

BIG DATA ANALYTICS ADOPTION AT HIGHER EDUCATION INSTITUTIONS IN IRAQ

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ABSTRACT

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 transform the business world and society on a large scale. Given that the higher education institutions in Iraq are still in the early stages of using big data, studying factors affecting big data analytics (BDA) adoption in Iraq is critical and timely. Grounded in the Technology-Organization-Environment (TOE) framework, an integrative model was developed to study factors affecting the adoption of BDA. The Technological Context was measured by the relative advantage, compatibility, complexity, and data and information quality factors. The Organizational Context was measured by the top management support, the intensity of organizational learning, and organizational readiness. Lastly, the Environmental Context was measured by the security/privacy regulatory and institutional policy and regulatory factors. The proposed model was tested using a survey with data collected from 352 lecturers from three Iraqi universities. Results indicated that the three elements, Technology-Organization-Environment, significantly influence the intention to adopt BDA. The R^2 of 0.514 was reported in the analysis. This study gives a new look into the factors that influence BDA adoption, giving insight into promoting and inhibiting BDA adoption that can benefit higher education institutions. This study's findings would help both the ministry and higher education institutions in Iraq to plan and implement high-impact strategies from the Technological, Organizational, and Environmental Context to increase participation and use of BDA in the future.

Keywords: *Adoption, Big Data Analytics, Critical Success Factors, Higher Education Institution, TOE Framework*

1. INTRODUCTION

Big data technology has been renowned in various areas in the past few years, extending across business management, government policy, market statistics, and research development [1]. Big data analytics (BDA) is a method to analyze data from a vast data set by utilizing computer algorithms,

programming, and mathematical modeling techniques to discover valuable trends promptly. This way, actionable viewpoints that direct management decisions inside an organization may be derived [2]. The main applications of BDA are to optimize consumer engagement, understand user behavior patterns, and leverage resources. It also allows for discerning patterns and abnormalities

from data sources [3]. Aldholay et al. [4] proposed that the practice of evaluating key variables might transform the business into an effective adoption of the new big data technologies.

Higher education is no exception; as interactive media usage and learning scenarios have grown, there has been an increase in concern about processing and updating the volume of educational data. Nazarenko and Khronusova [5] argued that several higher education institutions utilize analytics to improve students' learning experiences by presenting the right opportunities for their learning mode. BDA also helps teachers plan and strategize learning to enhance students' potential [6]. In general, colleges and universities gather a great deal of information about their students through enrolment, assessments, automated learning environments, or library lending schemes that automatically generate data. The generalization of digital in education is in line with the advent of technologies that enable the processing, storage, analysis, dissemination, representation, and visualization of big data [7].

Despite the significant advantages of big data explained in the literature, various obstacles are associated with technology, corporate culture, and strategy [8], [9], [10]. Adopting big data is an essential prerequisite for ensuring that its intended benefits materialize. Particularly in developing countries such as Iraq, the higher education sector has a range of institutions that have implemented e-learning and are producing big data that need to be analyzed [11], [12], [13]. Many studies have been conducted on BDA adoption. However, factors that influence the adoption of BDA at higher education institutions were not discussed. Besides, there is still a lack of awareness that influences such operations on big data adoption [14]. Therefore, defining the critical factors driving the big data adoption initiatives at higher education institutions is important. Moreover, according to Mohammed [15], there is a need to implement big data technologies in the higher education sectors in Iraq to enhance their institutions' facilities. This study will identify the critical factors that will motivate Iraqi higher education institutions to adopt BDA to improve their quality, efficiency, and communication.

The research objectives of this study are:

1. To identify the critical success factors for adopting BDA at higher education institutions in Iraq.

2. To propose a theoretical model for understanding the adoption of BDA.

2. BIG DATA IN HIGHER EDUCATION

Big data is a method for gathering, managing, and analyzing vast volumes of data to create information and reveal secret trends. The term big data was first referred to by Cox and Ellsworth [16] and defined as the challenge of storing large datasets for visualization purposes. Today, with the large growth and accelerated advancement of web-based technology, we are experiencing an unprecedented rise in the number of datasets known as the big data age [17]. He et al. [18] and Sun et al. [19] have shown that more than 75% of businesses are spending or planning to invest in big data. It is attributed to the reality that BDA improves company expertise in making proactive decisions [19]. Big data has been extensively used in the private sector, including retail and industry analysis. For example, big data technology has been used broadly in high-growth vertical markets such as banking and financial services, governments, and virtual consumable applications. This technology seems unpopular in the public exposure and higher education industries [9], [11], [20].

The growth of big data in the higher education sector remains unprecedented. Every year, many data are produced from the automated campus infrastructure system, such as the campus network, internal applications and servers, the learning management system, and other end-user equipment. However, educational institutions rarely use them to gain valuable perspectives on a wide range of issues [21]. This fact has resulted in negative feedback from graduated students' learning experiences. Professional educators were affected by the mass data and the robust education system. As a result, the professionals cannot closely monitor the students' performance and eventually limit their potential work in an optimal state [22]. Therefore, many big data solutions have been proposed for higher education organizations [9], [23]. According to Muhammad et al. [22], BDA has prompted the current integrative architecture to monitor and analyze diverse data from different sources, such as student registration systems, firewall data, site servers, remote sensors, networks, log files, mobile and online learning applications, legacy programs, application servers, and structured databases. This integrative architecture will use untapped computer data to detect challenges, threats, and opportunities.

In higher education, a high-level learning environment and an efficient management system were established [24]. A high-performance learning environment can be formed by combining human resources with advanced analytical techniques. From this point, the educator can closely observe their students' academic achievement from the data analysis pattern.

Educational evidence has long been collected via the academic record system and traditional assessments [25]. With the emergence of big data, traditional data analysis can no longer handle the vast amount of data produced today. Consequently, higher education management is challenged by innumerable semi-structured and unstructured mass data sets to retain innovative and effective data management in the accreditation process. The passion for big data is emerging due to the discovery of opportunities in many fields [26]. However, the big data concept remains unclear in various systems, such as social networks and business data [27]. The system's operation is varied based on the user's condition and needs. Educational institutions believe that they can replicate the big data systems in the business field. However, they should note that school systems and businesses differ in their sources, size, style, and environment. The higher education entity should transform its traditional data and information management to the BDA to align with the latest organization strategic plan, as highlighted in IR 4.0. [28].

3. BIG DATA ANALYTICS ADOPTION

Governments worldwide have been seeking to utilize big data technologies to enhance public facilities over the last decade [29]. Most countries have adopted big data technology. However, effective adoption and management rates vary by country. Wright et al. [30] discuss the use of big data in business and creativity, which leads to business-to-business (B2B) relationships. The conceptual document, backed by case studies, offers an opportunity to generalize the definition. It offers a structure for studying the effects of big data. The case studies are analyzed to remain ahead of the competition and extend their operations by leveraging big data to tap into the potential market and develop innovative products.

The advent of BDA plays a crucial role in precise decision-making and optimum productivity in the modern industrial environment [31]. BDA has received a lot of attention in the healthcare sector

because of its innovative approach that simplifies decision-making and increases strategic growth rates [32], [64]. Many factors have been studied in BDA adoption, as shown in Table 1 (Appendix A).

According to previous research, big data and the benefits of this modern, innovative technology provide competitive advantages to the higher education sector. Various explanations and suggestions for big data implementation in the higher education sector have been proposed herein.

4. CONCEPTUAL MODEL

This study is fundamentally based on Tornatzky and Fleischer's [37] Technology-Organization-Environment (TOE) framework due to the widely utilized research on organizational adoption. The TOE framework has helped understand how organizations adopt technological innovations, as indicated by the following studies. Pudjianto et al. [38] used the TOE framework to explain e-Government assimilation factors in Indonesia, taking advantage of its potential values and benefits for organizations. Awa & Ojiabo [39] developed the TOE framework to adopt a suitable information system model to initiate resource planning software for small and medium enterprises in Nigeria. Gangwar et al. [40] integrated the TOE framework for understanding the determinants of cloud computing adoption at the organization level. Ahmadi et al. [41] used the TOE framework to apply information systems in Malaysian public hospitals. Al-Hujran et al. [42] conducted a study to identify the challenges faced in cloud adoption in developing countries using the TOE framework. Literature proves that many researchers indicate the TOE framework as a helpful tool to explore technology adoption behavior in an organization.

The following studies on BDA adoption used TOE as the framework. The content-based literature reviews were conducted through the Web of Science, Scopus, and Google Scholar databases. The conceptual model was developed using prior work published between 2017 and 2022. Critical factors were selected based on their significance and relevance to the BDA context. The hypotheses are based on the TOE framework within the Technological, Organizational, and Environmental Contexts. These three elements are discussed next.

Technological Context refers to IT infrastructures and analytics platforms' ability to transform big data into valuable information and

provide valuable knowledge to decision-makers. The factors that are included in the Technological Context are relative advantages [43], [64], [67], compatibility [34], [44], [64], [65], [67], complexity [19], [26], [64], [65], [67], and data and information quality [36].

Organizational Context refers to the ability of the organization to strategize and manage the BDA implementation effectively [45]. It is regarded as the key element in applying big data in higher education institutions. The factors that are included in the Organizational Context are top management support [19], [33], [46], [64], [67], the intensity of organizational learning [47], and organizational readiness [48], [65].

Environmental Context refers to using big data to enhance organizational performance in higher education institutions. This element may facilitate the improvement of the BDA capability and create a new learning model. Security/privacy regulations [48], [64], [66], [67], and institution policy and regulation [49], [65], [67] are among the factors.

The proposed hypotheses are:

Hypothesis 1 (H1): Technological Context has a significant effect on the intention to adopt BDA.

Hypothesis 2 (H2): Organizational Context has a significant effect on the intention to adopt BDA.

Hypothesis 3 (H3): Environmental Context has a significant effect on the intention to adopt BDA.

Figure 1 shows the proposed conceptual model for this empirical study.

5. METHODOLOGY

This study used a quantitative method involving a survey to collect data from lecturers in three public universities in Baghdad (University of Baghdad, Al-Mustansiriyah University, and the University of Technology). These are the oldest universities in Iraq. The questionnaire has five sections. Section 1 collects the respondent's demographic profiles, such as gender, age, occupation, and education. Sections 2, 3, 4, and 5 consist of the statements representing the independent and dependent factors. All respondents were expected to score the statements in Sections 2, 3, 4, and 5 using a five-point Likert scale of 1 =

strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, and 5 = strongly agree.

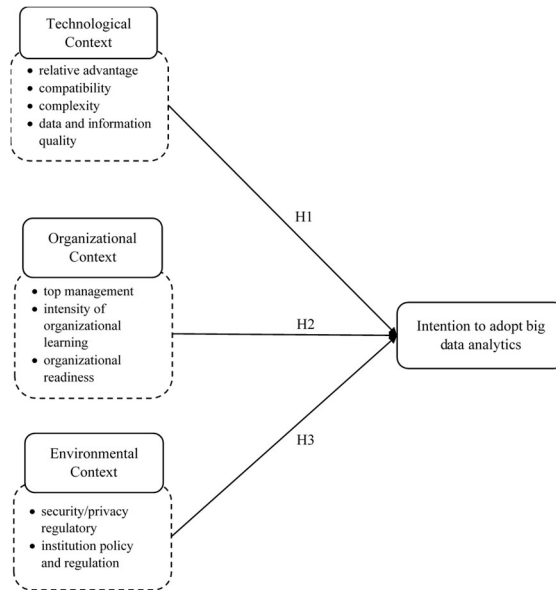


Figure 1: The proposed conceptual model

The questionnaire was designed as follows: Section 2 consists of 14 statements representing the Technological Context, Section 3 consists of 9 statements representing the Organizational Context, Section 4 consists of 6 statements representing the Environmental Context, and Section 5 consists of 3 statements representing the dependent factor. All statements were adapted from past studies. Table 2 describes the number of statements and the factors within the three elements.

Table 2: Factors and Number of Items

Elements	Factors	Code	Number of Items
Technological Context	Relative advantage	RA	3
	Compatibility	CA	3
	Complexity	CL	3
	Data and information quality	DIQ	5
Organizational Context	Top management	TM	3
	The intensity of organizational learning	OL	3
	Organizational readiness	OR	3
Environmental Context	Security/privacy regulatory	SR	3
	Institution policy and regulation	PR	3

A pilot test with 30 randomly selected lecturers at a university was conducted to test the reliability of the questionnaires. The Cronbach's alpha indicated that all items are above 0.70 [50], which is in the acceptable range of 0.778 to 0.898. Thus, the questionnaires were reliable and distributed without any modification.

Data collection was done by sending questionnaires using Google Forms to the randomly selected lecturers in the three universities mentioned above. The majority of the respondents are senior and junior lecturers. Some of these lecturers hold administrative posts, such as the university's top management, the dean, and the head of the department.

A total of 500 questionnaires were sent via email. There were 378 questionnaires collected using the simple random sampling technique, and they recorded a response rate of 75.6%. This feedback falls within the excellent range (> 50%) of the survey responses, as stated by Fincham [51]. However, 26 questionnaires were discarded because the respondents indicated that they did not know about big data technology. Thus, the total sample used in the data analysis was 352.

6. RESULTS

SPSS and SmartPLS were used to analyze the data and test the hypotheses. Table 3 summarizes the demography data. 73% of the respondents are male. Most of the respondents are between the ages of 31 and 50 years old (a total percent of 89.2%). The findings also indicate that 51.1% of the respondents have a master's degree, while the rest have a Ph.D. degree (48.9%). Regarding the use of BDA, the result shows that a large proportion of respondents (50.3%) used BDA tools, while the rest (49.7%) did not.

Table 3: Respondents' Demography Data

Demography	Characteristics	Frequency	Percentage (%)
Gender	Male	276	73
	Female	102	27
Age	21 – 30 years old	21	5.6
	31 – 40 years old	162	42.9
	41 – 50 years old	175	46.3
	51 – 60 years old	17	4.5
	Above 60	3	0.8
	MSc	192	51.1

Education background	Ph.D.	186	48.9
Have you used any BDA tools?	Yes	190	50.3%
	No	188	49.7%

The loadings of each item are higher than the cut-off point of 0.7, based on the recommendation by Chin [52] and further supported by Wong [53] and Ringle et al. [54] (Table 4). Therefore, there were no indicators deleted from the measurement list. The efficacy of the reflective measures was tested in the next phase. The reliability of the reflective measurements was measured using composite reliability. The results indicated that the Cronbach value in all the constructions was higher than 0.70. The combined reliability value in all the measurements is also higher than the reference value of 0.70 [55]. The findings show the internal accuracy of the interventions. Table 5 presents Cronbach's alpha and composite reliability.

Table 4: Factor Loading

Factors	Items	Loadings
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
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
SR	SR1	0.896
	SR2	0.930
	SR3	0.878
PR	PR1	0.841
	PR2	0.876
	PR3	0.872

Table 5: Reflective Constructs Reliability

Factors	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 Average Variance Extracted (AVE) is a standard measure of convergent validity with a minimum value of 0.50 [50]. Table 6 shows the AVE for the factors. It is highlighted that all the measure's values fulfill the minimum criteria of convergent validity.

Table 6: AVE for Constructs

Factors	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

Using the Hetrotrait-Monotrait ratio of correlation (HTMT), the validity of constructs was assessed through discriminant validity. The value of HTMT should be less than 0.85 [56] or 0.90 [57]. There was no issue resulting from the negative correlation in the HTMT. Table 7 (Appendix A) presents the results of the Hetrotrait-Monotrait ratio of correlation.

Meanwhile, the variance inflation factor (VIF) index shows that there was no issue with collinearity, based on the standard VIF cut-off point of 5.00 [50] (Table 8).

Table 8: Variation Inflation Factor

Factors	VIF
RA	1.257
CA	1.144
CL	1.23
DIQ	1.271
TM	1.054
OL	1.049
OR	1.028
SR	1.001
PR	1.001

SmartPLS was used to test the structural model. The bootstrapping produced 1000 samples for 352 cases. The PLS estimate was conducted using repeated items following the suggestion of

Wetzels et al. [58] and following the steps undertaken by Elias [59]. Table 9 (Appendix A) lists the path coefficient, significance level, and t-statistics results.

There are three direct relationships, and the result of the structural model is presented in Figure 2 (Appendix B). The results show that the Technological Context element significantly influences intention to adopt BDA ($p < 0.000$, $t = 7.482$), thus supporting the H1. Similarly, the results show that Organizational Context significantly influences the intention to adopt BDA ($p < 0.000$, $t = 7.966$), thus supporting the H2. And lastly, the results show that Environmental Context has a significant influence on the intention to adopt BDA ($p < 0.012$, $t = 2.525$) and supports the H3.

Figure 3 (Appendix B) shows the structural model with path coefficients and adjusted R^2 . The PLS result shows that the Technological Context contributes to BDA adoption ($\beta=0.398$), followed by Organizational Context ($\beta=0.380$). Meanwhile, the Environmental Context ($\beta=0.135$) is the lowest contributor. The R^2 of 0.514 reported from the analysis indicates that 51.4% of the variance in intention to adopt BDA can be explained by Technological Context, Organizational Context, and Environmental Context. Following the recommendation from Chin [52] and Henseler et al. [60], they suggested R^2 values of 0.67, 0.33, and 0.19 in PLS path models as substantial, moderate, and weak. Therefore, this result indicates that the model is significant.

7. DISCUSSION

The Technological Context results show a significant and strong influence on the intention to adopt BDA ($p < 0.000$, $t = 7.482$). Factors such as relative advantage, compatibility, complexity, and data and information quality can help higher education institutions realize the capability of the technology to adopt BDA. The findings show that these universities need to have the necessary technological resources to increase their electronic information sharing with the Ministry of Higher Education and Scientific Research (MOHESR) in Iraq. These universities have already acquired IT infrastructure and trained employees to use information technologies. Nonetheless, they continue to look for ways to improve their software, hardware, and IT skills [64]. Generally, most universities lack advanced computing resources and

limited IT skills and knowledge among their employees.

The results conclude that the Technological Context influences the increase in BDA in higher education institutions. The existing information technology and skills of the employees have created most of the big data projects [67]. Thus, universities can use their current skills and technologies to analyze big data while improving their skills and infrastructure to enhance e-learning. In this respect, a new technology might be beneficial to adopt for big data in higher education. Additionally, it can provide beneficial assistance by providing training and direct service through calls or email to the university staff. Universities may adopt suitable free smart mobile applications to adopt big data. On the other hand, public universities could acquire compatible technologies from the ministry's technology resources.

The Organizational Context results show a significant influence on the intention to adopt BDA ($p < 0.000$, $t = 7.966$). Factors such as top management support, the intensity of organizational learning, and organizational readiness are factors that can help the higher education sector realize the capability of the organization [45], [46], [61], [62] to adopt BDA. Based on the findings, the top management considers adopting big data in higher education as an important feature to support their university. They also encourage staff to use big data technology to ease their work and motivate them to increase their usage by offering rewards or incentives. Generally, the public university's top management is interested in electronically adopting the university's information using advanced technology such as big data. Additionally, according to the results, top management support is needed to ensure obtaining the necessary funding and other resources for using big data.

The Environmental Context results have a significant influence on the intention to adopt BDA ($p < 0.005$, $t = 2.525$). Based on the findings, public universities need legislation and policies to adopt and organize big data. The legislation and policies can decrease the staff's risks and fears and make them more comfortable sharing the university's information with the ministry using big data.

These findings show that the security/privacy regulatory, policy, or legal framework can influence the BDA adoption [48], [49], [65] at public universities in Iraq. Thus, it might

be beneficial to build a good environment of legislation and policies between universities and big data adoption. Therefore, the ministry must create understandable legislation and policies based on their requirements and the public universities' needs that are easy to follow by the staff from each side.

8. CONCLUSION

Big data offers a range of fascinating possibilities as well as daunting challenges. As investments in big data rise, realizing the adoption of big data technology by the higher education sector is critical and timely. The Iraqi big data technology market is projected to display lower growth rates than the western average [63]. The key objective of this study is to identify the factors influencing BDA adoption in Iraq's higher education sector. Based on technology adoption literature, salient factors were identified within the TOE framework, and their effects on BDA adoption have been assessed.

Based on the results, a list of factors has been identified, and a model of BDA adoption in the Iraqi higher education sector has been proposed. The findings from this study contribute to both the ministry and universities in planning and implementing high-impact strategies. It will increase participation and usage of big data among them in the future. Adopting big data in universities can help and support e-learning and their decision-makers to make better decisions for the lecturers and students. This provides a conducive environment that supports universities in making better, quality-driven, and fast decisions suitable for students to learn and develop their knowledge.

Future research will help develop the generalizability of the findings and lead in various ways to enhance the model for the use of BDA. First, the findings and results of this study are based on data from a single region. The results are not adequate to reflect the larger international community. In addition, this study was confined to data from three universities, which suggests the results might not be generalizable to the broader population. Future studies may generalize results by evaluating the proposed model in several other countries and benefiting from a wider range of organizations. This can provide guidance on the role of organization's types and sizes in future big data adoption studies.

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APPENDIX A

Table 1: BDA Adoption Related Works and Factors

	Cost	Relative advantage	Compatibility	Complexity	Data and information quality	Top management support	The intensity of organizational learning	Organizational readiness	Security/privacy regulations	Institution policy and regulation	Company size	IT capability	Economic	Social
[19]	√			√		√						√	√	√
[26]				√										
[34]			√									√		√
[35]						√					√	√		
[36]					√	√						√	√	
[43]	√													
[44]			√											
[47]							√							
[48]								√	√					
[49]										√				
[64]	√	√	√			√			√		√			
[65]			√	√				√		√				
[66]									√	√				
[67]	√	√	√			√			√					

Table 7: Hetrotrait-Monotrait Ratio of

Correlation (HTMT)

	CA	CL	DIQ	OL	OR	PR	RA	SR	TM
CA									
CL	0.086								
DIQ	0.040	0.480							
OL	0.049	0.189	0.391						
OR	0.104	0.142	0.110	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	0.170	0.249	0.168	0.180	0.146	0.062	0.065		
TM	0.465	0.257	0.232	0.232	0.172	0.315	0.246	0.375	

Table 9: Path Coefficients

Hypotheses	Relationship	Path Coefficient	T- Statistics	P-Value	Decision
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

APPENDIX B

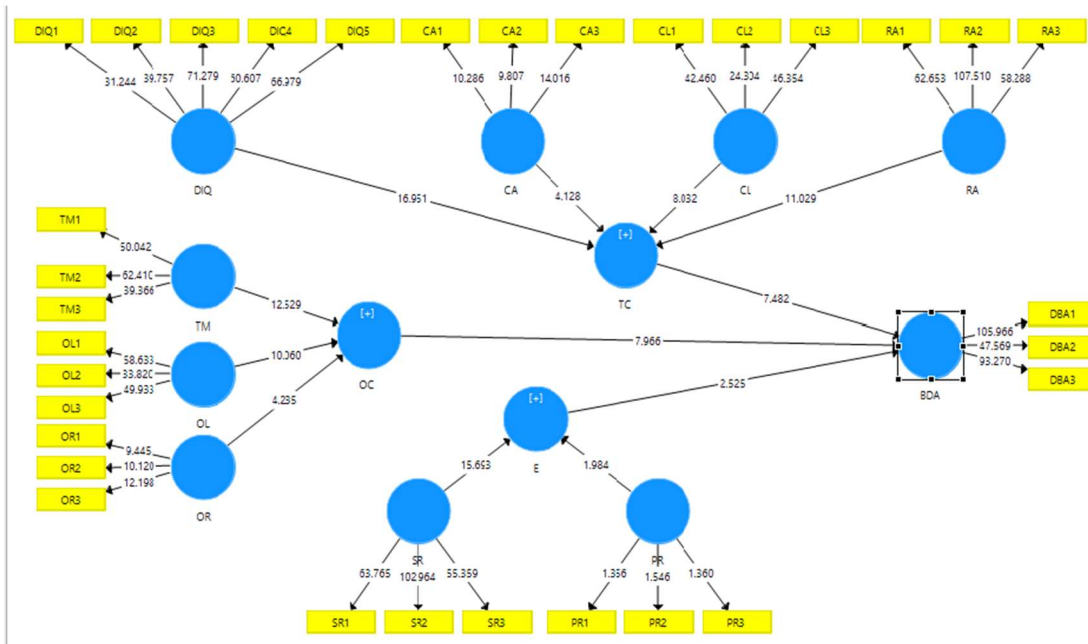


Figure 2: Structural Model with T-value

RA = Relative Advantage, CA = Compatibility, CL = Complexity, DIQ = Data and Info Quality, TC = Technological Context, TM = Top Management, OL = Intensity of Organizational Learning, OR = Organizational Readiness, OC = Organizational Context, SR = Security/Privacy Regulatory, PR = Institution Policy and Regulation, E = Environmental Context, BDA = Intention to adopt BDA

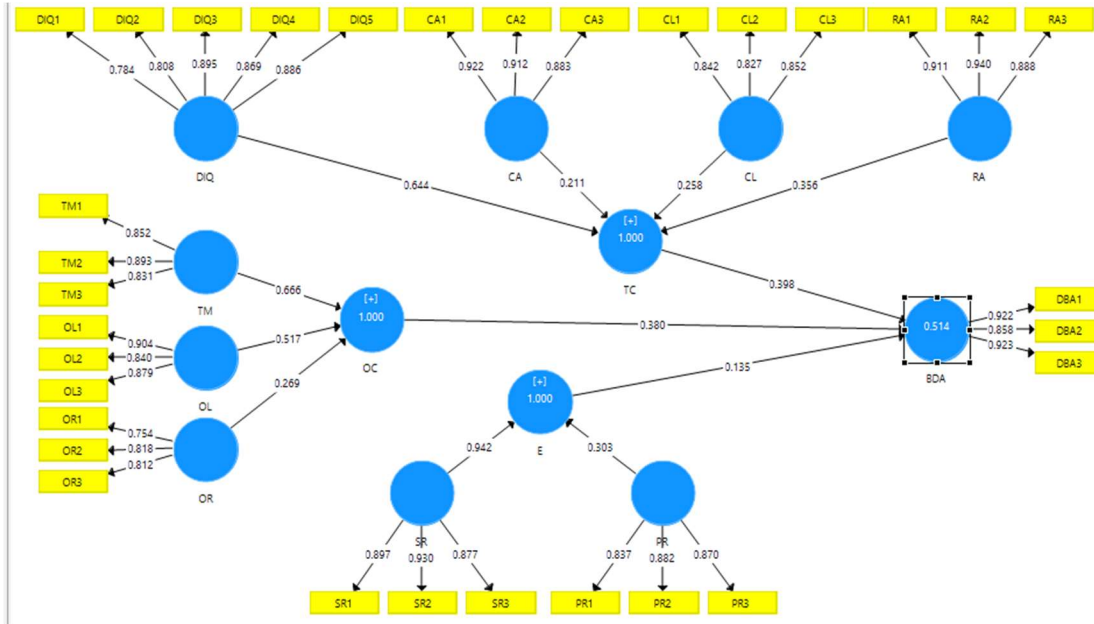


Figure 3: Structural Model with Path Coefficients

RA = Relative Advantage, CA = Compatibility, CL = Complexity, DIQ = Data and Info Quality, TC = Technological Context, TM = Top Management, OL = Intensity of Organizational Learning, OR = Organizational Readiness, OC = Organizational Context, SR = Security/Privacy Regulatory, PR = Institution Policy and Regulation, E = Environmental Context, BDA = Intention to adopt BDA