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Research Article

THE MEDIATING ROLE OF IOT READINESS BETWEEN TECHNOLOGICAL, ENVIRONMENTAL READINESS AND IOT ADOPTION IN (LHEIS)

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Abstract

The effective implementation of ICT and advanced systems like IoT is essential to modernising educational processes and resource management. Higher education system in Libya faces many challenges and barriers such as the lack of clarity on how different readiness factors influence the adoption of IoT in LHEIs complicates the prioritisation of initiatives and resource allocation. Therefore, this study seeks to address this gap by examining the technological and environmental determinants that influence the readiness of Libyan higher education institutions to adopt IoT technology. It also aims to identify the mediating role of IoT readiness between technological, environmental readiness and attitude toward IoT adoption in LHEIs among LHEIs. This study utilized a quantitative method for collecting and analyzing the data. Besides, a questionnaire was used to collect the data from the sample of the study (409) faculty members and academic professionals in University of Benghazi (UOB) and University of Tripoli (UOT) in Libya and data collected via random sampling method. The Smart-PLS4 technique was used to conduct the statistical analysis of the collected data. The study' findings showed that technological and environmental readiness were statistically positively influence on IoT adoption and IoT readiness in (LHEIs). Furthermore, IoT readiness was a partial mediating effect between technological, environmental readiness and IoT adoption in LHEIs. Moreover, the findings indicated the need to test technological and environmental factors that may provide a better explanation of IoT readiness and IoT adoption by the higher education universities sector of developing countries in general and Libya in particular. The study is also expected to be significant to stakeholders like decision-makers and educators attempting to shed light on technological factors (ICT infrastructure, data governance, security & privacy, compatibility) and environmental factors (government support, government regulation, competitive pressure) and its impact on their IoT adoption through IoT readiness in LHEIs as a mediating effect. In addition, the study is significant because of its implication for the overall productivity of Libyan universities which integrate digital technologies into their teaching and be knowledgeable about the accelerated development in various fields of knowledge. This will increase the opportunities for educators to adopt IoT and enhance educational experience for a new generation of learners known as digital natives in LHEIs.

Keywords: Technological, Environmental, IoT readiness, IoT adoption, Libyan Higher Education.

INTRODUCTION

ICT improves people's lives in many different contexts, including security, medical care, and education (Banica *et al.,* 2017; Zhamanov *et al.,* 2017).In recent years, the Libyan government and the Ministry of Higher Education and Scientific Research have shown a strong commitment to developing the country's educational infrastructure and adopting the widespread use of information and communication technologies (ICTs), as previously mentioned (Alshref *et al.,* 2021; Obaid *et al.,* 2021; Saleh 2020). The environment of the Fourth Industrial Revolution (4IR) is impacting production and services, including the education system (Azah Mansor *et al.,* 2020). The integration of IoT into higher education is currently revolutionising the education sector. Industrialised nations such as the United States, Canada, Europe, and Australia have adopted and developed the Internet of Things (Madni *et al.,* 2022; Greengard, 2021; Slimp & Bartels, 2019). In addition to other technologies, the Internet of Things (IoT) has been suggested as a technology that can enhance teaching and learning outside of conventional E-learning platforms (Aldowah *et al.,* 2017; Li & Pei, 2022; Rahman *et al.,* 2016).

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To develop teaching and learning in the twenty-first century, the education sector must modify its old frameworks (Sartaş, 2015). In contrast to conventional e-learning systems, the IoT offers a cutting-edge electronic teaching and learning platform with a choice of online learning items (Muskan, 2021; Abbasy & Quesada, 2017). Higher education institutions that implement IoT can benefit from it for both students and faculty. For instance, interactive digital tools like smart whiteboards, augmented reality, virtual reality, etc. assist teachers in creating immersive learning experiences. The Internet of Things can lower the expenses that educational institutions must incur while also enhancing their instructional systems. Libya is making impressive strides in upgrading its higher education system. The Libyan government has launched a number of initiatives and agreements to upgrade the infrastructure of higher education institutions, with a particular focus on incorporating information technology. The goal is to develop a comprehensive readiness framework that effectively supports the adoption of IoT and provides practical guidelines for enhancing IoT adoption in the Libyan higher education sector, thereby enhancing the quality of education and aligning with the government's efforts to modernise educational infrastructure. There is a scarcity of actionable, research-based guidelines tailored for the Libyan higher education sector on adopting IoT technologies, limiting the ability of institutions to implement IoT solutions effectively. Furthermore, the potential mediating effect of "IoT readiness in LHEIs" on the relationship between technological, environmental readiness and attitude toward IoT adoption. is underexplored, suggesting a gap in understanding how IoT readiness contributes to attitude toward IoT adoption in LHEIs.

Problem statement

The successful adoption of emerging technologies, such as IoT, is hindered not by a lack of access but rather by a deficiency in comprehension among key stakeholders. Decision makers, educators, and the community often resist digital transformation due to uncertainties about its effective implementation within educational institutions (Azevedo & Almeida, 2021; Moreira *et al.,* 2018).Therefore, the effective implementation of ICT and advanced systems like IoT is essential to modernising educational processes and resource management (Mansor *et al.,* 2020; Kamar *et al.,* 2016). Higher education system in Libya faces many challenges and barriers such as the lack of clarity on how different readiness factors influence the attitude toward IoT adoption in LHEIs complicates the prioritisation of initiatives and resource allocation. Moreover, The potential mediating effect of "IoT readiness in LHEIs" on the relationship between readiness factors and IoT adoption. is underexplored, suggesting a gap in understanding how IoT readiness contributes to attitude toward IoT adoption. Scholars in Libya, such as Ramadan *et al.* (2019) and Salem & Mohammadzadeh (2018), believe there is a need for additional research from academia and industry on the uptake and adoption of ICT technologies in Libyan higher education institutions. Thus, this study seeks to address this gap by examining the technological and environmental determinants that influence the readiness of Libyan higher education institutions to embrace IoT technology. It also aims to identify the mediating role of IoT readiness between technological, environmental readiness and attitude toward IoT adoption in LHEIs.

LITERATURE REVIEW

IoT Applications

The IoT solutions spread due to advances in technology. RFID tags and low-cost, low energy sensors are prevalent today. High bandwidth is afforded to IoT devices by wireless and more recent cellular networks. Innovative machine learning techniques provide rapid data analysis. In addition, cloud computing facilitates storage, transfer, and analysis of data. IoT simplifies, enhances, and automates processes as a result of this continuous link between machines, humans, and data. The combination of sensors, connectivity, and artificial intelligence has the potential to increase the efficiency of several systems. In recent years, IoT has emerged as one of the most significant technologies of the 21st century. Now that we can connect everyday objects kitchen appliances, automobiles, thermostats, and baby monitors to the internet through embedded devices, communication between people, processes, and things is frictionless. Physical objects can share and collect data with a minimum of human intervention using low-cost computers, cloud, big data analytics, and mobile technologies (Malekshahi *et al.,* 2020; Gillis, 2022). Digital systems can record, monitor, and alter every interaction between connected objects in this hyperconnected world. The physical and digital worlds interact cooperatively. Increases in the number of Internet-connected devices will have several positive effects and enormous influences on organisations' operations, goals, and strategies (Rahmani *et al.,* 2022; Debnath & Chettri, 202; Malekshahi *et al.,* 2020).The literature does, however, show that the integration of IoT in higher education is currently poor and has to be improved. In higher education institutions in developing nations, especially Libya, an adequate evaluation of the influence of organisational environments and individuals on readiness for IoT adoption is also lacking. Digital systems can record, monitor, and alter every interaction between connected objects in this hyperconnected world. The physical and digital worlds interact cooperatively. Increases in the number of Internet-connected devices will have several positive effects and enormous influences on organisations' operations, goals, and strategies (Rahmani *et al.,* 2022; Malekshahi *et al.,* 2020).

The IoT in Higher Education

In light of the Internet of Things' transformative role in education as a whole, it is essential to investigate its specific implications for Higher education institutions. With their complex structures and diverse needs, higher education institutions present unique opportunities and challenges for the integration of IoT technologies. The adoption of contemporary ICT practises in higher education institutions is not a passing fad. Universities must endure reforms due to the rapid changes occurring in the world, which impact all stakeholders, including students, employers, and faculty (Mkrttchian *et al.,* 2021).As a result of the urgent need to digitalize training and education processes for academicians who lack the innate technical skills required for online education, higher education institutions are undergoing profound transformations. The Integration of IoT in Higher Education Higher education institutions (HEIs) are often vulnerable to changes in governmental directives, social conditions, and technological developments since these factors firmly interfere with their performance (Laáková *et al.,* 2017). This is the reason HEIs have rapidly grown, altering higher education's character to become more competitive. This fuels the desire to raise the level of services offered through cutting-edge technologies (Chweya & Ibrahim, 2021). As an Internet based technology, IoT has significant implications for higher education (Chweya & Ibrahim, 2021). Saeed *et al.* (2021) state that IoT is a relatively new technology that has taken root in various industries, particularly education systems. The widespread use of this technology is anticipated to result in additional alterations in this area. According to Al-Emran *et al.* (2020), Numerous institutions of higher education around the globe adopt IoT in an effort to generate profound changes in their performance (teaching, learning, management, training, facilities, etc.). IoT spans a variety of disciplines, including computer and information science, engineering, the social sciences, and mathematics. Bayani *et al.* (2017) assert that the Internet of Things has transformed traditional education elements such as institutions, universities, and students into smart variants (electronic elements). Due to the fact that a significant number of educational institutions are not connected to one another or communicate information, the IoT is better adapted to fill this void.

Overview of Higher Education in Libya

Higher education in Libya has encountered significant transformations over the years, shaped by the country's historical, political, and social contexts. As Libya continues to navigate the complexities of post-revolutionary recovery, the higher education sector faces both considerable challenges and unique opportunities. The history of higher education in Libya dates back to the mid-20th century; in December 1955, King Idris I of Libya issued a Royal Decree establishing the University of Libya in Benghazi. This event is regarded as the beginning of the annals of the Higher Education (HE) System in Libya. This directive elucidated in greater detail the objectives for the establishment of additional institutions. In 1973, after a period of time had passed, the Libyan University was separated into two universities, Benghazi and Tripoli, as a manifestation of this direction. According to data provided by the Tempus project of the European Commission in 2016, the number of universities and institutes for higher technical and vocational education in Libya has increased continuously since 2016 (Al Barhami, 2022; Al-Ashhab & Al Ashhab, 2022; Elkhouly *et al.,* 2021; UNIMED, 2020; Rhema, 2018). Currently, the higher education system in Libya consists of 26 public universities located throughout the country, 8 accredited private universities, and technical and vocational schools, all of which are administered by the Ministry of Higher Education and Scientific Research through a dedicated board. The number of universities has steadily increased over the past decade (Ministry of Higher Education and Scientific Research, 2023; MEdirections, 2022).

Technology-Organization-Environment (TOE) Model

The Technology Adoption Theory (TOE) is a theoretical framework that demonstrates the factors that shape the adoption and implementation of technological innovations within organisations. The model aims to illustrate the influence of the technological, organisational, and environmental context on decision-making related to technology innovation. Technological context encompasses factors such as technological characteristics and availability. environmental context encompasses aspects such as market and industry structure, technology support and infrastructure, and government regulations (Baker, 2012). The technological context encompasses both internal organisational equipment and practises as well as externally available technologies. Moreover, the theory of TOE has a high degree of alignment with existing technology adoption theories, hence lacking competitive explanatory power and distinctive predictive capabilities (Oliveira and Martins, 2011).

Technological Readiness

The assessment of technology utilisation and comprehension of the factors influencing acceptance and resistance towards technology are essential in formulating policies that promote economic progress (Cirera *et al.,* 2022). To achieve successful implementation of the IoT, it is necessary to provide significant financial resources, ensure the availability of skilled personnel capable of efficiently managing IoT operations, and conduct a comprehensive assessment of the technology readiness level to verify the satisfaction of technological requirements (Parra *et al.,* 2021). The adoption of the IoT requires comprehensive preparation prior to its execution, owing to its complex and innovative nature. It encompasses more than only presenting innovative technological advancements. The use of IoT solutions necessitates organisational adjustments aimed at efficiently generating customer value (Zhuankhan & Renken, 2023). Significant scholarly attention has been devoted to the examination of technological factors that influence the adoption of the Internet of Things. In this study, there are three dimensions of individual readiness including ICT infrastructure, data governance, security & privacy and compatibility.

Environmental Readiness

Environmental readiness examines the external factors that influence an institution's ability to adopt IoT. It highlights the external drivers and constraints that impact an institution's capacity to adopt IoT, emphasising the need for alignment with external expectations and regulations. External environmental factors influence the adoption decision unquestionably. Organisations tend to be scrupulously aware of environmental conditions, particularly in their respective businesses (Ismail *et al.,* 2023). The impact of the external environment on an organisation is an ongoing process that transcends a given phase, particularly with regards to the incorporation and use of technology (Saghafian *et al.,* 2021). The adoption of IoT is influenced by a range of elements within the environmental dimension.

Conceptual Framework and Hypotheses Development

The adoption of the IoT is affected by several challenges in technological and environmental readiness. Therefore, it is crucial to conduct a thorough analysis within a theoretical framework to study the factors that support readiness for IoT adoption, covering these four essential components. The conceptual framework of the current study includes two main exogenous variables (technological and environmental readiness) and one endogenous variable (IoT adoption) as well as one mediating variable (IoT readiness) as shown in Figure 1. All the variables that made up the constructs were adapted from previous studies to ensure content validity.

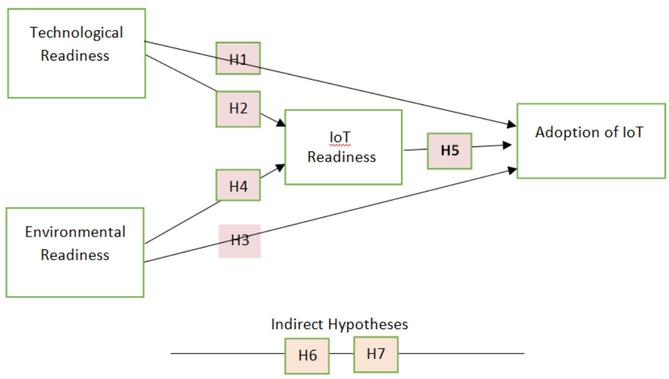

Figure 1. Conceptual Framework and Hypotheses Development

Hypotheses development

The relationship between Technological readiness and IoT Readiness in LHEIs and IoT Adoption: The term "technological readiness" refers to the extent to which an organisation has ICT infrastructure, including the hardware, software, and networks it needs to function effectively (Chen & Lai, 2022; Lutfi *et al.,* 2022; Olushola, 2019; Zhang *et al.,* 2020; Chweya & Ibrahim, 2021; Yang *et al.,* 2015). Previous studies have indicated that the readiness of technology plays a crucial role in the effective deployment of IoT projects (Chen & Lai, 2022; Ancarani *et al.,* 2019; Olushola, 2019; Dewi *et al.,* 2018). Organisations with a technological infrastructure have a greater level of technological preparedness, thereby increasing the likelihood of their adoption of the IoT (Martins *et al.,* 2016). Hence, in the context of the proposed framework, it is postulated by the researcher that technological readiness plays a crucial role in determining the level of preparation for IoT. Consistent with the findings obtained, hypotheses were formulated:

H1: There is a significant positive relationship between technological readiness and the adoption of IoT in LHEIs.
H2: There is a significant positive relationship between technological readiness and IoT Readiness in LHEIs.

The relationship between Environmental readiness and IoT Readiness in LHEIs and IoT Adoption: Environmental factors affect the adoption decision unquestionably. Organisations tend to be scrupulously aware of environmental conditions, particularly in their respective businesses (Ismail *et al.,* 2023). The impact of the external environment on an organisation is an ongoing 95 process that transcends a given phase, particularly with regards to the incorporation and use of technology (Saghafian *et al.,* 2021). The adoption of IoT is influenced by a range of elements within the environmental readiness construct. Certainly, these environmental dimensions have received great attention in the literature (please refer to Section 2.12). Environmental readiness is the degree of readiness and willingness among organisational users to adopt new technology (Zhang *et al.,* 2020; Dewi *et al.,* 2018; Yang *et al.,* 2015). Thus, the following hypotheses are proposed:

H3: There is a significant positive relationship between environmental readiness and the IoT Adoption in LHEIs.
H4: There is a significant positive relationship between environmental readiness and IoT readiness in LHEIs

The relationship between IoT Readiness in LHEIs and IoT Adoption: Technological and environmental with a higher level of preparedness for service are more inclined to adopt new services and technologies (Ghaleb *et al.,* 2021). The outcomes of IoT readiness can be classified into two categories: psychological outcomes at the technological level and overt outcomes at the environmental level. The prevalent psychological outcome variables in the technology adoption literature encompass attitude towards technology and intention to use technology (Venkatesh *et al.,* 2003). They are frequently utilised in empirical research as they can be quantified using psychometric instruments, similar to their predecessors (Yang *et al.,* 2015). Numerous studies have identified the readiness construct as an outcome for assessing preparedness in relation to several new technologies, including the Internet of Things, cloud computing, and big data (Ghaleb *et al.,* 2021; Chweya & Ibrahim, 2021; Yang *et al.,* 2015). Therefore, based on the data provided by previous researchers, hypothesis can be developed as follows:

H5: There is a significant positive relationship between IoT readiness in LHEIs and the IoT Adoption.

Mediating effect of "IoT readiness in LHEIs: Drawing upon the range of relations explored between organisational readiness (OR) and individual readiness (IR) with the outcome of IoT readiness in LHEIs, the current study posits that the outcome of IoT readiness may serve as a mediator in the relationship between the independent variables of OR, TR, ER, and IR and the attitude towards IoT adoption. In this context, each of these constructs is carefully examined to elucidate their relationships. Accordingly, the following sub-hypotheses are articulated to further investigate these dynamics:

H6: IoT readiness in LHELs mediates between technological readiness and the IoTAdoption
H7: IoT readiness in LHELs mediates between environmental readiness and the IoT Adoption

METHODOLOGY

Research Design

This study used the quantitative research approach by collecting primary data to answer the research questions and to test the direct and indirect hypotheses that requires a quantitative technique to deal with the data. These methods were chosen due to its practically, where time and budget are the main constraints.

Population and Sampling

The target of population of the study was the faculty members and academic professionals in University of Benghazi (UOB) and University of Tripoli (UOT) in Libya. A sample refers to a group of individuals selected to serve as the participants of an investigation. Given that the study population for this research comprises 7189 individuals. The sample size for this study is determined to be 368 individuals according to the relevant sample size table (Azam *et al.,* 2021). In this study, data will collect via a self-administered survey using a sample random sampling method. The survey method is carried out among the academics and employees of the higher education sector in Libyan universities. The respondents included in the survey method are the employees and will count to a total number of 368 respondents. The use of simple random sampling is a statistical technique employed to choose a subset of individuals from a more extensive population.

Questionnaire Design

This study used the survey method to collect the primary data. The online questionnaire is designed at no cost using the Google Forms platform. The questionnaire is designed to include two parts. The first part includes demographic information about the respondents, including gender, age, education level, experience years, university name, teaching platform and platform used. The second part consists of two main exogenous variables (technological and environmental readiness) and one endogenous variable (adoption of IoT) as well as one mediating variable (IoT readiness). The hyperlink will then be sent through email, text message, and (using the WhatsUp app) to a selected sample of faculty members at the University of Benghazi and the University of Tripoli.

DATA ANALYSIS AND RESULTS

Test of Normality

The guidelines of Hair *et al.* (2014) have been utilized in the current study to take the cut-off critical value of ±2.58 into consideration. It is clear from Table 1 that each construct's skewness and kurtosis values fell within the specified range (± 2.58). The descriptive analysis illustrates that almost normal distribution with mean skewness ranged between -0.094 and -1.321 while kurtosis values ranged between -0.175 and 2.256. Table 1 indicates skewness and kurtosis for variables.

Table 1. Kurtosis and Skewness Test

		Skewness		Kurtosis	
Main Variables	Sub-Variable	Statistic	Std. Error	Statistic	Std. Error
Technological Readiness	ICT Infrastructure	-.131	.121	-1.127	.241
	Data Goverence	.110	.121	-.789	.241
	Security & Privacy	-.094	.121	-.463	.241
	Compatibility	-.616	.121	-.321	.241
Environmental Readiness	Government support	-1.321	.121	2.256	.241
	Competitive pressure	-.572	.121	-.175	.241
	Government Regulation	-.685	.121	.488	.241
IoT Readiness in LHEIs		-.372	.121	-.904	.241
IoT Adoption		-.548	.121	-.216	.241

Source: Prepared by researcher using SPSS

Histogram Test

Key assumptions for multiple regression exist. For multiple regression, the dependent or independent variables have to be an interval or scale level variable which is normally distributed in the population from which it is drawn. Figure 2 displays the standard deviation, which is close to 1 (0.998) and confirmed to the normally distributed feature.

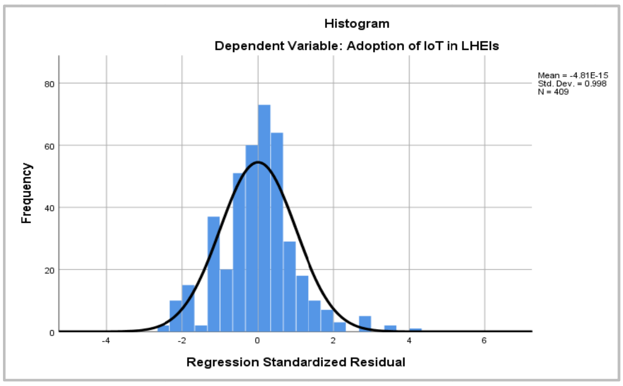

Figure 2. Normality Histogram

Descriptive Statistics for Variables

The results demonstrated the government support was the highest mean scorewith 3.922 out of 5 and followed by digital self-efficacy and competitive pressure were3.77 and 3.55making up 78% and 71% respectively. On the other hand, data governance was the lowest mean score at 2.82 or 56% and overall, the mean score was 3.46out of a maximum 5 making up 69% as indicated Table 2. Moreover, the computed standard deviation for every variable in this study ranged between 0.692 and 0.923, showing that the data set included a level of variability that was both acceptable and significant.

Table 2. Descriptive Statistics for Variables

Variables	Minimum	Maximum	Mean	%	S.D
ICT Infrastructure	1.40	5.00	3.2440	64.88	.90371
Data Governance	1.00	4.75	2.8295	56.59	.92394
Sucurity & Privacy	1.40	5.00	3.2685	65.37	.77570
Compatibility	1.00	5.00	3.4071	68.14	.92251
Government Support	1.00	5.00	3.9222	78.44	.69290
Competitive pressure	1.40	5.00	3.5540	71.08	.77753
Government Regulation	1.00	5.00	3.5286	70.57	.83066
IoT Readiness	1.40	5.00	3.5076	70.15	.88726
IoT Adoption	1.00	5.00	3.4432	68.86	.88768
Technological Readiness	1.30	4.84	3.1873	63.74	.79071
Environmental Readiness	1.00	5.00	3.5272	70.54	.82315
Overall	1.58	4.92	3.4687	69.37	.79630

Assessing of Measurement Model

The assessment of the reflective measurement model involves examining the indicator loadings, the internal consistency reliability including (Cronbach's alpha) and composite reliability. Furthermore, the measurement model assesses the constructing validity including convergent validity, discriminant validity of the reflective constructs. In the final measurement model, (5) items (ICTI4, SP1, SP3, GR5 and IoTR5) have been deleted from the initial measurement model due to the value of item loading was less than 0.60 for exploratory research (Hair *et al.* 2019). Hence, 37 items were retained out of 42 items inInitial Measurement Model (IMM)(See Figure 3 and Table 3).

Assessment of Reliability (Cronbach Alpha) and Composite Reliability: The findings indicated the reliability (Cronbach's alpha) values ranged from 0.787 (adoption of IoT) to 0.917 (ICT infrastructure), while composite reliability (CR) values ranged from 0.859 to 0.942 for the same variables as shown in Table 3. Eventually, all variables met the minimum estimation standards for measurement values, which are 0.60 for Cronbach Alpha and 0.70 for Composite Rollability (Hair *et al.* 2019).

Convergent Validity: In fact, where the factor loading range occurs between IoTA2 (0.653) as minimum and ICTI2 (0.941) as shown in Table 3, this is ample proof of convergent validity. Consequently, there is sufficient evidence for the convergent validity of the method used in this paper because all of the indicators are related to their respective variables. In this study, AVE values were greater than 0.50 and varied between 0.607 and 0.802, suggesting acceptable values and indicating that the convergent validity is adequate (Hair *et al.,* 2019). In addition, the square root of the AVE for a given construct was more than the absolute value of the correlation square of the given construct with any other factor (AVE > correlation square), as indicated in Table 3. Therefore, there is enough proof for the convergent validity of the framework because all items in the current paper are related to their variables.

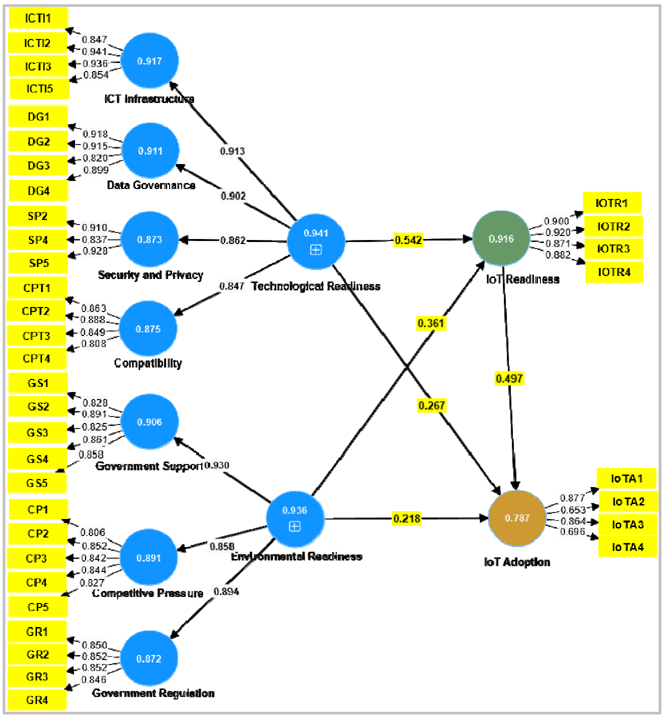

Figure 3. Measurement Model/ Factor loading (Algorithm)

Discriminant Validity: As indicated, the discriminant validity indicates how the paper variables differ from other variables (Hair *et al.,* 2013). Hair *et al.* (2013) and Fornell and Larcker (1981) proposed a measure to look at the discriminant validity. If the diagonal elements are being viewed as higher than the elements in other off-diagonal in their related columns and rows, then we can make the comparison and assume the discriminant validity. Furthermore, for any given variable, the AVE square root was bigger than the correlation square's absolute value with any other variable.

Table 4. Discriminant Validity for (Fornell & Larcker, 1981)

	IoTA	COM	CP	DG	GR	GS	ICTI	IoTR	SP
IoTA	0.779								
COM	0.683	0.853							
CP	0.635	0.701	0.834						
DG	0.770	0.700	0.583	0.889					
GR	0.749	0.615	0.597	0.648	0.850				
GS	0.767	0.657	0.684	0.703	0.827	0.853			
ICTI	0.775	0.679	0.587	0.802	0.671	0.752	0.896		
IoTR	0.778	0.692	0.637	0.751	0.729	0.794	0.798	0.893	
SP	0.722	0.668	0.574	0.761	0.606	0.670	0.664	0.695	0.893

Source: Prepared by researcher using output of Smart-Pls (Measurement Model)

Assessment of the Structural Model

This part presents the results of the structural model and test of hypotheses. Specifically, the section is concerned with the testing of hypotheses related to mediating effects. The next step in PLS-SEM path modelling was to test the hypothesised relationships. To do so, this study utilized the PLS algorithm and the standard bootstrapping procedure with a number of 5000 bootstrap samples and 409 cases to examine the path coefficients significance (Hair *et al.,* 2014; Hair *et al.,* 2011; Hair *et al.,* 2012; Henseler *et al.,* 2009). Standard assessment criteria, which should be considered, include the collinearity test (VIF), the coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure (Q^2), and effect size (f^2) to explain the statistical significance and relevance of the path coefficients.

Collinearity Test (Varainve Inflation Factors -VIF): The VIF values should be close to 5 and lower (Becker *et al.* 2015). In this study, the maximum VIF value for items is 3.695, indicating that DSE4 is less than 5, and the maximum VIF value is 1.484 for IoTA2, as shown in Table 5. Overall, the values of the VIF for items suggest that multicollinearity is not a threat among items in this study as might be suggested by a more restrictive VIF threshold.

Table 5. Collinearity Test (VIF)

Collinearity statistics (VIF)			
Item	value	Item	value
IoTA1	2.317	GR1	3.981
IoTA2	1.484	GR1	2.149
IoTA3	2.223	GR2	2.232
IoTA4	1.554	GR3	2.235
CP1	2.118	GR4	2.264
CP2	2.430	GS1	2.284
CP3	2.447	GS2	3.537
CP4	3.041	GS3	2.209
CP5	2.713	GS4	4.331
CPT1	2.135	GS5	3.002
CPT2	2.228	ICTI1	2.732
CPT3	2.734	ICTI2	4.133
CPT4	1.844	ICTI3	5.399
DG1	3.853	ICTI5	2.486
DG2	3.926	IOTR1	3.169
DG3	2.047	IOTR2	3.783
DG4	2.878	IOTR3	2.594
SP2	2.725	IOTR4	2.558
SP4	1.926		
SP5	3.139		

Determination Coefficient for R^2 (squared multiple correlation): The (R^2) value reveals the variance of the dependent variable, which is explained by the independent variables. In this study, the R^2 structural model for IoT adoption was 0.787. Therefore, the findings indicate the independent variables, technological environmental readiness and IoT readiness, explained 78.7% of the variance in IoT adoption among LHEIs. Meanwhile, technological and environmental readiness explained 91.6% of the variance for IoT readiness, as indicated in Figure 4.

Assessment of Effect Size (f^2): As a rule of thumb, values higher than 0.02, 0.15, and 0.35 depict small, medium, and large (*f2*) effect sizes (Cohen, 1988; Hair *et al.,* 2019).

Table 6. Effect Size of predictive Variables

Variable	Effect size (f^2)			
	IoT Adoption	Rating	IoT Readiness	Rating
Technological readiness	0.123	Small	0.396	Large
Environmental readiness	0.097	Small	0.176	Medium
IoT Readiness	0.440	Large	----	

The results showed IoT readiness had a large effect size (*f2*) on the predictive variable on IoT adoption in LHEIs at 0.440. Additionally, technological readiness had a large effect size on IoT readiness in LHEIs at 0.396, but environmental readiness was a medium (*f2*) effect size on IoT readiness at 0.176. On the other hand, technological and environmental readiness were small effect sizes on the adoption of IoT among LHEIs with 0.123 and 0.097, respectively, as indicated in Table 6 and Figure 4.

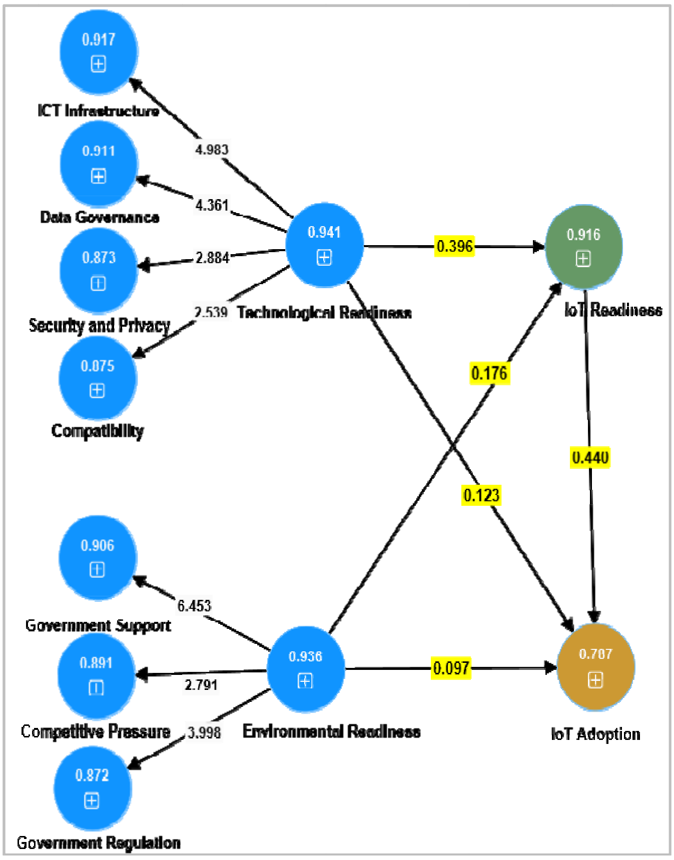

Figure 4. Measurement Model with (f^2) and (R^2) for main variables

Predictive Relevance (Q^2): The Q^2 is a criterion for measuring how well a model predicts the data of omitted cases (Hair *et al.,* 2014). A research model with Q^2 statistics greater than zero is considered predictively relevant. Table 7 and Figure 5 indicated the cross-validation redundancy measure $Q^2$for one dependent variables: IoT adoption and IoT readiness were above zero at 0.497 and 0.584, respectively. In this case, the model had predictive relevance (Henseler *et al.,* 2009).

Table 7. Construct Cross validated Redundancy

	SSO	SSE	Q² (=1-SSE/SSO)
IoTAdoption	1636.000	823.704	0.497
Compatibility	1636.000	806.588	0.507
Competitive Pressure	2045.000	1023.121	0.500
Data Governance	1636.000	595.593	0.636
Environmental Readiness	5317.000	5317.000	0.000
Government Regulation	1636.000	699.209	0.573
Government Support	2045.000	768.917	0.624
ICT Infrastructure	1636.000	553.024	0.662
IoT Readiness	1636.000	680.391	0.584
Security and Privacy	1227.000	509.665	0.585
Technological Readiness	4908.000	4908.000	0.000

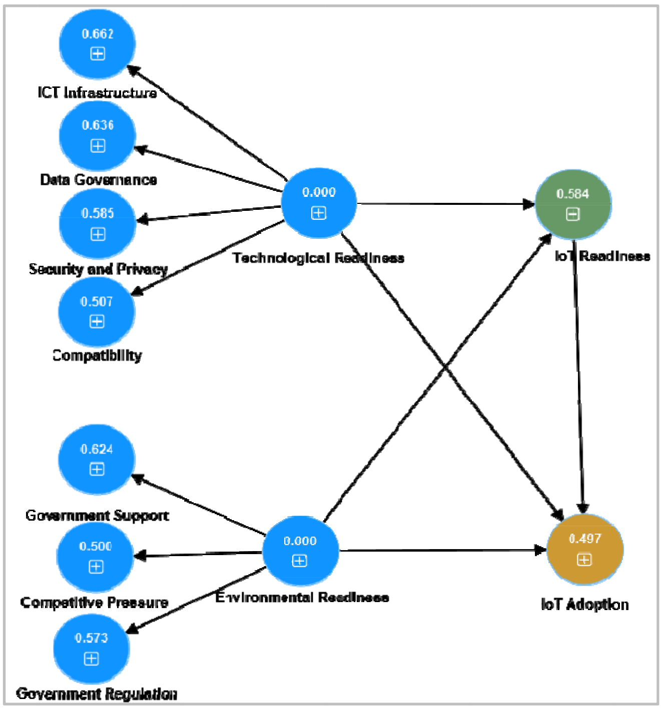

Figure 5. Predictive Relevance (Q^2)

Direct Hypotheses Results

In the current study, the findings showed that there was a statistically positive relationship between technological readiness and IoT adoption as well as IoT readiness in LHEIs (β = 0.267; t = 7.135; p < 0.001) and (β = 0.542; t = 13.767; p *< 0.001),* respectively, as shown in Table 8 and Figure 6. Therefore, the hypotheses (H1) and (H2) are accepted. Moreover, there was a significantly positive relationship between environmental readiness and IoT adoption as well as IoT readiness (β = 0.218; t = 4.893; p< 0.001) and (β = 0.361; t = 8.337; p < 0.001), respectively. Hence, the hypotheses (H3) and (H4) are accepted. Finally, there was a significant and positive relationship between IoT readiness in LHEIs and IoT adoption (β = 0.497; t = 13.031; p < 0.001); thus, the hypothesis (H5) is accepted.

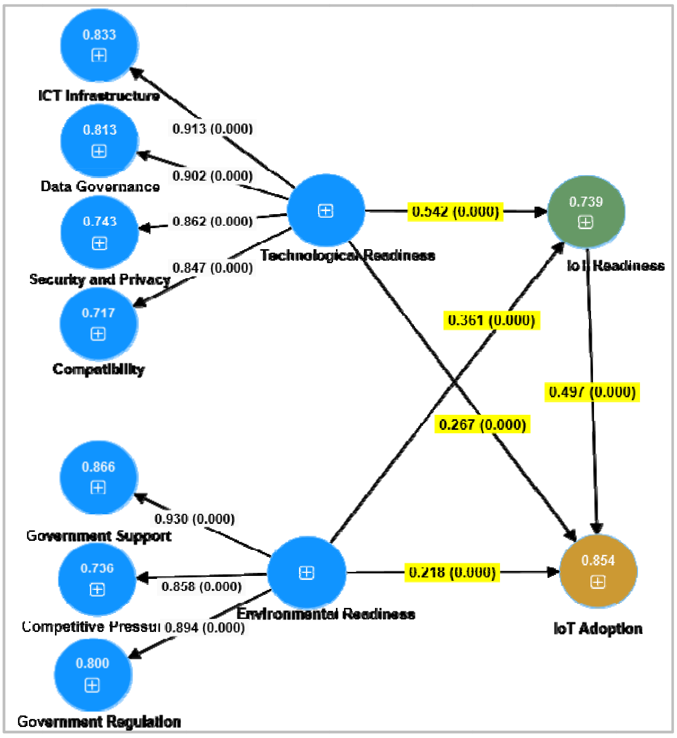

Figure 6. Hypotheses results with Path coefficient and P value (Bootstrapping)

Results of Mediating Effect (Indirect Hypotheses Result)

The study tested the mediating role of IoT readiness in LHEIs between the technological readiness, environmental readiness, and IoT adoption using (PLS-SEM). The study's findings revealed that IoT readiness was partial mediation between technological and environmental readiness and IoT adoption in LHEIs (β= 0.269, t=8.926, P< 0.001) and (β= 0.179, t=7.813, P< 0.001) as shown in Table 10. Hence, there was an indirect relationship between technological and environmental readiness and IoT through IoT readiness as a mediator; thus, the indirect hypotheses (H6) and (H7) are accepted as indicated in Table 9.

Table 8. Results of Direct Hypotheses

H	The relation	(path coefficient) (β)	S.D	C.R (t-value)	P-value	Result
H1	Technological Readiness ->Adoption of IoT	0.267	0.037	7.135	0.000	Accepted
H2	TechnologicalReadiness->IoT Readiness	0.542	0.039	13.767	0.000	Accepted
H3	Environmental Readiness ->Adoption of IoT	0.218	0.045	4.893	0.000	Accepted
H4	Environmental Readiness ->IoT Readiness	0.361	0.043	8.337	0.000	Accepted
H5	IoT Readiness ->Adoption of IoT	0.497	0.038	13.031	0.000	Accepted

Source: Prepared by researcher using output of PLS-SEM (Structural Model)

Table 9. Indirect Hypothesis Result (Mediating Effect)

Hyp.	Relation	Path coefficient (β)	S.D	T-value	P Value	Result
H6	Technological Readiness -> IoT Readiness -> Adoption of IoT	0.269	0.030	8.926	0.000	Accepted
H7	Environmental Readiness -> IoT Readiness -> Adoption of IoT	0.179	0.023	7.813	0.000	Accepted

Source: Prepared by researcher using output of PLS-SEM (Structural Model)

DISCUSSION AND CONCLUSION

The research objectives “in this study have been achieved in light of the previous discussion of results. The findings showed that there was a significant relationship between technological and environmental readiness and IoT readiness in LHEIs and IoT adoption. This study is the attempt to determine and integrate the technological factors (ICT infrastructure, data governance, security & privacy, and compatibility) and environmental factors (government support, competitive pressure, and government regulation) that influence the adoption of IoT in LHEIs. As noted from the results, IoT readiness was a partial mediating influence on the relationship between technological, environmental, and IoT readiness as well as IoT adoption in LHEIs. The study’s findings are supported by several previous studies that assert the deployment of the Internet of Things depends heavily on technological and environmental factors working together (Cirera *et al.,* 2022; Yahaya *et al.,* 2018; Sicari *et al.,* 2018). The study proposed a TOE framework that accounts for the utilisation of the united model within the Internet adoption behavior. Moreover, the study results provide solid support for the TOE framework model; the R-squared of the TOE model is 78.7%. This means that the model correctly classifies the decisions made with respect to the adoption of IoT in LHEIs. The study’s findings confirmed the validity of an empirical framework to analyse the impact of technological and environmental readiness on the adoption of IoT through the mediating role of IoT readiness in LHEIs. In addition, this work added to the understanding of acceptance of IoT within technology acceptance theories research and in the optional Internet behaviour context. The study provides insights into the state of IoT adoption to provide points of reference for academics, practitioners, and policymakers in promoting universities to adopt IoT among LHEIs. This study disregarded other factors such as technological and environmental readiness or other variables to obtain a more comprehensive understanding of the influence of IoT readiness in organizations. Furthermore, the researcher chooses IoT adoption rather than actual usage as a dependent variable because IoT is still in its introductory stage in Libya, and the number of actual users of IoT is limited. Some recommendations are made on the basis of the findings of this study. First, the majority of individuals in Libyan higher education institutions are not users and are unaware of the many benefits of IoT adoption, and the promotion of this awareness through information and training programs is thus necessary. Therefore, the government has the responsibility to develop the IT infrastructure and widen IT education in the Libyan universities. Second, the Libyan government should improve the legal infrastructure, like e-signature, privacy laws, and knowledge acquisition law. It can also help the LHEIs by ensuring better Internet infrastructure and help to encourage non-users to adopt IoT. Finally, the study recommends that Libyan universities need to provide specialised courses, workshops, and seminars targeted at helping their academics, employees, and students to understand the prerequisites for launching their Internet presence.

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