FACTORS OF BIG DATA ANALYTICS ADOPTION BY THE LECTURERS IN IRAQ

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As data drives the digital evolution, the role of big data becomes increasingly essential. Big data is making its presence known in almost every industry and has the potential to not only transform the business world but society on a large scale. Given that the higher education sector in iraq is still in the early stages of making use of big data, studying factors affecting the adoption of big data technology in iraq is critical and timely. Grounded in the technology-organization-environment (toe) framework, an integrative model is developed for studying factors affecting the adoption of big data technology. The model specifies technology factors, organization factors, and environment factors as determinants of assimilation. The proposed model is tested using survey data collected from 352 lecturers of iraqi universities (the university of bagdad, al-mustansiriyah university, and the university of technology). Employing statistical analysis through spss and smartpls, this study found that technology factors ($p < 0.000$, $\beta = 0.398$), organization factors ($p < 0.000$, $\beta = 0.380$), and environment factors ($p < 0.012$, $\beta = 0.135$) are significant with adoption of big data technology. The results indicate that the model is suited for studying the higher education sector adoption of big data technology. Finally, the findings have important implications for practitioners and researchers.

I. INTRODUCTION

In the past few years, Big Data technology has been renowned in various areas extending across business management, government policy, market statistic, and research development (Dagiliene & Kloviene 2019). Big Data Analytics is defined as a method to analyze data from a vast data set by utilizing computer algorithms, programming and mathematical modeling techniques to discover the valuable trend promptly. This way, actionable viewpoints that direct management decisions inside an organization may be derived (Del Vecchio et al. 2018). The main applications of Big Data are to optimize consumer engagement, understand user behavior patterns, and leverage resources. It also allows discerning patterns and abnormalities from data sources (O'Connor 2017). Aldholay et al. (2018), proposed that the practice of evaluating key variables might transform the business into an effective adoption of the new Big Data technologies.

Despite the significant advantages of the introduction of Big Data explained in the literature, the general issue of the research is the various obstacles associated with technology, corporate culture and strategy. The adoption of Big Data is an essential prerequisite for ensuring that its intended benefits materialize. There is, however, a lack of awareness as to the influence of such operational influences on the adoption of the Big Data adoption (Braganza et al. 2017). This research work will focus on analyzing the factors that would motivate higher education institutions to adopt Big Data. in Iraq, the higher education sector has a range of institutions that have implemented e-learning, producing Big Data that need to be analyzed (Mark 2019; Jovanovic Milenkovic et al. 2019; Prasetyo et al. 2019). It is also important to define the main success drivers for the adoption of Big Data initiatives in higher education institutions.

II. RESEARCH MODEL AND RESEARCH QUESTIONS

The main objective of this study is to propose a framework for the adoption of Big Data technology in higher education institutions in Iraq. In order to achieve this objective, the following are the sub-objectives that guide this study:

The first is to identify the critical success factors for the adoption of Big Data Analysis in Iraqi higher education institutions. And then propose a model that could support the adoption of Big Data Analysis in Iraqi higher education institutions. Finally, is to determine the state of Big Data analytics adoption in Iraqi higher education institutions.

Those objectives aim to answer the questions below:

- What are the critical success factors for the adoption of Big Data Analysis in Iraqi higher education institutions?
- What is the model that could support the adoption of Big Data Analysis in Iraqi higher education institutions?
- What is the state of Big Data analytics adoption in Iraqi higher education institutions?

III. LITERATURE REVIEW

Big Data is a concept used to characterize a vast quantity of data. Data can be organized or unstructured. Big Data analysis brings every company to stronger decision-making and decisive action. Companies in industries such as banking, engineering and government departments are using Big Data to achieve their market and strategic goals. Big data analysis also plays a crucial role

According to Zulkarnain et al. (2019), over the last decade, governments across the world have been seeking to utilize Big Data technologies to enhance public facilities for people. Big Data technology has expanded to most nations; however, the rate of effective adoption and management are varied from one country to another. The government has used the systematic literature analysis (SLR) to define the essential success factors (CSF) in Big Data implementation. This includes the crucial progress element in the government's implementation of Big Data during the last 10 years. It presents the general developments of 183 journals and various literary works relevant to government activities, the provision of public facilities, community engagement, decision-making and policymaking, and governance change. We picked 90 journals and established 11 classification criteria that relate to the successions of the procurement of Big Data by the Government (Zulkarnain et al. 2019).

Wright et al. (2019), discuss the application of Big Data in creativity and business leading in B2B relationships. It offers a structure for the study of the effects of Big Data, accompanied by four case studies. This is a conceptual document, backed by case studies, which offers an opportunity for generalization of the definition. Case study companies are innovating to remain ahead of the competition and extend their operations, leveraging Big Data to tap into marketing possibilities and to develop innovative products.

According to Maroufkhani et al. (2020), the advent of Big Data Analytics (BDA) is playing a key role in precise decision making and optimum productivity in the modern industrial environment.

According to Shahbaz et al. (2019), Big Data Analytics has received tremendous attention in the healthcare sector due to its creative approach that eases decision-making and increases strategic growth rate. Therefore, the research investigated the framework for introducing Big Data Analytics in healthcare institutions. There are many factors that have been studied in the adoption of big data as shown in Table 1

Table 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)					√		√	√	

Based on the above mention this literature can be concluding as the definition of Big Data has been described as well as providing the advantages of this modern innovation technology in order to give the higher education sector competitive advantages. Herein, the different explanations and suggestions on the Big Data implementation in the higher education sector have been proposed.

Furthermore, Technology adoption is the key to encourage hesitant users to use technology successfully. The need for technology adoption originates from rapid development and circumstances that compel people to adopt technology. Several theories have been used to examine technology adoption in information systems research (Oliveira & Martins 2010). One prominent model at the organizational level is technology–organization–environment (TOE) framework (Tornatzky & Fleischer 1990).

The current study attempts to adopt the big data analysis model to the higher education institution in Iraq. Based on a comprehensive review of information systems literature, the technology capacity e.g. (Akter et al. 2016; Ji-fan Ren et al. 2017; Kim & Park 2017; Wamba et al. 2017; Y. Wang et al. 2018), the organization capacity e.g. (Cao & Duan 2014; Dutta & Bose 2015; Gupta & George 2016; Halaweh 2015; Janssen et al. 2017), and environment e.g. (D. Q. Chen et al. 2015; Popovic et al. 2016; Y. Wang et al. 2018), are the main factors that affected to adopt big data analysis. These factors are discussing below.

- Technology capability refers to the ability of IT infrastructures and analytics platforms to transform big data into valuable information and provide valuable knowledge to decision-makers. The items that include technology capability are a relative advantage (Y. M. Wang & Wang 2016), compatibility (Alsaad et al. 2017), complexity (Verma, S. 2017), and data and Info quality (Park & Kim 2016). Therefore, data infrastructure is acknowledged as the key success factor in the application of big data in higher education institutions.
- Organization capability refers to the ability of the organization to strategize and manage the BDA implementation effectively (Kung et al. 2015) and is regarded as the key success factor in the application of big data in higher education institutions. The items that include organization capability include top management support (Halaweh 2015). the intensity of organizational learning (Ahmad Salleh et al. 2016). and organizational readiness (D. Q. Chen et al. 2015).
- Environment factor: refers to understand the advantage of using big data in enhancing organizational performance in higher education institutions. This factor may facilitate the improvement of the BDA capability and creating a new learning model. The items include the security/privacy regulations (D. Q. Chen et al. 2015). and Institution policy and regulation (Hsu et al. 2014).

IV. METHODOLOGY AND DATA COLLECTION

This study applies a quantitative method that involved a survey to collect data from public universities' lecturers in Bagdad (University of Bagdad, Al-Mustansiriyah University, and the University of Technology). In this study, the research methodology process is breaking down into five key stages. In the first stage, the target population, sample size, and sample technique are identified. The second stage focuses on questionnaire development. In this stage, the researcher illustrated the questionnaire items selection, the questionnaire validity, and the questionnaire reliability through a pilot study. The third stage is the procedures of data collection. The fourth stage focuses on data analysis. The result report is the last stage of the research process. The outline of the research framework is illustrated in the Figure 1 below.

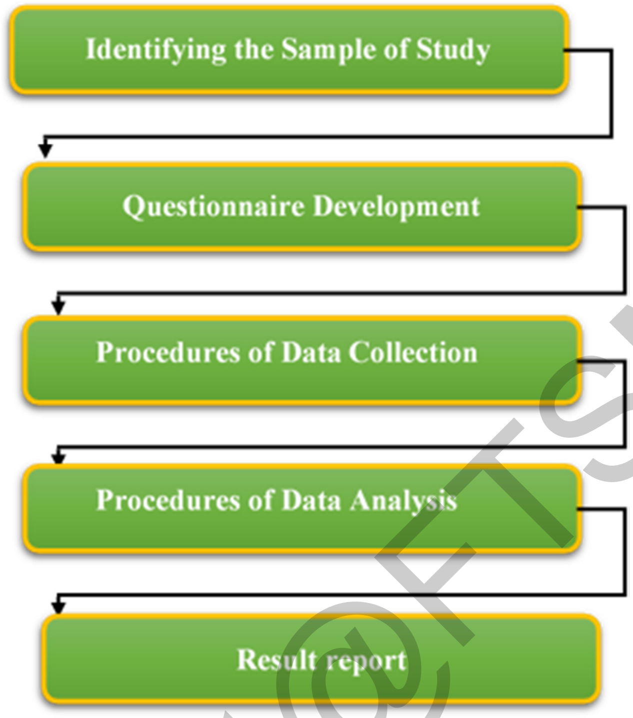

Figure 1: Research Framework

This section explains the study population, the simple frame, sample size, and sampling technique. the current study seeks to examine the factors that may influence higher education institutions' adoption of Big Data Analysis in Iraq. Therefore, the present study's target population is the academic staff of higher education institutions in Iraq. There are several public universities in Iraq, where three main universities have been chosen as samples (University of Bagdad, Al-Mustansiriyah University, and University of Technology). These universities are the oldest university in Iraq. The University of Technology is a university that specialized in technical sciences, which is the most familiar with the fields of Big Data analysis techniques. The number of the academic staff of these universities is 11,502 lecturers. Sample size refers to the subset of a population required to ensure significant results. According to Krejcie and Morgan 1970 as written by Sekaran and Bougie (2010) states that the sample size can be determined based on population number, then with a population of 11502 staff then the number of samples is 372 people. a 5-point Likert-type scale is considered appropriate for the multivariate analysis techniques used in the current study (Hair 2010).

Data collection was done by sending questionnaires using (www.google.com/forms/) t to lecturers who give classes in these three universities. three lists of emails from each university had been chosen from it randomly. Out of the 500 questionnaires have been sent by email to lecturers, those lectures are top managers such as deans, manager such as department leaders, and academic staff (senior and junior). From the data collected, as many as 378 respondents filled out questionnaires. 122 were discarded because questionnaires were not answered. A further 26 questionnaires were discarded because the respondents stated that they did not know about big data technology. Thus, the total number of questionnaires for data analysis was 352. Furthermore, the researcher had acquired help from a person as an enumerator to circulate the questionnaire link to motivate university lecturers that were selected.

V. RESULTS & DISCUSSION

A quantitative research method was conducted in order to measure and test the relationship between different factors. Quantitative research is defined as a mathematical approach to analyses the collected numerical data in statistic pathways (Jopling 2019). The main objective of the study is to examine the success factors on Big Data analysis adoption in Iraqi Higher Education Institutions. There are 378 questionnaires collected from the simple random sampling technique and recorded a response rate of 75.6%. This feedback falls within the excellent range (>50%) of the survey responses, as stated by (Fincham 2008). A further 26 questionnaires were discarded because the respondents stated that they did not know about big data technology. Thus, the total number of questionnaires for data analysis was 352.

Two mathematical applications were used to analyze the data and address the research questions. The first software application is SPSS. The second software program is Smart PLS. The first section of the questionnaire measured the demographic profile of the respondent. The SPSS analysis was used to analyze the responses/feedback for 378 respondents. The results presented that male respondents rate (73%) and females (27%). Meanwhile, the majority (46.3 %) of the 378 respondents were in the 41 to 50 years old age group, while the respondents whose age was 61 years or more were the smallest (0.8%). And 89.2% of the respondents were aged between 31 to 50 years. The findings also indicate that almost (51.1%) of the respondents have a master's degree, while the rest have a Ph.D. degree (48.9%). The majority (93.1%) of the respondents were knowledgeable about the subject of Big Data analysis. Regarding the use of Big Data analysis by respondents, the result showed a large proportion of respondents (50.3%) used Big Data analysis tools, while the rest (49.7%) do not.

On the other hand, the Normality test is one of the procedures primarily used for data which is used as a primary test of the data. Normality checking was conducted in this study to make the data normal for analysis. there is no value exceeding the acceptable range of normality (kurtosis and skewness), as kurtosis the range of normality between -3 and +3, and for skewness (-1.96, 1.96) as suggested by Hair et al. (2013). skewness ranged from (-0.340 to 1.154), and the kurtosis ranged from (-1.074 to 0.657). Therefore, the conclusion can be made that the data set of all items were normally distributed

Smart PLS was used for Structural Model. There are two types of the construct, namely first-order constructs and second-order constructs. The reflective model was used to measure the reliability and validity of this test.

Ringle et al. (2020) argued that the loading of the predictor should be greater than 0.70 and that the degree of importance should be at 0.05. At a value of 0.70 loads, the latent variable will describe the variance of its predictor by at least 50 percent (Ringle et al. 2020). Wong (2019) stated that researchers should obey PLS characteristics during the indicator elimination process. One should exclude the specific indicator if its reliability value is less than 0.70, and the exclusion is raised beyond the CR value. In this analysis, it is essential to note that the loading values are higher than the reference value of 0.70 (Wong 2019). Therefore, none of the indicators was deleted from the measurement list. Table 2 presents the construct's outer loadings.

Table 2 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

The efficacy of the reflective measures was tested in the next phase. The reliability of the reflective measurements was measured by means of composite reliability. According to Karakaya et al (2018), composite reliability is a safer alternative, as this approach considers the uniform loading and calculation error for each component above the alpha coefficient. The Cronbach alpha (α) has limitations; it suggests, for example, that all objects have a fair distribution of reliability; all parameters are used in this study to assess the degree of reliability. Our results highlighted that the Cronbach value in all the constructions is larger than 0.70. Also, the composite reliability value in all the measurements is higher than the reference value of 0.70. (Karakaya et al. 2018). The findings show the internal accuracy of the interventions. The Table 3 below presents the Cronbach's Alpha and composite reliability.

Table 3 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

The validity of the reflective measurement was determined using both tests, which are (i) discriminant and (ii) convergent (Açıkgöz & Latham 2018). The convergent validity was used to study the consistency within the multiple-operationalizations. In the literature, the t-statistics values show the significance of the entire factor loading at p< 0.000 (Açıkgöz & Latham 2018). Table 4 showed the AVE for the constructs. It is highlighted that all the measure's values fulfill the minimum criteria of convergent validity (Gefen et al. 2000). The Average Variance Extracted (AVE) is a standard measure of convergent validity, with a minimum value of 0.50 (Hair et al. 2013). A minimum of 50% of measurement variance (indicator) was selected to measure the latent construct. (Chin 1998). The reliability and validity of all the constructs were carefully assessed in this study.

Table 4 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

The validity of constructs is assessed through discriminant validity. The accuracy of discriminant validity can be determined using the Hetrotrait-Monotrait ratio of correlation (HTMT). HMTM can also be described from the variance-based-SEM approach (Templeton et al. 2019). The value of HTMT should be less than 0.85 (Kline 2011) or 0.90 (Henseler et al. 2015). There is no issue resulting from the negative correlation in the HTMT. Table 5 presents the results of the Hetrotrait-Monotrait ratio of correlation.

Table 5 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	

The validity of formative is different from the reflective measures (Ringle & Sarstedt 2016). Multicollinearity is one of the standard methods used to analyse the formative measure validity.

The weight and significance level of indicators relies on the collinearity between formative indicators (Hair et al. 2013). Which can be examined using the variance inflation factor (VIF). If the value is larger than the standard value of 5.00, it means the collinearity issues exist in the formative indicator. The results of the second-order formative construct multi-collinearity are presented in Table 6. All of the VIF results in the formative construct multi-collinearity is less than 5.00.

Table 6 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

To answer the research questions by testing the proposed research hypotheses is the main objective of the structural model. The inner and structural models can be used in the analysis after the confirmation of the variable's reliability and validity. The inner model examination shows how empirical data sports the underlying theories used in the present study. Furthermore, it also functions to predict the ability model and determine the relationships between hypothesized variables. The primary uses of PLS are to minimize error or maximize the variance, as explained in the dependent variable. PLS model can be achieved via controlling and analyzing the coefficient of determination (R^2) values for the dependent variables. Therefore, the validity of the structural model can be assessed using the coefficient of determination (R^2) and path coefficients. Table7 below presents the three direct relation hypotheses that analyzed in the structural model.

Table 7 List of Hypotheses

Hypotheses	**Relationship**
H1	TC→BDA

H2	OC→ BDA
H3	E→ BDA

There is a total of three direct relation research hypotheses. H1 shows the direct relationship of technology capability towards intention to adopt big data analysis, and h2 shows the direct relationship of organization capability towards intention to adopt big data analysis. H3 provides the direct relation of environment towards intention to adopt big data analysis.

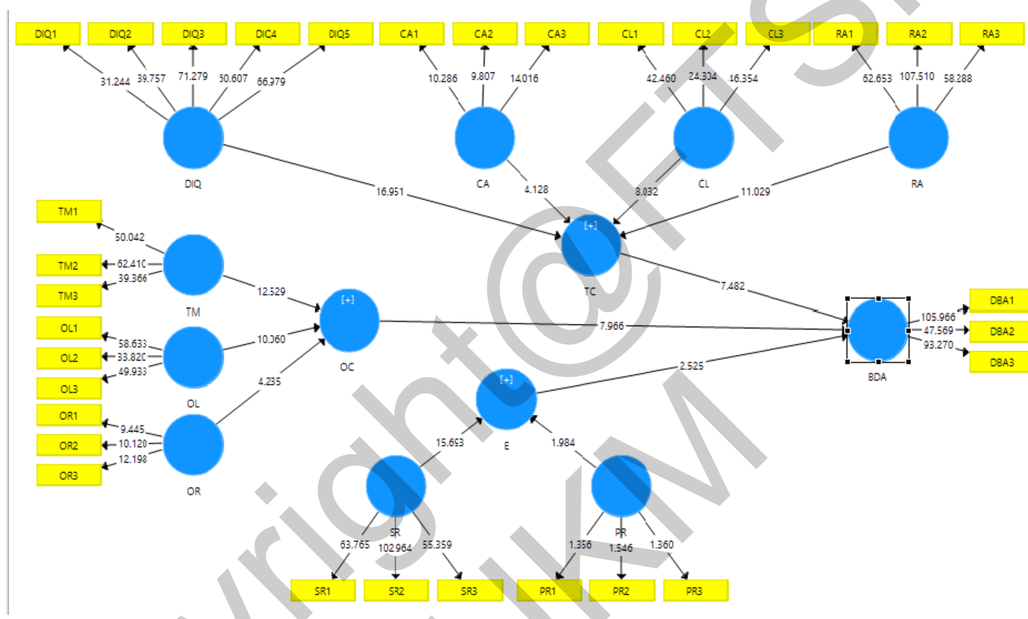

Figure 2: Structural Model with T-Values

RA = Relative Advantage, CA = Compatibility, CL = Complexity, DIQ = Data and Info Quality, TC = Technology Capability, TM = Top Management, OL = Intensity of Organizational Learning, OR = Organizational Readiness, OC = Organization Capability, SR = Security/Privacy Regulatory, PR = Institution Policy and Regulation, E = Environment, BDA = Intention to Adoption Big Data Analysis

There are three direct relationship research hypotheses and the result of the structural model presents that all hypotheses of this research are supported. The results show that Technology Capability has significant influence on Intention to Adoption Big Data Analysis ($p < 0.000$, $t = 7.482$) and supporting the H1. Similarly, the results show that Organization Capability has significant influence on Intention to Adoption Big Data Analysis ($p < 0.000$, $t = 7.966$) and supporting the H2. Moreover, the results show that Environment has significant influence on Intention to Adoption Big Data Analysis ($p < 0.012$, $t = 2.525$) and supporting the H3. The bootstrapping produced 1000 samples for 352 cases. While, Technology Capability, Organization Capability, and Environment are explaining $R^2 = 51.4\%$ variance in Intention to Adoption Big Data Analysis.

VI. CONCLUSION

Big Data offers a range of fascinating possibilities as well as a daunting challenge. As investments in Big Data rise, realizing the adoption of Big Data technologies by the higher education sector is critical and timely. As the Iraqi Big Data Technology market is projected to display lower growth rates than the Western average (Patil & Thakore, 2017). The key objective of this analysis was to recognize factors influencing the acceptance of Big Data technology by the higher education sector in Iraq. Centered on the innovation adoption literature, this project enables the identification of three adoption factors (TOE) in three broad contexts which are technology, organization and environment, and assessed their effect on the adoption of Big Data technology.

Based on the results of this study, a list of factors has been identified and a model of adopting big data in the Iraqi higher education sector have been finally proposed, these findings give a high contribution to both the ministry and universities' in terms of planning and implemented high-impact strategies; from the technological aspects, as well as from the organizational and environmental aspects in order to increase the participation and usage of big data among them in future. The adoption of big data in the universities can help and support e-learning and their decision-makers in order to make better decisions for lecturers. Thus, the ability to make a better decision can provide a good environment which supports the universities to make better, quality and fast decision on their own. Moreover, it can be a good environment for students too.

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