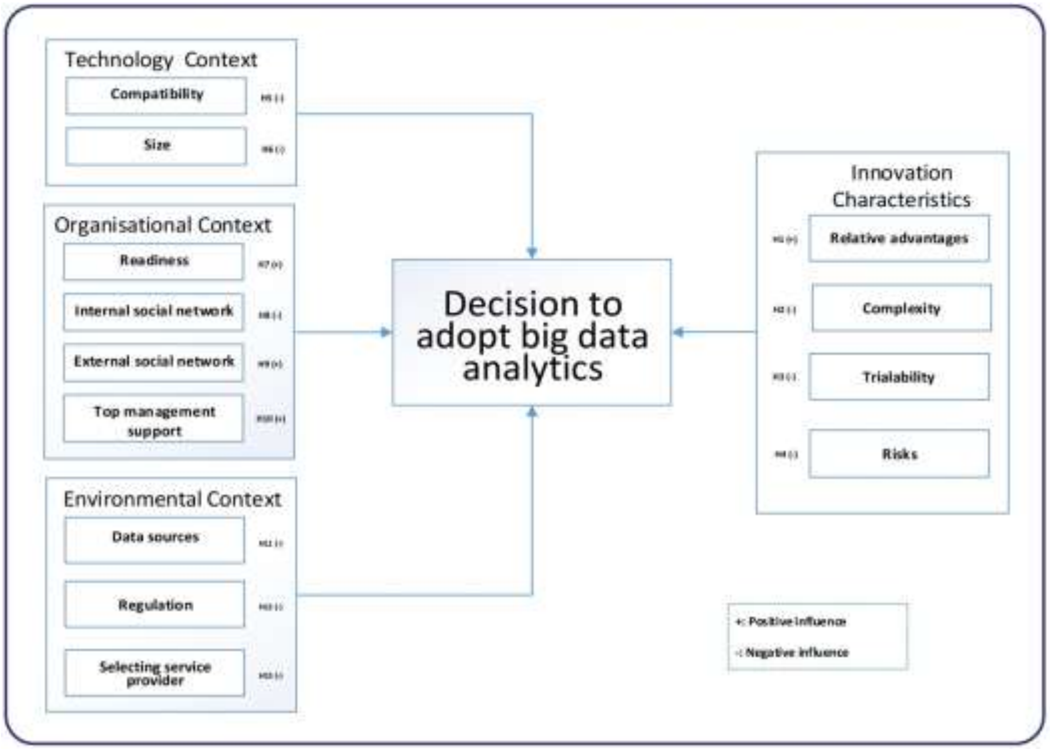
Context	Variable	Findings	Impact

Innovation Characteristics	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 data visualization, interpretation, analysis, predictive analytics skills, models and algorithms, Cost, The Engineering work needed to meet the specific requirements of different universities	Negative
	Triability (DOI)	Difficulty of testing, High capital investments	Negative
	Risks (DOI)	Data security and privacy, Concerns vendor lock in, Loss of control, Data ownership	Negative
Technology	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)	The large volume of, Legacy data	Negative
Organisation	Organisation readiness (TOE)	The Decision making culture needs to be changed toward data-driven decision making, Lack of Data Governance and policies Accessibility polices	Negative
	Internal social (TOE)	Need for adaptation, Successful adaption require disruption to current business processes, maturity of current IT infrasturcure	Negative
	External social (DOI)	Collaboration, Improve provisioning of needed data to outsider beneficiaries, Beneficiaries satisfaction	Positive
	Top management support (DOI)	Competitiveness, Ensuring informed Decisions, Process monitoring, Timely KPIs, Higher information reliability	Positive
Environment	Information sources (TOE)	Difficult access to information, Data quality	Negative
	Regulation (TOE)	Concerns of legal implication, data ownership, SLA	Negative
	Selection of service provider (TOE)	Selection of service providers is difficult, Configuration issues, Vendor lock-in	Negative

5 The proposed model

Based on the analysis of the exploratory phase, a model for identifying the determinants influencing the decision to adopt big data analytics was developed (see Fig. 1). It included the adoption variables within four contexts (innovation characteristics, technology, organization and staff, and environment) which are considered in the DOI and TOE frameworks. TOE and DOI have been widely accepted and used in IT adoption of innovation. The variables were selected from TOE and DOI models in a complementary way and are tailored to the context of big data analytics adoption. The identification of these variables was based on the exploratory phase in this study (literature review and 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.

Figure 1: the proposed model



5.1 Innovation characteristics and technology contexts

5.1.1 Relative advantages

Realization of the benefits of adopting an innovation is the first step in supporting the decision-making for adoption. 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. 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 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 tradition manner, but the measurements do not include all related data, such as that from social media platforms, because it is impossible to collect and analyze these 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 analysis of the information in this section led to the formulation of the following hypothesis:

H1: 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 a 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 requires data analytics experts which most universities do not have. Universities need experts with data visualization, interpretation, analysis, and predictive analytics skills, to develop predictive models and algorithms. 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 requires engineering work and raises security and privacy concerns.

H2: Universities that consider big data analytics as a complex technology will view the decision to adopt negatively.

5.1.3 Trialability
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.

H3: The difficulty of testing big data analytics will negatively influence the decision to adopt.

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 move from one service provider to another.

H4: High perception of risks will negatively influence the decision to adopt.

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.

H5: The perception that big data analytics is less compatible with existing systems will negatively affect the decision to adopt.

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.

H6: High volumes and variety of data in universities lead to less likely to be adopt

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 evidence-based and data-driven 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 in order to ensure successful implementation of big data analytics.

H7: An organization's readiness will positively influence the decision to adopt big data analytics.

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, successful adaption of big data analytics may require disruption to current business processes. This requires the development of business processes to ensure successful implementation of big data analytics.

H8: The impact of the diffusion on the internal social network will negatively influence the decision to adopt.

5.2.3 External social

The external social variable is one of the only three variables that have a positive influence on 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.

H9: The impact of diffusion on external social networks will positively influence the decision to adopt.

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.

H10: Greater management support is positively related to the decision to adopt.

5.3 Environment context

5.3.1 Information sources

The automatic collection of all relevant data can be an issue for the successful implementation of big data analytics. 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.

H11: The difficulty of collecting data from all sources and ensuring its quality negatively influences the decision to adopt big data analytics.

5.3.2 Regulation

Many organizations comply with regulators in their internal systems management, but by adopting big data analytics services, part of their service management will be outsourced. In this scenario organizations need to know how to continue their compliance with the regulators, which can present problems. Organizations need to review the general terms and conditions that providers usually include in SLAs. Universities need to review vendors' standard contracts, to see if their basic terms are sufficient for their organizational compliance requirements, and to ensure service providers' compliance with their regulators.

H12: Concerns about data ownership and legal implications are negatively related to the decision to adopt.

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.

H13: The process of selecting service providers is difficult which negatively influences the decision to adopt.

6 Model evaluation (hypothesis testing)

Structural equation modelling (described in Section 3) was used to evaluate the proposed model. This was achieved by testing the 13 hypotheses developed in this study (Section 4). Exploratory and confirmatory factor analysis were conducted and the results are discussed later in this section.

6.1 Exploratory factor analysis

The author applied a measurement model (reliability, convergent validity, discriminant validity, and descriptive statistics) and the results are shown in Tables 3, and 4. First, construct reliability was tested for a set of two or more constructs in order to examine the internal consistency. Second, the reliability of the scales was also tested using composite reliability (CR) (further details can be found in [41]). Cronbach's alpha [42] is a widely used method of testing CR. It provides coefficient values that range between 0 and 1 indicating the reliability level of the indicators. Fornell and Larcker [43] suggested that CR should be more than 0.70 for a suitable research quality. The formula for CR is: (Σ standardized loading)2 / (Σ standardized loading) 2 + Σ ε) where ε = error variance and Σ indicates summation.

Table 3: Reliability of reflective constructs and KMO and Bartlett's Test

Reliability Statistics

Cronbach's Alpha	N of Items
0.833	13

Results of the KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.693
Bartlett's Test of Sphericity	Approx. Chi-Square	421.621
	Degrees of freedom	79
	Sig.	0.00

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

Table 4: Descriptive statistical

Variable	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	2.0	5.0	4.0	4.02	0.93
I4 Vendor lock in	1.0	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 Varity of data	1.0	5.0	4.0	4.22	0.71
T1 Average	**1.0**	**5.0**	**4.5**	**3.95**	**0.88**
T2 Size	**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 Top management support	**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**

Composite reliability analysis shows a Cronbach's "α" value of 0.833 for the 13 hypotheses in the research model, which indicates high reliability as well as internal consistency (see Table 3). Furthermore, principal component analysis was applied to factor analyze the scale. Subsequently, the strength of association among the variables was tested. The construct validity was also tested by applying Bartlett's Test of Sphericity and the Kaiser-Mayer-Olkin (KMO) test for measuring sampling adequacy [44]. The results of the Bartlett Test of Sphericity and the KMO value were 0.000 and 0.693 respectively (see Table 3). These results show a high 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 Average Variance Extracted (AVE) is a commonly used statistical measure for discriminant validity. It is a comparison of the AVE with correlation squared [45]. In order to ensure a suitable discriminant validity, the AVE of two hypotheses must be more than the square of their correlation. The results of this analysis demonstrate that AVE mean square root of hypotheses' values are significantly greater than their correlation coefficient with other variables.

Overall, the results show acceptable reliability, convergent validity and discriminant validity, making the research model and its hypotheses appropriate for testing.

6.2 Confirmatory factor analysis

Confirmatory factor analysis was employed using SEM to test the hypothesized research model. A simultaneous test was performed for all variables. A measurement model was developed using AMOS software tool. The Maximum Likelihood Estimation (MLE) method was selected for confirmatory factor analysis. This is a common estimation procedure used in SEM software, and it ensures reliable results and usually does not require a large sample size. Thus, it has been widely used for hypothesis testing in theoretical models. The structural model shows path coefficient results. It shows the extent of the mutual influence among all variables. The path coefficient was calculated automatically by the AMOS.

7 Evaluation results

The results of the analysis of Stage 2 reveal that 11 out of the 13 variables identified in the research model (see Table 5) significantly influenced decision-making concerning the adoption of big data analytics in higher education. The relative advantages factor followed perceived risks and regulation confirmed to be the highest influence from the analysis. While the factors selecting service provider and trialability confirmed as not significant.

In the innovation characteristics context, the variable relative advantages is supported as a positive influence on the decision to adopt big data analytics in higher education systems. It has a significance of ($p < 0.05$) and positive coefficient of -0.19. The descriptive statistical analysis (see table 4) show high rating for all factors with in 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 DOI model, it is not supported by the findings of this study. 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 technology context, the compatibility is confirmed to be a negative influence on the decision to adopt big data analytics path coefficient: - 0.14. Data volume is also supported as an important factor for the decision, its path coefficient 0.10. In the organizational context, the findings showed that it was important to consider all four variables when assessing the decision to adopt. Organizational readiness, the impact on internal networks, the impact of the external networks, and top management have significant effects, their path coefficients are: - 0.16, 0.12, 0.15, and 0.14 respectively. In the environment context, the information source and regulation factors have a negative effect on the decision to adopt, while selecting a selecting a service provider is not supported by this analysis. Table 5 shows the final results of testing the research hypotheses.

Table 5: Results of hypotheses testing

No	Hypotheses	Coefficient	Result
H1 (+)	Universities' realizations of the relative advantages of big data analytics mean that they are likely to adopt them	-0.19	Supported (p<0.05)
H2 (-)	Universities that consider big data analytics as a complex technology will view the decision to adopt negatively	0.10	Supported (p<0.05)
H3 (-)	The difficulty of testing big data analytics will negatively influence the decision to adopt	0.04	Not supported
H4 (-)	High perception of risks will negatively influence the decision to adopt	0.17	Supported (p<0.05)
H5 (-)	The perception that big data analytics is less compatible with existing systems will negatively affect the decision to adopt	-0.14	Supported (p<0.05)
H6 (-)	High volumes and variety of data in universities lead to less likely to be adopt	0.10	Supported (p<0.05)
H7 (+)	Organizations readiness will positively influence the decision to adopt big data analytics	-0.16	Supported (p<0.05)
H8 (-)	The impact of the diffusion on the internal social network will negatively influence the decision to adopt	0.12	Supported (p<0.05)
H9 (+)	The impact of diffusion on external social network will positively influence the decision to adopt	0.15	Supported (p<0.05)
H10 (+)	Higher management support is positively related to the decision to adopt	0.14	Supported (p<0.05)
H11 (-)	The difficulty of collecting data from all sources and ensuring their quality negatively influences the decision to adopt big data analytics	-0.13	Supported (p<0.05)
H12 (-)	Concerns about data ownership and legal implication are negatively related to the decision to adopt	-0.17	Supported (p<0.05)

H13 (-)	The process of selecting services providers is difficult which negatively influences the decision to adopt	-0.03	Not Supported

8 Conclusion and future work

Big data analytics have demonstrated a number of advantages that can significantly improve the performance of higher education organizations as well as overcome many existing challenges. However, the decision to adopt big data analytics in an ongoing higher education system 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 analytics in higher education, 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 creditability of the findings of this research. However, the identification of the determinants alone is not sufficient to support the adoption of big data analytics by higher education, and further research is needed to achieve this goal. The findings of this study can be used as a basis for developing a suitable decision support system. Such systems need to address the factors that have a negative effect on the decision to adopt. 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 successful implementation may require re-engineering of current business processes, future research is needed to help universities to improve those processes. Finally, the primary data for this study was collected from decision-makers and practitioners who work at universities in Saudi Arabia, but the proposed model could be used with data collected from universities in other countries. Such use of the model would increase the validity of the results, enabling it to be used in all universities regardless of location.

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