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CHAPTER I

1.1 OVERVIEW

Big data technology has been recognized in many fields of public policy, market statistics, and research development over the last few years (Dagiliene & Kloviene 2019). Big Data Analytics is defined as a strategy for swiftly revealing a pattern by analyzing data from a huge data set utilizing computational, programmatic algorithms, and mathematical modeling tools. It is feasible to collect actionable information that can be used to inform management decisions within a company by doing so (Del Vecchio et al. 2018). The optimization of customer interaction, understanding of user patterns, and resource growth are the major applications of Big Data. It also makes it possible to discern models and anomalies from data sources (O'Connor 2017).

With the invention and expanding use of interactive media and Learning scenarios in higher education, challenges about processing and updating the volume of education data have surfaced (Aguilar 2018). Many higher education institutions, according to Nazarenko and Khronusova (2017), use analysis to improve students' learning experiences by introducing students to the proper options for their learning mode (Nazarenko & Khronusova 2017). Enrolment, evaluations, and an automated learning environment, or Library lending templates that automatically create data, are common ways for colleges and universities to collect a lot of information about their students. In comparison to the development of technology that can process, store, analyze, distribute, portray, and examine presenting data, there has been a generalization of the use of digital in education (Reidenberg & Schaub 2018).

Education data has traditionally been collected utilizing the school records system and standard evaluations, according to Viloria et al. (2018). (Viloria et al. 2018). Traditional data analytics can no longer handle the massive amounts of data generated today, thanks to the rise of Big Data. As a result, the school's administration

faces an unfathomable number of semi-structured managers and unstructured mass data when it comes to maintaining innovative and efficient data management during the certification process. On the one hand, a person's interest in Big Data grows as they learn about new possibilities in a variety of fields (Verma & Bhattacharyya 2017). Furthermore, the Big Data concept's functionality in diverse systems, such as commercial social media data, is unknown (Yakobi et al. 2020). The system's functionality is determined by the user's position and requirements. Although educational institutions are responsible for assuring successful submission, commercial software and data systems can also be duplicated for educational purposes. It's worth noting, though, that school systems and businesses differ in terms of funding, size, style, and environment. H As outlined in IR 4.0, educational institutions must change traditional news and Big Data Analytics Information Management to align with the organization's most recent strategic strategy (Eybers & Hattingh 2017).

According to (Adrian et al. 2018), in-depth analysis of parameters is required to increase the Big Data system's efficiency and participation in a range of fields. The process of evaluating critical factors, according to (Aldholay et al. 2018), could transform the business into an effective adoption of new big data technologies. (Aldholay et al. 2018). Sensor data, mobile device position data, electronics data, Internet data between web searches and social networking sites, and other data sources generate massive volumes of data, as seen below (Figure 1.1).

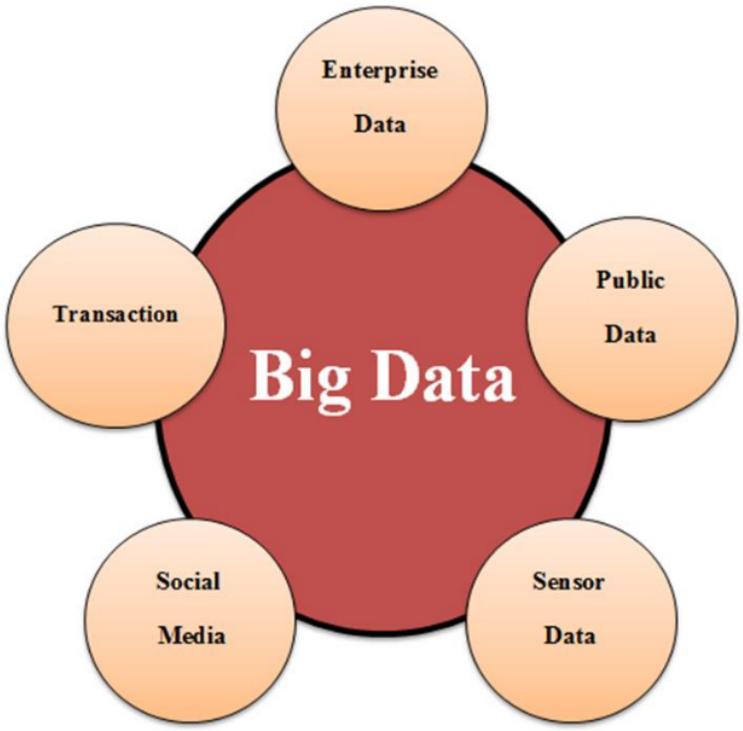

Figure 1.1: The Various Sources of Big Data

Despite the substantial advantages of introducing big data explained in the documentation, The overall research question addresses the various barriers associated with technology, culture and commercial strategy. The adoption of Big Data is a necessary condition for realizing the expected benefits. But there is a lack of awareness of how these business influences influence the uptake of big data (Braganza et al. 2017).

1.2 PROBLEM STATEMENT

Big Data represents an important breakthrough in the new ICT environment and has previously been one of the top 10 Chief Information Officer (CIO) infrastructure

priorities within organizations (Adrianto 2018). Because of the numerous benefits of contemporary technology (Trabucchi & Buganza 2019), it can be especially beneficial in Third World nations who lack the financial resources to invest in their own IT and infrastructure (Urbinati et al. 2019).

Big Data is incredibly valuable, allowing both men to process and utilize large volumes of data and to capture value using the capture and analysis process (Lv et al. 2020). Using big data successfully changes industries and creates a new era of prosperity for large companies. In addition, previous studies (Chatzithanasis & Michalakelis 2018; Mohammed, G. J., & Burhanuddin 2018; Moudud-Ul-Huq et al. 2020; Aldholay et al. 2018; Yoo & Kim 2019). Experienced difficulties in making informed judgments on the adoption of Big Data technology by IT administrators. Furthermore, the inappropriate treatment of the sociotechnical complexities of Big Data businesses is another reason.

The lack of understanding of the causes for Big Data adoption was also mentioned (Braganza et al. 2017; El-Gazzar 2014; Njenga et al. 2019). In order to recognize the benefits of their technological investment, organizations must also provide a good view of the technical developments involved with the introduction of Big Data.

However, (Chaurasia & Frieda Rosin 2017) admit that the Big Data framework may be merged with current technology and that higher education institutions continue to face a significant impediment (Chaurasia & Frieda Rosin 2017). As a result, modern technology costs and data security are top priorities. University administrators must prioritize what is required to convert traditional higher education into a more successful environment, including a better understanding of learning (Yasin et al. 2018). In industrialized countries like Iraq, for example, a variety of higher education institutions have used eLearning, resulting in large amounts of data that must be examined (Mark 2019; Jovanovic Milenkovic et al. 2019; Prasetyo et al. 2019). It's also crucial to determine the most critical success elements for Big Data initiatives in higher education institutions. Furthermore, according to (Mohammed 2017), Big Data technologies must be implemented in the Iraqi higher education sector in order to strengthen the institutions' infrastructures (Mohammed 2017).

The use of big data in Iraqi higher education institutions is projected to improve quality, effectiveness, communication, and motivation, among other things, by:

- Encourage the use of big data in the classroom to enable more informed, evidence-based, and student-specific decision-making.
- Improve the accuracy and efficiency of care operations by supporting cross-border data sharing and allowing emerging technology to approve best practices.
- Why By removing barriers to good education, we can reduce errors and improve access to it.

The goal of this study is to look into the use of big data analytics in Iraqi higher education institutions.

Research Questions

- What are the most important success elements for Big Data Analytics implementation in Iraqi higher education institutions?
- What model would be most conducive to the use of big data analytics in Iraqi higher education institutions?
- Where are huge data analytics being used in Iraqi higher education institutions?

Research Objectives

The study's major goal is to offer a framework for the implementation of Big Data technologies in Iraqi higher education institutions. The study is directed by the following sub-objectives in order to achieve this goal:

- Determine crucial success elements for the implementation of big data analysis in Iraq's higher education institutions.
- Propose a model to help Iraqi higher education institutions implement big data analytics.

To estimate the level of Big Data analytics usage in Iraqi higher education institutions.

1.3 SCOPE OF STUDY

Iraqi public universities participated in the survey, which are overseen by the Iraqi Ministry of Higher Education. Furthermore, because these colleges are not lucrative, they work more closely with government agencies and society. They follow the same policies and rules, and they have a large number of students. This study employs a quantitative methodology that involves a survey of Baghdad's public university faculty members (University of Baghdad, Al-Mustansiriyah University and Technical University). These are Iraq's largest institutions. At the same time, the three universities are in Baghdad, Iraq's capital.

For the purposes of the present study, the scope is limited to those who understand big data (Al-Dhalmy et al. 2012). Moreover, the study focused on university staff working at these universities because they have a good idea and a good knowledge of technology. The scope also emphasizes data on submissions in public universities to make better decisions, to deliver quality education and enhance the civil service. However, this research is based on the Technology-Organization-Environment (TOE) framework, due to the widely utilized in research on organizational adoption. A research model for studying corporate adoption of big data technology was developed based on an adoption review and Big Data documentation, where assumptions are based on the TOE framework in the technical, organisational and environmental context.

1.4 SIGNIFICANCE OF THE STUDY

Big data can reduce costs, time and decision-making efforts in online learning technologies through the analysis of data and information. It also improves decision-making to improve the services offered by the university that can support the principle of online learning within Iraq's higher education sector. As a result, this study identified factors in favour of big data technology in the academic community. Therefore, a suggested model for the adoption of big data at Iraqi state universities. This theoretical model has identified factors that have a positive impact on Big Data at these universities and which can be used as a road map for its passage.

1.5 PROPOSED RESEARCH METHODOLOGY

This research would employ investigative methods to facilitate evaluation the variety of relationships among components of the technological organizational environment (TOE) theory and Big Data's adoption. Optional plans based on data to obtain knowledge that could be gathered with sufficient accuracy are covered by the analytical method. This report collects data from Iraqi higher education institutions using a survey methodology. For this investigation, a simple random sample methodology would be employed for data collecting, as well as a five-stage analysis process. The preparation of a questionnaire and data gathering with the target audience is the first step in the testing process. The survey will be completed when the data has been collected, and the demographic and descriptive data will be assessed.

Summary

This chapter discusses the study's context in detail, stressing current research challenges, the research goal, the research topic, the scope of research, and the value of research. The goal of this study is to find out what motivates higher education institutions to embrace big data. The history, benefits, concerns, characteristics, components, and relevant studies will all be covered in the next chapter.

LITERATURE REVIEW

2.1 INTRODUCTION

Big Data is a concept that makes it possible to characterise a large amount of data. It can be organized or it can be unorganized. Big data analysis allows every business to make firmer decisions and act decisively. Companies in the banking, engineering and public administration sectors use Big Data to achieve their strategic and commercial goals. Big data analysis also plays an important role. Related literature is discussed and described in this chapter and framework which concentrate on the subject of this thesis in order to provide more research and discussion.

2.2 BIG DATA

Cox and Ellsworth (1997) coined the term "Big Data," which they defined as the difficulty of storing enormous datasets for display. With today's robust growth and quickly evolving Web technologies, the era of big data has seen an unparalleled surge in the quantity of datasets (Palanisamy & Thirunavukarasu 2019). Big Data is a technique for gathering, managing, and analyzing enormous amounts of data in order to generate information and uncover hidden patterns (He et al. 2017). (Sun et al. 2020) It was shown that over 75% of businesses spend or plan to spend money on Big Data. This is due to the fact that Big Data Analytics enhances the company's ability to make proactive decisions (Sun et al. 2020). In the private sector, big data has been employed widely in areas such as retail sales and industry analytics. Big data technology, for example, is frequently used in a fast increasing vertical market such as banking and virtual financial, government, and consumption services. From the standpoint of public awareness and higher education, this technology appears to be unpopular (Ekambaramet al. 2018).

2.3 BIG DATA CHALLENGES

Despite the fact that Big Data is expected to have a massive revolutionary impact on many parts of society, extracting useful information from it is not a usual practice. Furthermore, the value of Big Data is always contingent on situations in which specific data is highly valued by one organization but useless to another (Sivarajah et al. 2017). Even businesses that invest in disruptive big data adoption are on their own since there is no direct path to value. Understanding the data is the true challenge (Deepa Mishra et al. 2017). Businesses that do not use Big Data technologies may face poor revenue, expensive human capital costs, and inefficient data management. In fact, data specialists could devote up to 80% of their time to maintaining a data system (Mishra et al. 2017). Decisions may not be made in a timely manner without the requisite data processing tools and a framework that promotes the use of data, resulting in a potential decline in organizational productivity. Furthermore, when it comes to big data, on-the-spot adoptions can entail considerable commercial risks as well as expensive infrastructure. C Organizations may be unable

to use this technology if it requires constant maintenance (L'Heureux et al. 2017). As a result, new technologies such as BigData should be implemented in a range of sectors to ensure that work is completed effectively and on schedule (Lee 2017).

2.4Big Data Adoption

Despite the absence of evidence and the high cost of Big Data's financial benefits, early adopters highlighted advancements in higher education institutions, as well as the adoption of safety measures and Iefficiency metrics, as key catalysts for big data investment (Alhuwail 2020). It ensures that a company's financial capital is available to invest in risky technologies without risking the company's solvency. According to experts, the number of employees in a company is the most important factor in accepting Big Data (Baig et al. 2019).

Similarly, (Yadegaridehkordi et al. 2018) discovered that physicians at a large scale are more likely than not to utilize big data (Yadegaridehkordi et al. 2018). (Al-Rahmi et al. 2019) discusses the use of Big Data technology, which is linked to some of the group's employees as well as the ownership structure (Al-Rahmi et al. 2019). Large institutions belonging to various medical associations usually have complete framework policies to support and incorporate Big Data, according to (Haddad et al. 2018). (Haddad et al. 2018).

The goal of a Big Data user is to introduce Big Data. Immediate adopters encounter financial obstacles such as a low return on investment or a high startup cost, as well as ongoing maintenance expenditures. Furthermore, (Al-Qirim et al. 2017) discovered that imminent adopters are more likely to receive financial incentives for implementing big data, recommending which financial incentives could be used to tip the scales in favor of Big Data adoption for those who see financial difficulties as a barrier (Al-Qirim et al. 2017).

2.5 BIG DATA IN HIGHER EDUCATION

In the higher education industry, the expansion of megadata is still unprecedented. The automated campus infrastructure system, campus network, in-house apps and servers, learning management system, and other end-user devices generated a substantial amount of data each year. Schools, on the other hand, rarely employ them

to deliver relevant knowledge on a number of subjects (Chaurasia et al. 2018). This resulted in negative reviews about the learning experience of graduate students. The huge data and excellent education system had an impact on the professional trainer. As a result, the professional is unable to closely monitor student accomplishment, and as a result, their prospective job is limited (Muhammad et al. 2020). As a result, HEIs have been presented with a slew of Big Data possibilities (Chaurasia & Frieda Rosin 2017). (Muhammad et al. 2020) came to the conclusion that Big Data analysis has resulted in the current oversight of the integration architecture and analysis of various data from various sources such as student registration systems, firewalls data, site servers, remotely located sensors, networks, log files, mobile and online learning applications, existing programs, application servers, and structured databases (Muhammad et al. 2020). This integrative architecture will detect difficulties, dangers, and opportunities using underdeveloped computing data. Parallel to this technology, higher education has established a high-level apprenticeship and efficient management structure (Murumba & Micheni 2017). A combination of human resources and modern analytical techniques can be used to create an effective learning environment. Using the data analysis technique, the educator can now closely monitor his or her pupils' academic achievement.

2.4 CRITICAL SUCCESS FACTORS FOR BIG DATA

Big data is a major topic of discussion among successful academics and digital workers. Big Data is a valuable tool that has piqued the curiosity of many executives from various organizations that want to collect information rapidly and earn a lot of money (Sivarajah et al. 2017). Big Data technology begins to replicate in the workplace to solve human limits as it advances in the administration of large amounts of data. Man has not been able to meet the criterion for studying a wide range of data (Ghani et al. 2019). Many businesses employ a variety of methods to discover and evaluate the value of their big data investments in the marketplace. The critical success factor methodology has been used in a number of investigations (Eybers & Hattingh 2017) . The important success factor technique is used to identify the critical components of success, which was originally intended to match the technology strategy with the organization's strategic planning (Eybers & Hattingh 2017). Because

best practices are often developed after certain actions have been done, they are critical success factors. As a result, those success variables are comparable to real-life situations (Al-Rousan & Al-Shargabi 2017). Furthermore, the application of crucial success criteria can have a significant impact on the IS's preparation, growth, design, development, and acceptance (Ismail et al. 2019). Leaders should use success factors to find the most relevant data when making strategic decisions about their company (Vicente et al. 2017). As a result, decisions based on information related to organizational success factors can be made more effectively and reliably. The issues that must be solved for success must be familiar to decision makers. The reasons of origin will be determined, and these key factors will be highlighted (Ismail et al. 2019).

UNDERPINNING THEORY

Technology adoption is essential in order to encourage reluctant users to use it successfully. Technology adoption is necessary because of rapid development and circumstances that force people to adopt technology. A number of theories were used to investigate the adoption of technologies in research on information systems (Oliveira & Martins 2010). A key enterprise-wide model is the Technology, Organization and Environmental Framework (TOE) (Tornatzky & Fleischer 1990).

2.4.1 Technology, Organization, and Environment (TOE) Framework

The Technology-Organization-Environment (TOE) framework is an organization-wide theory by (Tornatzky & Fleischer 1990) The TOE is a multisectoral framework that defines three aspects of an organization's environment that impact the process by the technological innovation it adopts and implements. The adoption and deployment of innovative technologies is affected by the environment, technology and organization. (Gui et al. 2020), as illustrated in Figure 2.1. Technology integration, organizational, and Due to environmental considerations, the TOE is better for adoption and use than other adoption models and value creation of the technology (Cruz-Jesus et al. 2019). According to (Oliveira et al. 2014), the TOE framework has undergone extensive testing in IT and IS adoption studies and has demonstrated ongoing empirical support. The framework is very much used to describe the adoption of information technology in its broadest sense (Wainwright 2014; Borgman et al.

2013; Low et al. 2011; Nedev 2017; Saedi & Iahad 2013). These observations have shown continuous backing for the capability of the TOE to provide a real organized standard on the assumption of innovation while stimulating the smoothness to identify and categorizing various variables that may occur under appropriate circumstances.

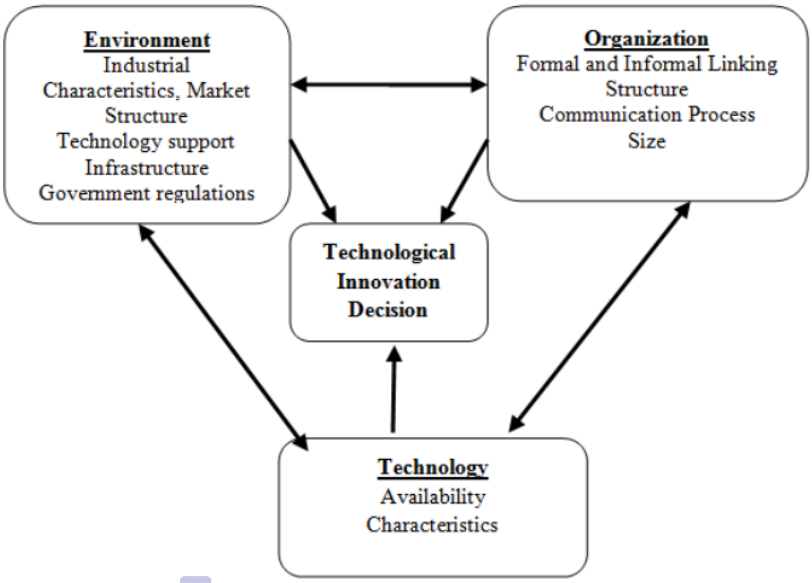

Figure 2.1: TOE Framework Components

Source: (Tornatzky & Fleischer 1990)

Depending on the TOE framework, the adoption of technology within the institution is influenced by the technological environment, The Organizational Context and Environmental Context. Specifying the variables in each of these three contexts varies depending on the type of technology involved in adoption (Y. M. Wang & Wang 2016). Below is a detailed description of the three structural concepts of the TOE.

The first concept is the technology environment. The technology context within the TOE refers to the existing technology available to the company as well as new technologies relevant to the company (Jia et al. 2017). The technology environment is also driven by innovation features (Bhattacharya and Wamba 2015)

and Technological considerations that influence the adoption of innovative information systems within the organization (Jia et al. 2017).

Although the organizational context within the TOE refers to descriptive measures associated with the complexity of the organizational structure, financial support, the beliefs of managers, the size of the business, and support from senior management (Jia et al. 2017). The organizational context describes the organisation and its features (Bhattacharya & Wamba 2015) that reflect the capabilities of SI, the preparedness of the organization for the adoption of IT and IT infrastructure (Dewi et al. 2018).

The final element is the environmental environment. The environmental context of the TOE refers to the environment in which the organisation operates. The environmental context underlines that the adoption of a company by IS is strongly influenced by many external factors independent of the company's will (Jia et al. 2017). The environmental context under the TOE focuses on external factors that influence businesses to adopt new technologies, such as government incentives and external pressurization (Dewi et al., 2018).

The TOE framework has been a useful tool for understanding how organizations are embracing the technological innovations identified in future studies. For example, (Pudjianto et al. 2011) used the TOE framework to explain the assimilation factors of cyber government to Indonesian organizations to capitalize on its potential values and advantages for organisations. (Awa & Ojiabo 2016) Developed the TOE framework for the adoption of an appropriate information system model for enterprise resource planning software for small businesses and Mid-Market Companies in Nigeria (Hemlata Gangwar, Hema Date 2015) Integration of the TOE framework to understand cloud adoption factors across the organization (Ahmadi et al. 2017) used the TOE framework to implement information systems in publicly funded hospitals in Malaysia (Al-Hujran et al. 2018) conducted a study to determine the challenges associated with adopting cloud computing in developing countries using the TOE framework. Literature proved that many researchers indicated that the

TOE framework is a useful tool for exploring the adoption behaviour of technologies in the organization.

2.5 PREVIOUS STUDIES

(Al-Rahmi et al. 2019) Develop a system for assessing educational resiliency and integrating education with the acquisition of big data and the exchange of managerial skills. This article covers some of the factors that influence big data analysis adoption. The impression of value, usability, danger, and behavior in the usage of big data has been identified as having an impact on big data adoption. Furthermore, age diversity, cultural diversity, and encouragement have a significant impact on management information exchange. Information sharing has an impact on how people utilize technology and how they make decisions about it. Big Data doping will have a good impact on schooling in the future. As a conceptual framework, this article used TAM variation and reward theory. A Quantitative data was collected and analyzed using a comprehensive survey. A survey of 214 university students was conducted at random. The replies and criticism from students were arranged into 11 different study programed . The focus of the study was on long-term education. The data was then quantitatively examined using structural equation simulation (BME). The research revealed that big data adoption is influenced by perceived benefits, perceived usability, perceived damage, and behavioral intent. Age, cultural variety, and motivation were all important factors in knowledge sharing. According to the findings, 66.7 percent of educational resiliency can be considered when adopting management knowledge exchange, technological capability, and the introduction of general information (Al-Rahmi et al. 2019).

According to (Alalawneh & Alkhatib 2021), The introduction of Big Data (BDA) and its threats, opportunities and Researchers and practitioners are increasingly interested in future benefits. The BDA is very important to emerging economies; however, they do not understand the obstacles they face. The goal of the present study is to address the challenges faced by BDBAs in developing markets and their relative relevance by industry to the assessment of the preparedness of sector-specific BDBAs. In a semistructured interview with Big Data (DB) professionals and others, the AHD identified five series of hurdles and 19 sub-obstacles. A single questionnaire survey is

carried out. Each sector's set of barriers was described, analyzed, examined, and contrasted. The analytical hierarchy method (PLA) was utilized to categorize the relative relevance of these hurdles between sectors, while TOPSIS (Optimum Solution Choice Order Method) was used to grade sectors based on their BDBA preparedness. The study is aimed at academics and practitioners who are interested in BDA in advanced economies (Alalawneh & Alkhatib 2021).

Big Data is an essential tool for startups to gain a competitive edge and specialization (Haddad et al 2020). The application readiness concept can be used to measure an organization's expertise and preparation for big data technology. The AMOS tools have been used to test 381 samples using simulation and structural equation analysis. The technology maturity theory is used to assess characteristics that may influence big data uptake. The current research focuses on one of Abu Dhabi's government institutions (ADPO). The main independent structures in this model are comparable to innovation, optimism, and vulnerability, and it's uneasy to be willing to take advantage of this massive amount of data. Dependent builds in ADPO are focused on the availability of large amounts of data. The relationship between the various structures is established in this study. This research backed up our previous findings on the online social networking paradigm. The findings revealed that the four independent variables had a strong relationship with forecasting the acceptability of varied percentages of big data. When Big Data was introduced, the stated paradigm allowed for the clarification of 50% of the gap (Haddad et al 2020).

(P. T. Chen et al. 2020) Over the last two decades, considerable advancements have been made in the computerized system of clinical information. Due to patient data overload, healthcare organizations are voluntarily advancing big data technology to replace the previous way. More recently, the Big Data Health Information System has been gradually evolving and responsive to patient information in order to generate new health advancements and promote timely preventative care. The purpose of this research is to determine the technical problems that come with implementing a big data-based health information system. To identify the weighting of the problem and a dds VIKOR at the end of an exceptionally successful problem-solving technique, a network system analytics approach is necessary. As a result, by deploying the Big Data Health Information System in the health sector, it is possible to overcome the organizational hurdle. The findings would help to improve the efficiency and accuracy

of the health-care industry's large-data clinical information system. Understanding the importance of strength variables allows managers to build constructive approaches to resolving difficulties based on acceptable objectives (P. T. Chen et al. 2020).

Big Data is expected to catalyze new digital changes across culture, government, and industry, according to Park and Kim (2019). However, just a small percentage of businesses are introducing and utilizing big data. The deployment of Big Data faces a number of challenges and risks. Using the Technology-Organization-Environment (TOE) approach, this study tries to uncover the factors that influence the adoption of Big Data in Korean businesses. The regression analysis and the results of the analytical hierarchy methodology (PLA) were tested with 50 experts and 226 companies. The benefits of big data, technical capabilities, financial investment skills, data coherence, and convergence between specialists and companies are found to be the most important predictors of acceptance. Big data advocacy, protection and security, as well as government support and regulation, are all significant factors in businesses accepting big data (Park & Kim 2019)

According to (Zulkarnain et al. 2019), governments all over the world have emphasized the use of big data technology to improve public services during the last decade. Although big data technology has grown throughout most countries, adoption and management rates differ. To determine critical success factors (KSCs) for Big Data implementation, the government used a systematic literature review (VSA). This contains a major component of the government's ten-year work on Big Data implementation. It summarizes the findings of 183 publications and a wide range of literature on governmental actions, such as delivering public services, involving the public, making choices and policies, and altering governance. We chose 90 reviews and created 11 classification criteria for the government's huge data collection estate (Zulkarnain et al. 2019).

(Wright et al., 2019) highlight how big data can be used to improve creativity and business connections. It lays out a framework for examining the effects of big data, which is supported by four case studies. It's a conceptual paper supported up by case studies that allows the definition to be generalized. Business case studies pave the way for companies to stay ahead of the competition and expand their activities by leveraging Big Data to capitalize on marketing possibilities and produce new products. Because of the expanding scope of online business and consumer purchases,

the organizations are both benefactors and collectors of Big Data. Big data, its understanding, and implementation, according to a qualitative case study, can be viewed as a measure of a company's willingness to evolve and adapt to economic prospects. The world of online marketing is complicated, and businesses must develop in order to succeed. The case study addressed the lack of an appraisal of individual creativity. The document's examples were confined to successful businesses where Big Data, data analysis, and analysis aided in the attainment of the contract's strategic goals. The outcome of products and services to clients determines the market's evolution inside B2B enterprises. Clients can create end-to-end (B2C) value in their innovation activities and completely participate in B2C business with their B2B customers from beginning to end. From policy to human capital, it has an impact on society as a whole. If a B2B organization's genealogy contains B2C transactions that are similar to those of its clients but are not aggressive, it may give them a competitive edge, however If their B2C business competes with the B2C business of their clients, it may cause friction and revenue loss. This implies that dividing the marketing campaign throughout the company's numerous divisions raises the risk of friction. The document's significance lies in its ability to enhance awareness of Big Data's role in market innovation, particularly in B2B organizations. They can, for example, create and personalize customer service skills to innovate with end clients at the end of the value chain. By explaining how creativity affects business-to-business partnerships, this paper contributes to the literature (Wright et al. 2019).

The introduction of Big Data Analytics (PDA) plays a crucial role in correct decision-making and optimal productivity in a modern industrial setting, according to (Maroufkhani et al. 2020). The determinants or effects of its function on small and medium-sized firms, on the other hand, are unclear. This disadvantage is highlighted in this study, which included a survey of 171 small and medium-sized Iranian manufacturing businesses. The study found that obstacles, uncertainty, and a lack of testable, observable, executive support, preparation, and external support all had a significant impact on BDA adoption. The findings also show that small and medium-sized businesses' commercial and financial growth has been impacted by the adoption of the BDBA. Incorporating BDBAs into a company can assist management in efficiently resolving the problem. The findings enable BDBA service providers to

build and distribute BDBA to small and medium-sized businesses (Maroufkhani et al. 2020).

Massive data analytics has attracted substantial attention in the health sector because of its unique approach to aiding decision-making and enhancing the rate of policy growth, according to (Shahbaz et al. 2019). As a result, the study concentrated on developing a framework for incorporating big data analysis into healthcare settings. The task-based technology and the technology adoption model were found to be perfectly aligned with the expected behavioral aspects. To test the hypotheses, 224 appropriate answers were analyzed in AMOS v21 using the survey questionnaire. Our findings suggest that the credibility of the application adoption paradigm, as well as the suitability of the working approach, increases the behavioural objectives of the usage of the Big Data analytics framework in health care, finally leading to practical implementation. Simultaneously, trust and safety in the knowledge system have frequently had a favorable impact on the behavioural goal to be applied. Determine the association between the desire to employ big data analytics and its actual application in healthcare, as well as the workers' aversion to reform. Our findings should be applied by health facilities to raise awareness of the use of big data analysis and to enable personnel to take this ground-breaking approach through social empowerment (Shahbaz et al. 2019).

Table 2.1: Related Work

	Risk	Cost	Compatibility	Complexity	Top management support	Company size	IT capability	Economic	Social
(JETZEK ET AL. 2014)	√				√		√		
(JANSSEN ET AL. 2017)			√				√		√
(SUN ET AL. 2018)		√		√	√		√	√	√
(MIKALEF & KROGSTIE 2020)					√	√	√		
(PARK & KIM 2019)					√		√	√	

2.6 CONCEPTUAL FRAMEWORK

The goal of this research is to implement the Big Data Analysis paradigm in Iraqi higher education institutions. B The most important factors are the organization's capacity, such as (Cao & Duan 2014; Dutta & Bose 2015; Gupta & George 2016; Halaweh 2015; Janssen et al. 2017), and the environment, such as (D. Q. Chen et al. 2015; Popovic et al. 2016; Y. Wang et al. 2018). Following is a discussion of these factors.

• The ability of IT infrastructure and analytics platforms to turn large data into meaningful information and offer decision-makers with valuable knowledge is referred to as technology competency. A relative advantage (Y. M. Wang & Wang 2016), compatibility (Alsaad et al. 2017), complexity (Verma, S. 2017), and Quality of Data & Information are the sub-factors of the technological competence aspects (Park & Kim 2016). As a result, data infrastructure is widely acknowledged as the most important success factor in the use of big data in educational institutions. Organizational capacity is defined as an organization's ability to establish plans and effectively manage the implementation of the BDBA (Kung et al. 2015), and it is recognized as a critical success factor in the use of Big Data in higher education institutions. Senior management support (Halaweh 2015), organizational learning intensity (Ahmad Salleh et al., 2016), and organizational readiness are all elements that contribute to corporate capability (D. Q. Chen et al. 2015).

• Understand the benefits of leveraging big data in higher education institutions to boost organizational performance. This could help EDC expand its capabilities and establish a new learning model. This comprises the institution's policy and rules as well as the security and protection of personal information requirements (D. Q. Chen et al. 2015). (Hsu et al. 2014).

2.7 HYPOTHESIS DEVELOPMENT

2.7.1 To meet the study's goals, three assumptions have been made. The research assumptions are detailed in the subsections that follow.

2.7.2 Technology Capability

The relative benefits, interoperability, sophistication, and consistency of data and information are all sub-factors determining technological ability, according to previous empirical investigations.

"The extent to which innovation is viewed as superior to the assumption that it comes first" is how relative advantage is defined (Sun et al. 2018). Numerous studies on the use of big data in various domains have been conducted in terms of data availability, cost, application, efficiency, and effectiveness. Security Higher education institutions have access to a massive amount of data, which is stored in a variety of places and managed using a variety of methods. As a result, big data has the potential to improve the quality of decision-making in the education sector in the futureFor example, big data can help students maximize their learning achievement because some students are unsure about which primary subject to take and how to proceed. Inquire of practitioners how learning paths might be modified to ensure that no students are left behind (Muhammad et al. 2020)

Compatibility refers to the ability of any government agency to deliver equal levels of software, materials, and competences (Shin 2016). It includes both organizational and technical compatibility. The compatibility of people's skills across all levels of government is linked to organizational compatibility, which can contribute to big data (Shin 2016). The unification of information technologies

(software and hardware) required of staff to electronically share government information is referred to as technological compatibility (Christen et al. 2016).

"The degree to which innovation is perceived as somewhat difficult to understand and implement," according to complexity (Ward & Barker 2013). Because of the usage of certain technologies, a higher level of complexity is regarded to be a higher level of difficulty (Baig et al. 2019). The importance of big data and related technology is reflected in this aspect. Users will be concerned about the difficulties of using the technology in the form chosen for implementation. S Cholars observed the negative consequences of ambiguity on innovation adoption (Ekambaram et al. 2018). Because big data relies significantly on technology to process and investigate enormous amounts of data, its adoption may be limited by a high level of expertise.

Consistent Big Data analysis is essential for making good decisions during the Big Data adoption phase (Adrian et al. 2018). "Data availability that satisfies user needs" is what data quality means (Ghadiri & Khani 2019). Given that "knowledge obtained from treated analyses" is what data quality refers to (Ghadiri & Khani 2019). The importance of coherence in knowledge analysis applicable to big data analysis is crucial to the success of an organization. According to Alhaboobi (2019), higher education institutions should integrate big data analysis with authentic data to provide significant information that will help the school make better decisions, which could include major changes in higher education learning techniques (Alhaboobi et al. 2019). Furthermore, relying on faulty evidence might result in erroneous decisions, jeopardizing the organization's stability. As a result, we arrive to the following hypothesis:

Hypothesis 1: The capabilities of a company's technology has a considerable impact on its desire to use big data analytics.

2.7.3 Organization Capability

Past research has demonstrated that sub-factors that influence organizational capacity include senior management support and the strength of organizational learning and organisational readiness.

A level of recognition of importance is referred to as senior management support and Commitment of Big Data technologies to relevant leadership initiatives

(Ahmad Salleh et al. 2016) More management support will help businesses address the challenges and uncertainties of emerging technologies and accelerate their uptake (Zailani 2015). Strong senior leadership creates a supportive and supportive care environment and speeds up the process of implementing the technology within the enterprise. The central role of management in the implementation of all innovations was highlighted in the literature (Verma, S. 2017).

Institutions that have established exploration and accumulation capacities are referred to as the organizational learning force. Knowledge sharing and transformation is a vital reservoir of valuable information that can be used to validate and contextualize Big Data outcomes (Lozada et al. 2019). For the compilation and proper analysis of big data, high degrees of organizational learning are accessible, resulting in effective institutional decision-making (Calvard 2016).

The ability to deliver the appropriate technological, financial, and human resources might be defined as organizational preparedness (Zhu et al. 2006). The right procedures, technology systems, libraries, and applications, as well as Architectural data needs for the gathering, transformation, and value of Big Data, are referred to as Technology Services (Nasrollahi & Ramezani 2020). Financial capital represents the willingness to pay for the installation or modernization of institutional information systems, as well as to cover current expenses throughout times of use and repair (Lai et al. 2018). Human resources have the knowledge and skills needed to carry out Big Data efforts (Nasrollahi & Ramezani 2020). To put it another way, big data will only be integrated into the supply chain if the best people are employed. Institutions that are operationally ready are projected to be better prepared to accept big data in the end. The following is a hypothesis:

Hypothesis 2: The intention to use big data analytics is heavily influenced by organizational capacity.

2.7.4 Environment

Environmental sub-factors include safety and personal information protection requirements, as well as institutional policies and regulations, according to past study.

Consumers of big data are concerned about security and privacy breaches, as well as technological risks to security (Salleh & Janczewski 2016). Protection and confidentiality issues are frequently highlighted in the literature as one of the challenges to Big Data implementation (Abouelmehdi et al. 2017). (Schüll & Maslan 2018) discovered that the presence of Big Data leads to a slew of security issues, prompting businesses to invest in new security solutions and technologies. Meanwhile, when it comes to their actions, Big Data businesses are under a lot of pressure to follow the rules (Schüll & Maslan 2018). Security and privacy concerns are frequently cited as major roadblocks to big data adoption.

The second sub-component of climate change is institutional legislation. There's no denying that the spread and use of information technology in many areas has necessitated government assistance. A favorable administrative climate can essentially lead to the diffusion of innovations. The regulatory environment has been identified as a critical factor in the spread of innovation (Zhu et al. 2006). The Ministry of Higher Education's regulations and regulations, which stipulate that an organization must adopt cutting-edge technology in order to continue receiving funding from the Ministry of Advanced Education, are thus an important tool and process for guiding organizations in the adoption and use of digital technologies (Hsu et al. 2014). Scuotto et al. (2017) He stated that a conservative government approach would impede the implementation of IT. In other words, the administrative leadership of an organization can modulate the decision-making process in various ways (Scuotto et al. 2017). This leads to the following hypothesis.

Hypothesis 3: The environment has a significant impact on the intention to proceed with big data analysis.

The conceptual model suggested for this empirical study is described in Figure 2.3.

Figure 2.2: Proposed Conceptual Model

2.11 CHAPTER SUMMARY

2.12 The literature relevant to the research described is discussed in this chapter. The merits and drawbacks of this new revolutionary technology in bestowing competitive advantages on the higher education industry were explained, as well as the concept of Big Data. The study outlined the disadvantages of using Big Data in Iraq's tertiary education industry. Various explanations and recommendations for implementing Big Data in higher education were provided.

CHAPTER III

METHODOLOGY

3.1 INTRODUCTION

This section explains how to plan a study, collect data, and analyze it thoroughly. This part goes over the specifics of data set preparation, data processing, analytic tools, the research's nature, and the data evaluation procedure.

3.2 RESEARCH METHODS

The research methodology is a "structured set of guidelines or activities designed to produce valid and reliable research results" (Pascal et al. 2018). It's critical to pick a strategy that maximizes generalizability, realism, and precision (Turner et al. 2017). Every method of study raises fundamental difficulties (Dennis et al. 2018). From a study standpoint, the problems of employing can be mitigated by using an alternative approach that compensates for the limitations of others. According to Johnson and Walsh (2019), no approach to science will yield the wealth that information systems

as a discipline requires for continued advancement (Johnson & Walsh 2019). This study's research framework is divided into five distinct phases. The identification of the target population, sample size, and sampling technique are all part of the first stage. The development of questionnaires is the second step. Through a pilot study, the investigator demonstrated the selection of questionnaire parts, the validity of the questionnaire, and the survey's dependability. The data gathering procedures are the subject of the third stage. The data analysis step is the fourth stage. The research process comes to a close with the final report. Figure 3.1

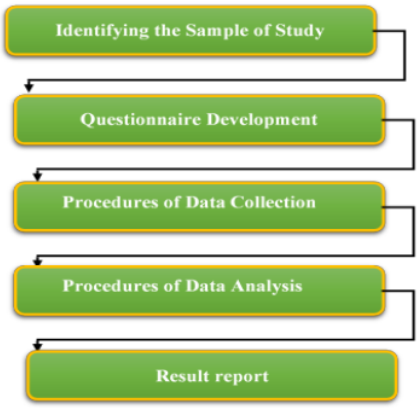

Figure 3.1: Research Framework

The quantitative method was chosen for this project because it may provide profound insights into a phenomenon through the use of numbers. The main goal of this research is to look at the elements that contribute to the adoption of Big Data analysis in Iraqi higher education institutions. As a result, the study's focus is on Iraqi higher education institutions; the quantitative technique is thus an ideal tool for gathering information on a phenomenon affecting a large number of people.

The study used a survey approach to investigate the relationship between technological advancements and the organizational capabilities and environment required for big data adoption. The search is conducted using a transverse sampling method. The study entailed collecting data from the general public at a specific site

over a period of time. The data was collected using a basic random sampling procedure.

3.3 IDENTIFYING THE SAMPLE OF STUDY

3.3.1 The study population, single frame, sample size, and sampling method are all described in this section.

3.3.2 Population

According to Ary (2009), "population" refers to the total number of people in a society who may have a set of qualities that the researcher is interested in. Bakker (2018) refers to the population as a group, which helps to generalize the findings of the study (Bakker 2018). The purpose of this research is to look into the elements that may affect higher education institutions in Iraq to adopt huge data analysis. As a result, the university employees of Iraq's higher education institutions are the study's target demographic. In Iraq, there are a number of government universities, three of which have been chosen as examples (University of Bagdad, Al-Mustansiriyah University, and University of Technology). Those universities have existed in Iraq for the longest time. The Université de Technologie is a university that specializes in technological sciences and is well-versed in big data analytics technologies. In such universities, there are 11,502 professors. The details of that university can be seen in Table 3.1.

Table The Number of Population :3.1

University name	**Year of foundation**	**Number of staff**	**Reference**
University of Baghdad	1958	6410	https://en.uobaghdad.edu.iq/?page_id=15029
Mustansiriyah University	1963	3655	https://uomustansiriyah.edu.iq/
University of Technology	1975	1437	https://www.uotechnology.edu.iq/index.php/ar/#
Total		**11502**	

3.3.3 Sample, Unit of Analysis and Respondents

The sample size is the proportion of a population that must be studied in order to obtain statistically meaningful results. The sample size can be determined as a function of the number of persons, as shown in Table 3.2, according to Krejcie and Morgan 1970 as reported by Sekaran and Bougie (2010). With a population of 11,502 employees, the number of
samples is 372, as shown in the graph below.

Table 3.2: Sample size and number

N	*S*	*N*	*S*	*N*	*S*
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335
70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	381
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Note.—*N* is population size. *S* is sample size.
Source: Krejcie & Morgan, 1970

3.4 QUESTIONNAIRE DEVELOPMENT

The primary data collection approach in this study is a questionnaire, which is an efficient method of gathering information. The questionnaire design for this study, according to Sekaran and Bougie (2010), is based on three criteria: how questions are worded, how variables are classified, and the questionnaire itself.

This research has been included in earlier surveys on the questionnaire's specialized domains. The investigation is divided into two parts. The goal of the pre-test was to produce a survey that was quicker and more accurate. The pre-test was carried out by introducing the survey and discussing it with the expert. Prior to the final transmission of the questionnaire, their findings were taken into account.

There are five sections to the questionnaire. The demographic profile of respondents, including gender, age, occupation, and education, is included in the introduction. Parts 2, 3, 4, and 5 are all independent variables. All respondents were instructed to use a five-point Likert scale to answer the questions in Section 2: 1 = strongly disagree, 2 = not supportive, 3 = neutral, 4 = supportive, 5 = extremely supportive.

The five-point Likert scale is an effective measure that provides for adequate distinction and is easily comprehended by survey participants (Sekaran & Bourgie 2019). For the multi-variable analytical procedures utilized in this study, a five-point Likert scale was found to be adequate (Hair 2010). The questionnaire for the study was written in English. Teachers in higher education are expected to be able to communicate in English.

Table 3.: Five-point Likert- scale

Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
1	2	3	4	5

In terms of technical capacity, the questionnaire covers 14 characteristics derived from previous studies. The technological competency drivers, as well as the four sub-drivers, are listed in Appendix A. (related benefits, compatibility, complexity and quality of data and information).

The third section assesses the impact of organizational capabilities on broad data analytics adoption. The questionnaire has nine variables adapted from prior studies when it comes to the organizational ability factor. The constituents of the organizational capacity factor, including the three subfactors, are shown in Appendix A. (Senior Leaders, Organizational Learning Intensity and Organizational Readiness).

Section 4 examines how the environment influences big data analysis adoption. The questionnaire has six components derived from prior studies when it comes to the environmental capacity factor. Environmental factors, including the two sub-factors, are included in Annex A. (safety and privacy regulations and institutional policies and regulations).

Section 5 assesses the likelihood of implementing big data analysis. The questionnaire, as indicated in Appendix A, consists of three parts adapted from previous studies in order to adopt the big data analysis aspect.

3.4.1 Pilot Study

Before distributing the questionnaire to the final respondents, a pilot test is performed to identify gaps, remove bias, and test the efficiency of the access calculation factor. A pilot test was conducted to calibrate the test instrument prior to data collection. This is a prerequisite for gathering final data from Iraqi university instructors. A total of 30 people took part in the pilot study.

The term "reliability" refers to the ability to track the stability and accuracy of measurement instruments. The degree to which the measurement is not tainted by random errors is known as scale reliability, and it indicates how similar the two scales are. Internal coherence in pilot test outcomes is measured using Cronbach alpha. In addition, the Cronbach alpha coefficient, which runs from 0 to 1, is an average indicator of the relationship between scale objects. Cronbach's alpha is regarded high when the correlation between the various elements of the questionnaire is significant. A minimum of 0.7 Cronbach alpha is advised as a guideline (Hair 2019).

Table 3.4 Reliability Test for the Pilot Study

Constructs	No. of original items	Cronbach's Alpha	Items Deleted
Technology capability	14	.898	Nil
Organization capability	9	.815	Nil
Environment	6	.778	Nil
Intention to adoption Big Data Analysis	3	.860	Nil

In all of the data, Cronbach's alpha looks to be greater than 0.70, which is considered acceptable. The findings are summarized in Table 3.4. The dependability of each build ranges from 0.778 to 0.898. As a result, the questionnaire will be circulated unmodified in order to collect data quickly.

3.5 DATA COLLECTION PROCEDURES

Faculty members who teach at these three universities were sent questionnaires (www.google.com/forms/) to collect data. According to the information gathered, 378 people responded to the survey. Three email lists were picked at random from each site. Senior managers, such as deans, managers, such as department heads, and university personnel are among the 500 people who received surveys via email (senior and junior). The refusal of 122 people was based on the fact that they had not completed the questionnaires. Furthermore, 26 surveys were discarded due to respondents' lack of familiarity with Big Data technologies. This means that a total of 352 questionnaires had to be analyzed. In addition, the researcher enlisted the help of an enumerator to circulate the link to the questionnaire in order to entice the chosen academic speakers to participate.

3.6 DATA ANALYSIS PROCEDURE

A method of constructing, structuring, and organizing data inside a data collection is known as data analysis (McKim 2017). This strategy is referred to by several academics as a conceptual quest. Data analysis is a type of quantitative study that is used to show data trends, discover relationships, and spot trends. It aids prospective researchers in presenting data in general (Opie 2019). Quantitative evidence, on the other hand, must be studied in a methodical manner in order to be appropriately arranged. Quantitative data analysis, according to researchers such as Lucero et al., 2018, is beneficial since it gives knowledge at numerous levels. Quantitative outcomes, according to Mihas (2019) and Lucero et al. (2018), work meaningfully through conceptualization in addition to their interpretation (Lucero et al. 2018; Mihas 2019). It must be logical and distinguishable between the data and the framework in order to ensure that, while quantitative research necessitates the employment of ideas, those ideas must be directed by the data being examined. The content of the information gathered should be represented in the study.

Almost all studies necessitate analytical results or data that can be quantified in a meaningful way in order to properly address these research questions and meet the study's goals. The data has been analyzed and evaluated. Depending on the aim of the analysis, there are a variety of mathematical methods for interpreting data (Bell 2017).

To evaluate the data and answer the study questions, two mathematical applications were used. SPSS is your primary software application. SSPS is a commonly used mathematical analysis software in the social sciences and information systems (U Sekaran & Bourgie, 2013). Because SPSS is a commonly used programming package for data analysis, it was chosen. Furthermore, this is a straightforward logarithmic program that may be used to substitute complex formulas and equations in a variety of statistics. Researchers can spend more time analyzing data using these technologies (Ghauri et al. 2020) It is typically used early in the analysis to analyze the relationship between freelancers and dependencies by measuring correlation coefficients (Ghauri et al., 2020).

SmartPLS is the name of the second program. By modeling structural equations, this technology was utilized to validate the SPSS findings (SEM). It's

simple to use because all the user has to do is enter in a structural model and specify the relevant statistics (Cheah et al. 2018). Theoretical measurements are more precise than traditional studies because to these technologies (Sarstedt & Cheah 2019). Its statistical efficiency also gives a simple approach for dealing with several relationships at the same time. It can also look at the structural model I by looking at the relationship between an independent and dependent variable, and (ii) the psychometrical qualities of constructs by looking at the link between a latent variable and its indicators.

3.7 CHAPTER SUMMARY

This part concludes with a full examination of the study methodology, research design, data collection techniques, sample size, analysis unit, and number of respondents. A discussion on the questionnaire's development was also held. Finally, a step-by-step statistical approach has been introduced.

CHAPTER IV

DATA ANALYSIS

4.1 INTRODUCTION

This section contains a full analysis of the data as well as a discussion of the study's findings. The research was carried out in Iraq's post-secondary education sector. The response was assessed using SPSS and Smart PLS after a survey questionnaire was employed. The findings provide an overview of technology, organizational capabilities, and the environment in relation to Big Data analysis adoption.

4.2 QUESTIONNAIRE FOR DATA COLLECTION

To assess and test the association between various components, quantitative research was done. Quantitative research is a quantitative approach to analyzing numerical data gathered by statistical routes (Jopling 2019). The study's major goal is to look at the factors that influence the adoption of big data analytics in Iraqi higher education institutions. With a response rate of 75.6 percent, the sampling approach was successful in collecting 352 surveys. As mentioned, this comment is in the upper range (>50%) of survey respondents (Fincham 2008).

4.3 Coding and Data Entry

The process of coding clarifies how respondent data and questions are transformed into specific categories for analytical purposes. Bougie and Sekaran (2016) Before entering the data set, it is advised that the gathered sample data be coded and transcribed from the questionnaire (Sekaran & Bougie 2016). In addition, each item on the questionnaire must have its own name, with some explicitly indicating gender, age, educational level, and so on. The data were encoded with numeric values in this study, while the elements were encoded using character symbols, and they were then entered into the SPSS software. The worksheet for coding articles and data can be found in Appendix B.

4.4 ANALYSIS OF DEMOGRAPHIC PROFILE AND DESCRIPTIVE STATISTICS

The demographic parameters of the person interviewed were measured in the first phase of the survey. The responses and feedback were analyzed using SPSS software. Table 4.1 was used to compile frequency and numerical statistics from the results.

This section contains the demographics of all interviews. Overall, the researcher sent the surveys to teachers at Iraqi universities by e-mail (The University of Bagdad, Al-Mustansiriyah University, and the University of Technology). However, only 378 people responded with legitimate questionnaires after this time frame. Table 4.1 shows demographic information for all responders. Men (73%) and women (33%) were among those who responded (27 percent). Meanwhile, the majority (46.3 percent) of the 378 respondents were between the ages of 41 and 50, with those aged 61 and up making up the smallest group (0.8 percent). Table 4.1 shows that 89.2 percent of respondents were between the ages of 31 and 50. Furthermore, 90.5 percent of those who responded to the study were married, with the remaining 9.5 percent being single.

Nearly 51.1 percent of respondents had master's degrees, while the rest have PhDs, according to the findings. The vast majority of responders (93.1 percent) were familiar with the concept of big data analysis. In terms of respondents' use of big data analytics, the results suggest that a large percentage of them (50.3%) do so, while the rest (49.7%) do not.

Table 4.1: Respondents' Demographic Profiles

Demographic	Characteristics	Frequency	Percent%
Gender	Male	276	73 %
	Female	102	27 %
Age	21-30 years	21	5.6 %
	31-40 years	162	42.9%
	41-50 years	175	46.3%
	51-60 years	17	4.5%
	Above 60	3	0.8%
Education	MSc	192	51.1%
	PhD	186	48.9%
Marital status	Single	36	9.5%
	Married	342	90.5%
Do you know what is Big Data analysis	Yes	352	93.1%
	No	26	6.9%
Have you used any Big Data analysis tool?	Yes	190	50.3%
	No	188	49.7%

Respondents completed 378 questionnaires, 26 of which were invalid and were not included in the study. The major aspects of the dataset from the respondent's perspective in regard to each element were described and summarized using descriptive statistical analysis.

The average and standard deviation for the search variables are shown in Table 4.2. All responses were given on a 5-point Likert scale, with 1 indicating strong

disagreement and 5 indicating strong agreement. To clarify the definition of the degree of agreement for the variables, award standards based on average values were employed.

An average score of 2.49 or lower was regarded "poor," while a score of 2.50 to 3.49 was considered "moderate," and a score of 3.50 or higher was considered "high."

The following were the average scores for the factors: Relative Advantage (mean = 3.2121, SD = 1.19398), Compatibility factors (mean = 3.2633, SD = 1.03446), Complexity (average = 3.2169, SD = 0.95879), and data and information quality (mean =2.8562, SD = 1.04721) are the four characteristics that make up Technological Ability. There are three aspects to organizational capability. Top Management (mean = 3.1629, standard deviation =.98355), Organizational Learning Strength (mean = 2.1004, standard deviation =1.00302), Organizational Readiness (mean =2.8731, standard deviation =.91330), and Environment (mean = 3.1089, standard deviation =1.05850) Table 4.2 Descriptive Statistics Mean, Standard Deviation

Variables	Mean	Std. Deviation
RA	3.2121	1.19398
CA	3.2633	1.03446
CL	3.2169	.95879
DIQ	2.8562	1.04721
TM	3.1629	.98355
OL	2.1004	1.00302
OR	2.8731	.91330
SR	3.1089	1.05850
PR	3.0814	.99205

4.5 NORMALITY TEST

The normalcy test, which is employed as the principal data test, is one of the most commonly utilized processes for data reduction and synthesis. Performing a Normality Check The normalcy test is one of the processes most commonly used to reduce data and summarize, and it is also the primary test for data. As part of this investigation, a

normality audit was performed to standardize the data for analysis. There is no value above the approved range of normality (kurtosis and skewness), as indicated in Table 4.3, for kurtosis (normalcy range between -3 and +3), and for asymmetry (-1.96, 1.96) as suggested by Hair et al (2013). Asymmetry ranged from (-0.340 to 1.154) and kurtosis from (-0.340 to 1.154), as seen in Table 4.3. (-1.074 to 0.657).

As a result, it may be stated that the dataset was regularly distributed among all objects.

Table 4.3: Assessment of Normality for Model

Items	**Skew**	**Kurtosis**	**Distribution Statues**
BDA1	. 275	-.391	Normal
BDA2	.257	-.355	Normal
BDA3	-.005	-.649	Normal
CA1	-.227	-.749	Normal
CA2	-.306	-.661	Normal
CA3	-.114	-.792	Normal
CL1	.013	-1.002	Normal
CL2	-.141	-.665	Normal
CL3	-.340	-.391	Normal
DIQ1	.051	-.835	Normal
DIQ2	.303	-.853	Normal
DIQ3	.037	-.910	Normal
DIQ4	.123	-.986	Normal
DIQ5	.123	-.870	Normal
TM1	-.182	-.680	Normal
TM2	.130	-.752	Normal
TM3	.084	-.714	Normal
OL1	1.154	.657	Normal
OL2	.809	-.260	Normal
OL3	1.089	.550	Normal
OR1	.376	-.818	Normal
OR2	.223	-.696	Normal

Items	Skew	Kurtosis	Distribution Statues
OR3	.105	-.683	Normal
PR1	-.075	-.664	Normal
PR2	-.035	-.646	Normal
PR3	.088	-.638	Normal
RA1	-.141	-1.074	Normal
RA2	-.191	-1.097	Normal
RA3	-.200	-1.052	Normal
SR1	-.059	-.880	Normal
SR2	-.038	-.769	Normal
SR3	-.196	-.793	Normal

4.6 REFLECTIVE MEASURES RELIABILITY

The test's accuracy and validity were assessed using a reflecting design. The former and the latter are two sorts of structures. Furthermore, the item count is given.

The prediction factor should be greater than 0.70, and the significance threshold should be 0.05, according to (Ringle et al. 2020). The latent variable will describe its expected variation by at least 50% at 0.70 load (Ringle et al. 2020). During the indicator reduction phase, researchers should follow PLS criteria, according to Wong (2019). If a given indicator's reliability value is less than 0.70, it should be excluded, and the exclusion should be expanded to include more than the RCA value. It's worth noting that the load numbers in this analysis are higher than the reference value of 0.70. (Wong, 2019). As a result, none of the indications were dropped from the action list. Table 4.4 shows the costs of external construction.

Table 4.4: Factor Loading

Factor	Sub-Factor	Items	Loadings
TC	RA	RA1	0.912
		RA2	0.940
		RA3	0.887
	CA	CA1	0.923
		CA2	0.911
		CA3	0.882
	CL	CL1	0.840
		CL2	0.828
		CL3	0.853
	DIQ	DIQ1	0.784
		DIQ2	0.808
		DIQ3	0.895
		DIQ4	0.869
		DIQ5	0.885
OC	TM	TM1	0.852
		TM2	0.894
		TM3	0.830
	OL	OL1	0.904
		OL2	0.841
		OL3	0.878
	OR	OR1	0.753
		OR2	0.821
		OR3	0.810
E	SR	SR1	0.896
		SR2	0.930
		SR3	0.878
	PR	PR1	0.841
		PR2	0.876
		PR3	0.872

During the next phase, the effectiveness of the reflective measures was tested. Composite reliability was used to assess the accuracy of the reflex readings. The reliability of composites, according to Karakaya et al. (2018), is a more secure approach since it accounts for uniform charge and calculation mistakes for each component above the alpha factor. Cronbach alpha () has limits; for example, it implies that all items have an equal distribution of reliability; in the current study, all characteristics are utilized to assess the level of reliability. The Cronbach value in all buildings, according to our findings, is greater than 0.70. Furthermore, the total confidence value for all measures is higher than the reference value of 0.70. (Karakaya et al. 2018). As a result, the results attest to the procedures' internal accuracy. Cronbach's Alpha and composite dependability are shown in the table below.

Table 4.5: Reflective Constructs Reliability

Construct	Cronbach's Alpha	composite reliability
RA	0.900	0.938
CA	0.890	0.932
CL	0.793	0.878
DIQ	0.903	0.928
TM	0.822	0.894
OL	0.846	0.907
OR	0.709	0.837
SR	0.884	0.928
PR	0.830	0.938

4.7 REFLECTIVE MEASURE VALIDITY

Both discriminatory and converging criteria were used to determine the validity of the reflexive measurement (Açkgöz & Latham 2018). To test consistency across several transactions, convergent validity was used. The statistical values t show the significance of the total factor burden at p 0.000 in the literature (Açkgöz & Latham 2018). Table 4.6 shows an example of the eTA for structures. It's worth noting that all

of the measure's values match the minimum converging validity requirements (Gefen et al. 2000). With a minimum value of 0.50, the mean extracted variance (VA) is a typical metric of convergent validity (Hair et al. 2013). For latent structure measurement, at least 50% of the measurement variance (indicator) was chosen (Chin 1998). In this study, the reliability and validity of all designs were rigorously assessed.

Table 4.6: AVE for Constructs

Construct	AVE
RA	0.834
CA	0.820
CL	0.706
DIQ	0.721
TM	0.738
OL	0.765
OR	0.632
SR	0.812
PR	0.746

Discriminant validity is used to evaluate the validity of structures. The term discriminant validity refers to a set of independent conceptions that are each constrained to only one indication (Hair et al. 2014). To assess discriminating validity, several approaches are utilized, including (I) the Fornell-Larcker criterion, (II) cross-loads, and (III) Heterogeneous Monotherapy Analysis (HTMT). To begin, check the square root of the eTA for each factor along with its connections with other factors to determine discriminating validity (Cheung & Wang 2017). Table 4.6 indicates that eTA 2 is bigger than the correlations between the factors for each factor. The discriminatory validity of the factors is obtained when the relevant factor exceeds the variance of the measurement error.

Furthermore, within its own indicators, the PLS trajectory model was used to reinforce the concept of dominant thought (Hair Jr, Hult, Ringle, & Sarstedt, 2016). This is yet another way to verify the validity of discriminant validity assessment. As evidenced by a simulation study, these methodologies systematically identify the absence of discriminating validity in frequent research scenarios, according to Sarstedt et al. (2014). (Sarstedt et al. 2014). The Hetrotrait-Monotrait correlation ratio can also

be used to determine the accuracy of discriminatory validity (HTMT). The variance-based MET technique can also be used to explain HMTM (Templeton et al. 2019). HTMT is expected to be less than 0.85 or 0.90 (Kline 2011). (Henseler et al. 2015). The EMHT's negative correlation isn't a problem. The relationship between Hetrotrait and Monotrait is depicted in Figure 4.7.

Table 4.7: Hetrotrait-Monotrait Ratio of Correlation (HTMT)

	CA	**CL**	**DIQ**	**OL**	**OR**	**PR**	**RA**	**SR**	**TM**
CA									
CL	0.086								
DIQ	0.04	0.48							
OL	0.049	0.189	0.391						
OR	0.104	0.142	0.11	0.147					
PR	0.055	0.285	0.242	0.095	0.173				
RA	0.362	0.252	0.317	0.165	0.095	0.033			
SR	0.17	0.249	0.168	0.18	0.146	0.062	0.065		
TM	0.465	0.257	0.232	0.232	0.172	0.315	0.246	0.375	

4.8 FORMATIVE MEASURE VALIDITY

The training validity differs from the reflexive measurements in terms of reliability (Ringle and Sarstedt, 2016). There are three techniques to determine the validity of a formative measure (Hair et al. 2014). One of the accepted ways for determining the validity of formative measurement is multilinearity.

4.8.1 Multicollinearity

The weight and level of importance of the indicators depends on the colliarity among the training indicators (Hair et al. 2013) which can be viewed through the Variance Inflation Factor (LIVELY). If the value exceeds the standard value of 5.00, then there are collision issues in the formative indicator. Table 4.8 shows the results of the secondary multi-collinear formative design. All VIF observations in the multiple collinear formative construction are less than 5.00.

Table 4.8: Formative Constructs Multi-Collinearity

Factor	Sub-Factor	VIF
TC	RA	1.257
	CA	1.144
	CL	1.23
	DIQ	1.271
OC	TM	1.054
	OL	1.049
	OR	1.028
E	SR	1.001
	PR	1.001

4.9 ANALYSIS STRUCTURAL MODEL ESTIMATION

The structural model's main goal is to answer research questions by putting submitted research hypotheses to the test. After confirming the variable's reliability and validity, internal and structural models can be used in the study. A look at the internal model reveals how the empirical evidence supports the underlying hypotheses in this research. It also determines the relationships between hypothetical factors and predicts the competency model. The SDLC's major purposes, as mentioned in the dependent variable, are to minimize error or maximize variance. The CDS model can be created by verifying and analyzing the values of the dependent variables' coefficients of determination (R2). The coefficient of determination (R2) and the trajectory coefficients can thus be used to assess the validity of the structural model. The three assumptions for the direct relationships investigated in the structural model are listed in the table below.

Table 4.9: List of Hypotheses

Hypotheses	Relationship
H1	TC→BDA
H2	OC→ BDA

H3	E→ BDA

Three research assumptions are inextricably intertwined. H1 shows the direct link between technological competence and the desire to use big data analytics, while H2 shows the link between organizational capability and the desire to use big data analytics. H3 establishes a direct link between the environment and the desire to use big data analytics.

4.9.1 Coefficient of Determination (R2)

The total variance between the independent variable (IV) and the dependent variable (D) is represented by R2 (V). The higher the R2, the better the forecasting power of a structural model. In this exam, the value of R2 is calculated using the Smart-PLS algorithm's function, while the t-statistics value was calculated using the Smart-PLS bootstrap function. The bootstrap generated 1000 samples for 352 patients in this study. At the same time, the 51.4 percent discrepancy in intent to embrace big data analytics is due to technological capacity, organizational capacity, and the environment.

4.9.2 Path Coefficients

Within a structural model, the route coefficient specifies the relationship between the latent variable (VG). When two GVs are linked together, an assumption is formed. Meanwhile, the trajectory coefficient can be used to calculate a summary of all results. It is also marked as "p" in the structured model, which was initially unknown and estimated in connection with the resolution of the PLS-SEM technique. The building scores, which are used to evaluate the regression model, were then produced by the method. Only when the p-value (probabilistic value) is less than 0.05 and the t-value is larger than 1.96 does the result appear meaningful. The structural profile is depicted

in Figure 4.1, along with the result of the bootstrapping method.

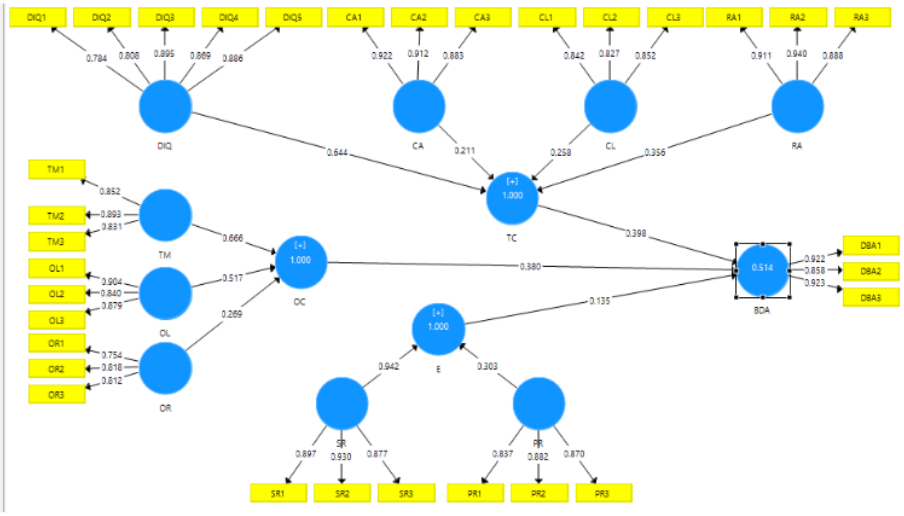

Figure 4.1: Structural Model with Path Coefficient

The magnitude and level of relevance of the trajectory coefficients can be determined using the structural model. However, the outcome should be assessed using SEMS-structural SDP's model. The assumptions developed were tested using the SDP by looking at the path coefficient, meaning of the path, and explanation of the variance. The proper model validity level was tested for convergent validity, discriminant validity, and reliability prior to the hypothesis test. Table 4.10 shows the results of the trajectory coefficient, degree of meaning, and statistics t.

Table 4.10: Path Coefficients

Hypotheses	**Relationship**	**Path Coefficient**	**T-Statistics**	**P-Value**	**Direction**
H1	TC→BDA	0.398	7.482	0.000	Supported
H2	OC→ BDA	0.380	7.966	0.000	Supported
H3	E→ BDA	0.135	2.525	0.012	Supported

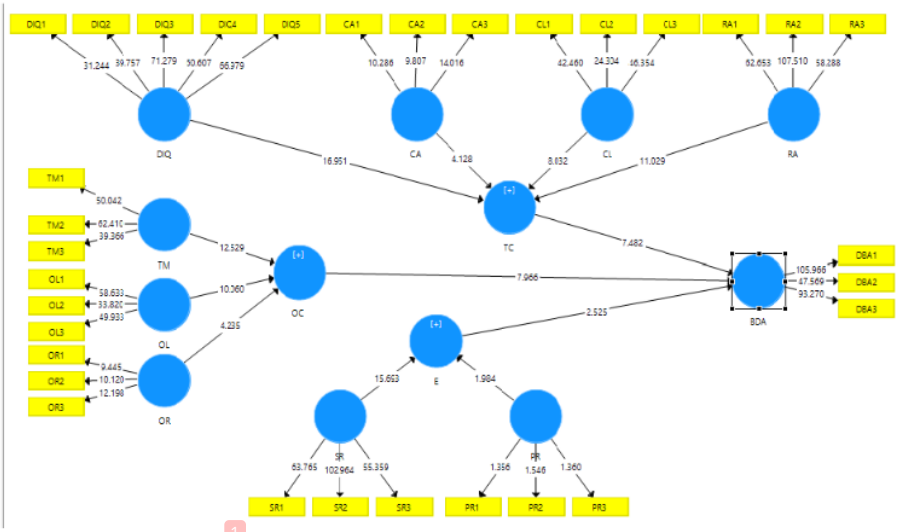

Figure 4.2: Structural Model with T-Values

AR = relative profit, AC = compatibility, CL = complexity, IQD = data and information quality, CT = technology capability, MT = senior management, OL = organizational learning intensity, RO = organizational preparation, CO = organizational capacity, SR = Security/Privacy Regulatory, PR = Institution Policy and Regulation, E = Environment, BDA = Intention of adopt large data analysis.

There are three research assumptions connected to direct relationships, and the structural model's conclusion reveals that all of the research assumptions are supported. The findings reveal that technical capacity has a substantial impact on the intention to use big data analysis (p 0.000, t = 7.482), indicating that the H1 hypothesis is supported. Similarly, organizational capability has a substantial impact on the intention to use big data analytics (p 0.000, t = 7.966) and supporting the H2 hypothesis (p 0.000, t = 7.966). Furthermore, the findings demonstrate that the environment has a substantial impact on the intention to do big data analysis (p 0.012, t = 2.525) and supports the hypothesis H3.

4.10 CHAPTER SUMMERY

The results of the statistical analysis of the data acquired through the survey of Iraqi university teachers are reported in this section. There were 378 questionnaires returned, 26 of which were disabled and were excluded from the study. The findings showed that technology capacity, organizational capacity, and the environment all had a statistically significant and favorable impact on the desire to use Big Data Analytics. As a result, these findings show both the theoretical and practical benefits of success factors for big data analytics adoption in Iraqi higher education institutions.

CHAPTER V

DISCUSSION, CONCLUSION AND IMPLICATION

5.1 INTRODUCTION

The fifth chapter of this study is the concluding one. The current chapter is a wrap-up of the preceding chapters, in which the search results are examined and relevant

recommendations are provided based on the findings. The findings of the study revealed that the study's goal, namely, the result of the recognition of technology, the organization, and the environment with the use of Big Data, had been met. Nonetheless, the first section of this chapter will cover an overview of research accomplishments, management engagement, theoretical involvement and limitations, as well as further exploration and conclusions.

5.2 SUMMARY OF RESEARCH ACHIEVEMENTS

This section summarizes the accomplishments of the research objectives as derived from the research questions.

5.2.1 Research Question 1: What are the critical success factors for the uptake of big data analytics in Iraqi higher education institutions?

Research Objective 1: Identify critical success factors for the adoption of big data analysis in Iraqi HEIs.

A literature review was used to achieve this research purpose.

The literature study reveals that three primary elements influence the intent of big data: technological, organizational, and environmental capability; these characteristics are critical for the effective adoption of big data analytics at higher education institutions. These aspects are relevant to establishing a hypotheses-driven research model to give a foundation for the propositions made in this study, as they take into account the environment. As a result, in that investigation, the TOE framework was used.

5.2.2 Research Question 2: What model could support the uptake of big data analytics in Iraqi higher education institutions?

Research Objective 2: Propose a model that could support the adoption of mass data analysis in Iraqi higher education institutions.

The second goal was accomplished through the development of a theoretical model that can help Iraqi higher education institutions adopt enormous data analytics. A theoretical model has been proposed in order to achieve the latter. The proposed approach is being evaluated using data from a survey of 352 speakers from Iraqi universities (University of Baghdad, Al-Mustansiriyah University and Technological University). The study found that technological factors (p 0.000, ß = 0.398), organizational factors (p 0.000, ß = 0.380), and environmental variables (p 0.005, ß = 0.135) are relevant with the adoption of big data technology, according to statistical analysis using SPSS and Smart PLS. The findings imply that the model is acceptable for investigating the higher education sector's use of big data technology.
The goal of this research is to look at the factors that influence the use of big data analytics in Iraqi higher education institutions. Three assumptions are made in this analysis. All of the assumptions are backed up by evidence.

Hypothesis 1: Technology capacity has a major impact on the intention to adopt big data in Iraqi higher education.

Hypothesis 2: Organizational capacity has an important impact on the intent to adopt big data in higher education in Iraq.

Hypothesis 3: The environment has a significant impact on the intention to adopt mass data in higher education in Iraq.

5.2.3 Research Question 3: What is the status of the adoption of Big Data analyses at Iraqi HEIs?

Research Objective 3: To determine the status of the adoption of big data analytics in Iraqi HEIs.

A survey of 352 instructors from three Iraqi institutions was done in order to examine all three criteria. To determine the association between the proposed variables and big data technologies, the smart CDS was utilized. According to the findings, higher education institutions considering adoption should seek assistance from senior management, since their constructive involvement is critical to the adoption process. This research demonstrates a high level of IT expertise in the

adoption of information technology. The findings also show that a lack of technology has an impact on the application of technology. Similarly, the higher education industries are facing considerable developmental issues as a result of uncertainty, which is expected to be exacerbated by a lack of internal IT capabilities. As a result, higher education institutions should strive to improve internal IT competencies through preparedness and recruitment in order to manage sophisticated computing challenges and security risks associated with big data technologies. As a result, workers in the higher education industry must identify and prepare for the challenges of technology adoption, which IT suppliers can exploit by providing resources to help them increase their capacity and IT skills. The findings of this study also suggest that the effectiveness of technological development can influence the adoption of big data technologies. As a result, in addition to materializing on technology hardware, previous fundamental knowledge of Big Data technology, particularly the management operating system, must be adopted in the higher education sector. According to the findings, the proposed research framework is significantly linked to the use of megadata technologies in higher education. Furthermore, there is a scarcity of research on big data documentation (Oussous et al. 2018). As a result, this work adds to the body of knowledge on the use of submitted data in eLearning technologies.

5.2.3.1 Technology Capability

Iraq's higher education industry has the technological capability and the desire to embrace big data. The findings reveal that technological capability has a significant impact on the desire to use big data analytics (p 0.000, t = 7.482). The studies revealed that these colleges require technology resources to improve electronic information interchange with MOHESR. While their staff have received training in the use of information technology, these colleges appear to have already created some level of IT infrastructure, and they are seeking to increase their software, hardware, and IT capabilities. Most colleges, on the whole, lack cutting-edge computing facilities, and workers have little computer skills and experience. The study's findings open up the possibility of a conversation about how technological aptitude effects the rising usage of big data in higher education. The majority of big data projects rely on existing information technologies and individual talents. This allows institutions to make advantage of their existing big data skills and technology while also enhancing their

skills and infrastructure for boosting online learning. In this regard, a new technology could be very valuable for integrating big data into higher education. In order to use Big Data, it is proposed that universities adopt appropriate free intelligent mobile applications. The department's technology resources, on the other hand, can be leveraged to assist public institutions in acquiring compatible, low-cost technologies. Additionally, it can aid by training university staff and offering direct assistance via phone or email.

5.2.3.2 Organization Capability

In Iraq's higher education industry, organizational competence and willingness to adopt big data. The findings demonstrate that organizational capacity has a significant impact on big data analytics adoption intentions (p 0.000, t = 7.966). The findings demonstrate that senior executives consider big data use in higher education as a critical component of their university's success. Employees are also encouraged to use big data technologies to help them do their tasks more efficiently. They can also utilize awards or incentives to encourage their personnel to use big data more. In general, government university officials are interested in using cutting-edge technology like big data to digitize university information. Furthermore, the findings show that top management support is required to give the necessary financing, and that additional resources are available to exploit big data.

5.2.3.3 Environment

The environment and the use of big data in Iraq's higher education industry. The findings reveal that the environment has a significant impact on the decision to use big data analytics (p 0.005, t = 2.525).

The findings suggest that legislation and regulations for big data adoption are needed at public colleges. As a result, public institutions are looking for legislation and policy to help them organize their massive amounts of data. Furthermore, legislation and procedures can help to reduce hazards to employees while sharing university information with departments using big data. As a result, legislation and rules can help employees feel more at ease with big data.

Based on these findings, it can be stated that the policy/legal framework in Iraqi public universities can accommodate big data. Having a robust legislative framework

in place, as well as interuniversity policies, could aid in the adoption of big data in these universities. As a result, the ministry must create laws and policies that are tailored to their needs as well as the needs of public institutions. Furthermore, these laws and regulations must be intelligible and simple to implement for party officials.

5.3 CONTRIBUTIONS OF STUDY

As we will see in the subsections that follow, this study has ramifications for both management and theory.

5.3.1 Managerial Implications

The successful implementation of big data technologies is influenced by a few key aspects. To begin with, senior management views and decisions are critical in determining the adoption rate at all levels of company transformation, from traditional to IT management. This function, as well as the position of senior management, has been shown in several studies to have a substantial impact on the adoption rate in the formation of a positive organizational climate in new technology innovation. Executives also have the ability to include and organize sufficient business capital to inspire, acquire, and implement new advances. Managers are in charge of properly planning and managing assignments, as well as the capital invested in the use of Big Data to allow for more efficient practice in their movies. This suggests that senior management should concur that it has the biggest influence on the adoption process. As a result, given the importance of senior management support in advancing the adoption of Big Data technology, leaders should be actively involved at every stage of the process.

Second, it is apparent that the perceived obstacle and lack of IT skills in the area of human resources is limiting big data adoption. In terms of complexity, our findings support the notion that the more the perceived complexity of advancing IT, the higher the cost of behavioral adjustment, which precludes prospective adopters from monitoring implementation after a decision is made. Low IT skills are an impediment to adoption, but not to decision-making, according to this study. If not, senior management should offer extensive training and a skilled IT workforce capable of

enhancing the worker's ability to deal with IT challenges. In the end, the measurement boosts staff productivity and profits. The current issue, as well as the adoption decision, is seen as a challenge, and the application of security issues in Big Data technology can be addressed by hiring new employees with computer skills and improving IT literacy in human capital through internal education and sharing. However, because of the restricted amount of IT expertise within the associated organization, it is also crucial to mention that the recruitment process is becoming more difficult. As a result, existing workers should be prepared to give internal computer skills. The strategies indicated above are vital for senior management to consider as the Big Data market expands over time in order to successfully lessen the impact of anticipated hurdles and a lack of IT knowledge associated to technology adoption in the near future.

5.3.2 Theoretical Implications

5.4 This research is a first step toward developing a strategy for investigating the operational adoption of Big Data technology. This document adds to the growing body of knowledge on Big Data and Innovation. First, the study conducted a thorough examination of scientific education understanding and empirical analysis of big data technologies across the organization, including in Iraq. Second, the study evaluates the validity of the TOE framework for big data assimilation using a range of models such as SPSS and PLS. Third, the study looks at how variables should be measured and conceptualized in the context of big data adoption. The study's final conclusion is that the implementation process, rather than the decision, should drive successful adoption of big data.

5.5 LIMITATIONS AND FURTHER RESEARCH

This research sheds new light on the factors that influence the adoption of Big Data technology. As a result, higher education can benefit from a better knowledge of the factors that drive and stifle the adoption of big data technology. In addition, several studies on big data adoption are gaining traction as a result of this research. Future study will focus on making the findings more widely available and improving the

organizational foundation for using big data technology in a variety of ways. To begin with, the analysis is based on data from only one location, and the conclusions are insufficient to represent the worldwide community as a whole. Future research could produce generalized findings by evaluating the proposed research paradigm in a number of different nations. Furthermore, this research was limited to three university experiments, implying that the findings may not be applicable to the general population. In terms of scale, future studies may benefit from examining a larger number of organizations. This could provide insight into the importance of company size as a factor to consider in future Big Data adoption research.

CONCLUSION

Big Data presents a plethora of intriguing opportunities while also being a significant obstacle. It is important and suitable for the higher education sector to embrace big data technology as investments in big data grow. The Iraqi big data technology market is expected to grow at a slower rate than the rest of the world (Patil and Thakore, 2017). The goal of this study was to identify the elements that influence the acceptability of Big Data technology in Iraq's higher education sector. Using the literature on innovation adoption, this project identified three adoption factors (TOE) in three major contexts: technology, organization, and environment, and assessed their impact on big data technology adoption.

1. Based on the findings of that study, a list of factors was developed, and finally, a model for adopting big data in the Iraqi higher education sector was proposed. These findings contribute significantly to departmental and academic planning, as well as the implementation of high-impact strategies; technological, organizational, and environmental issues, in order to increase engagement and Big Data usage between them in the future. Adopting Big Data at universities can aid and enhance e-learning while also assisting decision-makers in making better judgments for teachers. In this approach, the capacity to make better decisions may create a favorable climate that encourages universities to perform at a higher level of quality and to make quick decisions for themselves. Furthermore, this might be a beneficial setting for pupils.

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