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PLS-SEM BASED ANALYSIS OF FACTORS AFFECTING THEUSAGE OF E-LEARNING LIBYAN HIGHER EDUCATION INSTITUTIONS

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ABSTRACT

The main objective of the study is to determine the variables that influence the decision of Libyan universities to transition to online instruction. An important performance map analysisalgorithm will be used to examine the most significant aspect of these elements, and structuralequation modeling (SEM) will be used to evaluate their relative relevance. to provide definitions for key terms such technology adoption models, obstacles, and e-learning adoption.

Methodology: A review of the literature and success variables for e-learning acceptance thatlink to LHEI technology adoption are presented at the outset of the study. We can also encounter other theories, such as the Theory of Reasoned Action (TRA) and the Theory of Strategic Behavior (TSB), in addition to the previously stated ones. The UTAUT frameworkof this study considered subjective enjoyment, self-efficacy, inventiveness, and favorable conditions in addition to hedonic motivation when assessing variety. The deductiveapplication and the philosophical underpinnings of positivism. Data for the study is gatheredthrough a survey and a quantitative methodology. Depending on earlier studies, the reported questionnaires are disseminated electronically.

Significance: The results of the normality, demographic, and outlier tests provide important details for the data analysis stage and bolster the reliability and validity of the studyconclusions.

Conclusions: This study's conclusions could be useful to researchers looking into how technology is being used in schools all throughout the world, especially in underdeveloped nations like Libya.

Keywords: Adoption, SEM, Educational Applications, and E-learning.

INTRODUCTION

In the modern educational landscape, e-learning has become a disruptive force alteringold learning paradigms and providing students with options never before seen. This study investigates the factors influencing students' adoption and use of e-learning at HEIs. Through an analysis of the theoretical, practical, and historical aspects, we can gain a thorough understanding of the dynamics within the Libyan environment. Libya's education system has seen a substantial transformation due to its rich cultural past. Libyan education has historically been classroom-focused and shaped by social and cultural standards. But theintroduction of technology—more specifically, the internet—has sparked a movement in education toward a more digital focus. It is essential to comprehend this historical development to place the current e-learning condition in Libyan HEIs in context. Libya has seen political and social unrest over the last ten years, which has affected the education sector. A growing emphasis on creative teaching strategies has resulted from the need for consistency and continuity in education, with e-learning emerging as a workable answer. Examining this historical background will help us understand the potential and problems that have shaped the current state of e-learning in Libyan higher education institutions.

The ongoing acceptance of e-learning across the globe can be attributed to both the growing desire for personalized, flexible, and accessible education and technological developments. Digital platforms are being adopted by higher education institutions across the globe as a complement to or replacement for traditional classroom-based instruction. Given Libya's distinct socio-cultural and economic context, this worldwide trend calls for an investigation into the ways in which Libyan Higher Education Institutions (HEIs) conform to or depart fromthese international norms. E-learning is an instructional approach that uses the Internet to helpteachers and students learn synchronously or asynchronously (Qiu et al., 2022). It incorporates a number of ICT-based elements, including email, the internet, applications, and other onlinetools. To improve users' learning experiences, e-learning makes use of a variety of platforms,including Web 2.0, Moodle, Blackboard, and Web CT platforms. Cruz & Consuegra, 2023; Evans, 2023). Virtual, online, and remote education are examples of common e-learning choices. Learning management systems, as well as mobile learning (Komuhangi et al., 2022). Because of its affordability, ease of use, accessibility, and environmentally friendly nature, e-learning has become more popular (Adam, 2023; Hussein & Hilmi, 2021). According to GMI(2023), the e-learning market is expected to grow from its estimated USD 379.3 billion in 2023 to USD 1 trillion in 2032, a gain of more than 14%. This demonstrates the importance of e-learning tools and platforms.

Innovative methods of delivering education and learning have often been described as e- learning. The goal of the ICT-based learning strategy was to enhance and broaden the reach of the conventional process rather than to replace it (Islam & Azad, 2015). In recent years, theInternet has completely transformed traditional education, lowering costs and increasing accessibility for learning regardless of time or place. Boateng et al. (2016) and Komuhangi etal. (2022). E-learning provides a more flexible and tailored learning experience than the traditional approach (Hussein & Hilmi, 2021). E-learning has become a feasible means of minimizing disruptions to learning and guaranteeing the continuation of education (Maatuk et al., 2022). To stay competitive and continue providing education to their students, several institutions who had not planned to implement e-learning were forced to do so. Nonetheless, various establishments and students encountered various obstacles. As a result of their inability to accept and use e-learning (Jafar et al., 2023; Almaiah et al., 2020). Many advantages come with e-learning, including cost-effectiveness, accessibility, flexibility,and ease. Interactivity, data management, frequent updates, customisation, and educational materials are further noteworthy advantages. Moreover, distributed libraries, assessment techniques, testing resources, and simple system integration are all offered by e-learning platforms. Additionally, distant learning can be facilitated by the e-learning system (Almajaliet al., 2022; Al Ghawail et al., 2021). However, there are several obstacles to the efficient adoption and application of e-learning. Two prominent obstacles are insufficient infrastructure and a shortage of skilled personnel (Komuhangi, 2022; Maphosa, 2021; Arkorful & Abaidoo, 2015). Owing to these difficulties, traditional teaching methods continue to be widely used in the majority of underdeveloped nations (Komuhangi, 2022; Ramadan etal., 2019; Tarhini et al., 2016). The viability and efficacy of e-learning depend heavily on student acceptance and engagement. Therefore, it is critical to evaluate the elements that influence the effective adoption and use of e-learning, especially in developing nations.

ICT presents Libya's e-learning industry with outstanding growth and possibilities. Africa's mobile device penetration index rate for the nation is 91.61. Given Libya's strong mobile penetration rate, over 92% of the country's 100 residents are anticipated to be smartphone owners (David & Grobler, 2020). Furthermore, data show that the nation has sophisticated mobile telecommunications infrastructures (David & Grobler, 2020). According to a report, Libyans do not view e-learning as a viable educational model, despite its convenience (Mustafa & Hussin, 2017). According to a poll conducted in 2019, e-learning has not becomewidely used in the Arab world. The authors came to the conclusion that this is because e- learning technologies are not widely accepted in this area. Such opinions of e-learning may be influenced by certain elements, challenges, and environments.

These studies show that e-learning has the potential to spread throughout the Arab area, including Libya, despite its low adoption rate in comparison to other nations. The requirementfor in-person interactions between academic lecturers and students was removed by e-learning platforms. However, funding and restricted access to electronic learning tools hampered somestudents in higher education (Fatima, 2021; Elberkawi et al., 2021). As a result, these challenges had a substantial impact on how well Libyan academic students used and implemented e-learning. According to a study by Elberkawi et al. (2021), students are more prepared to recognize obstacles to the adoption of e-learning because they are its primary stakeholders. This suggests that university students may view these issues from their points of view. In the end, students' contentment with the system may have an impact on their decision to embrace and apply it (Mustafa & Ali, 2023; Cavus et al., 2021). Nonetheless, in order to encourage and maintain the expansion of e-learning in Libya, a number of obstaclesand adoption concerns must be resolved.

METHODOLOGY

The design and technique are covered in this part. Additionally provided are the research instruments, methodologies, and sampling strategy. There is discussion of research methodologies, procedures, data gathering techniques, and study sampling. A summary of the software and design experiments used is also included. The selection of the cross-sectional survey, quantitative research approach, and positivist paradigm is justified.

Research Variables

Effort Expectancy (EE), Technology Awareness (TA), Social Influence (SI), Technology Anxiety (TAX), Performance Expectancy (PE), Facilitating Conditions (FC), and Behavioural Intentions (BI) are among the independent factors. Actual Usage (AU) is the dependent variable at the same time. Furthermore, the mediating concept is BI. between the independent and dependent variables. Additionally, as moderators are gender and experience.

Furthermore, the literature has empirically tested UTAUT in a variety of scenarios (Chao, 2019; Alkawsi et al., 2021; Parameswaran et al., 2015). Using a UTAUT model, Attuquayefioand Addo (2014) investigated the barriers to ICT acceptance among students pursuing postsecondary education. They found that behavioral intention is highly impacted by effort anticipation. In addition, use behavior was altered by facilitation situations. Surprisingly, therewas no impact of behavioral intention, social influence, or performance expectancy on use behavior. A different empirical study (Chao et al., 2019) assessed factors based on UTAUT that predicted students' behavioral intentions toward mobile learning (m-learning). Perceived enjoyment, trust, contentment, and mobile self-efficacy were the external variables. The moderating impact of perceived risk on the proposed associations was investigated by the authors. Their findings showed that effort expectancy, performance expectancy, trust, and satisfaction positively affected behavioral intention. Self-efficacy had a positive influence onperceived enjoyment.

Operationalization of the Constructs

Conceptualization involves providing a concise and unambiguous definition of a construct that can be easily understood (MacKenzie et al., 2011). In contributing to the growing body of literature, this thesis examines the predictors of e-learning adoption in Libya. Table 3.1 presents the constructs' definitions and their sources adapted to fit the study purpose in this thesis. The proposed model for this study is grounded in UTAUT and the extended UTAUT 2, as presented in Table 1.

Operational Definition of the Constructs

Table 1

No.	Code	Constructs	Operational Definition	Source
1	PE	Performance Expectancy	PE refers to the degree to which students believe that utilizing an e- learning system would improve their performance.	Venkatesh et al.(2003)
2	EE	Effort Expectancy	EE refers to the ease of use that users have with the e-learning system.	Venkatesh et al. (2003)
3	SI	Social Influence	SI addresses students' perceptions onhow others feel they should utilize the e-learning platform.	Venkatesh et al.(2003)
4	TA	Technology Awareness	TA refers to a person's level of understanding and knowledge aboutvarious types of technology.	Abubakar & Ahmad (2013)
5	TAX	Technology Anxiety	TAX refers to the discomfort people experience when using noveltechnologies.	Song et al. (2022)
6	PI	Personal Innovativeness	PI refers to an individual's willingnessto adopt and use new ideas, technologies, or practices for personal and professional development. It represents an individual's inclination to embrace innovative solutions or products and engage in activities promoting change and advancement.	Rogers (2013)
7	FC	Facilitating Condition	FC refers to a student's belief that theutilization of an e-learning system will be supported by institution and technical resources.	Venkatesh et al.(2003)
8	BI	Behavioural Intentions	BI explains an individual's inclination to perform a specific behavior.	Venkatesh et al. (2003)

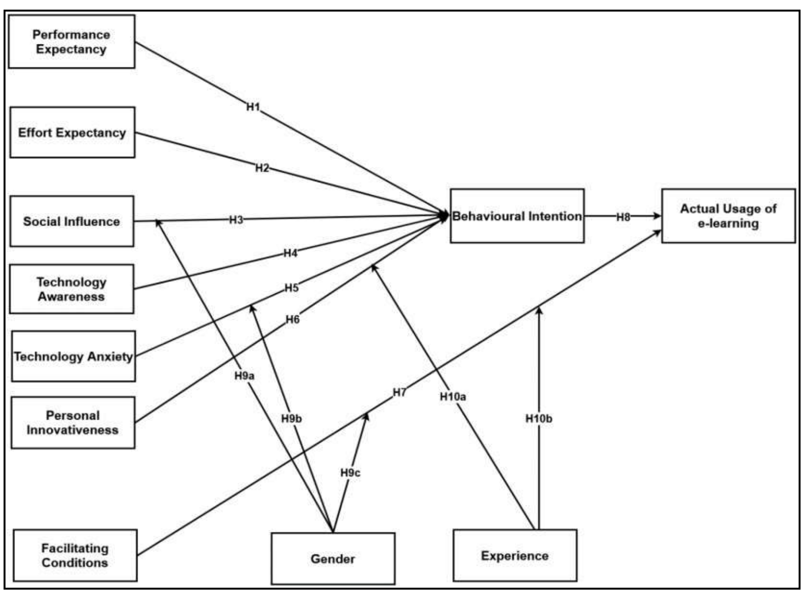
9	AU	Actual Usage	AU refers to the use of the e-learning system.	Venkatesh et al. (2003)

The Research Model and Hypotheses

The Technology Acceptance Model (TAM) is usually a foundational framework for initiating research in technology adoption. Researchers have recognized the explanatory power of the UTAUT. However, fewer studies have applied the theory than TAM. The UTAUT is also a prominent theoretical model in technology adoption. Some studies have incorporated TAM constructs into the UTAUT (Yakubu & Dasuki, 2019). Accordingly, applying the UTAUT constructs to LHEIs can provide additional insight into the behavioral intention of students toadopt e-learning in LHEIs. The research framework is based on UTAUT to examine the relationship between its constructs. The proposed model will help researchers and information systems developers identify the significant predictors of e-learning adoption and utilization inLibya. The theoretical framework is presented in Figure 1.

Proposed Research Model

Figure 1



From the model, there are relationships between the constructs, and there are eight hypotheses. The three two moderators have five hypothesized relationships. The twelve hypothesized relationships that will be tested in this thesis are presented in Table 2.

Research Hypotheses

Table1

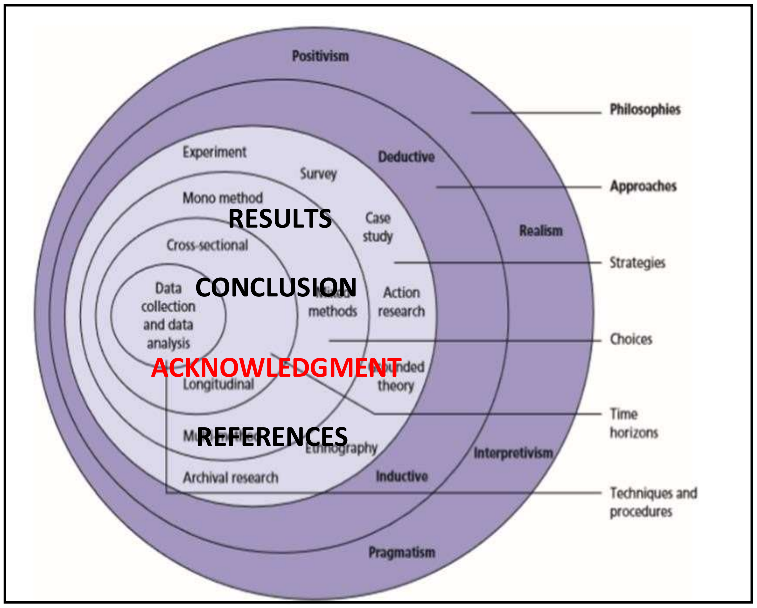
	Hypothesis
H1	Performance expectancy influence student behavioural intention to use e-learning.
H2	Effort influence student behavioural intention to use e-learning.
H3	Social influence student behavioural intention to use e-learning.
H4	Technology awareness influences students' behavioural intention to adopt e-learning.
H5	Technology anxiety influences students' behavioral intentions to utilize e-learning.
H6	Personal Innovativeness influence student behavioural intention to use e-learning.
H7	Facilitating conditions influence student actual usage of e-learning.
H8	Behavioural intention influence student actual usage of e-learning.
H9	The influence of social impact on behaviour intention moderated by Gender.
H10	The influence of technology anxiety on behaviour intention moderated by Experience.

Research Process

The systematic literature review (SLR) approach developed by Kitchenham and Charters (2007), adopted or modified by other researchers (Bukar et al., 2020; Hansen & Schaltegger,2016; Qasem et al., 2019) was used for this thesis. The primary SLR processes in this investigation included research identification, study selection, research quality evaluation, data extraction, data organization, and synthesis. In the study selection phase, determine if the full text of selected articles meets this thesis's inclusion and exclusion criteria. This is crucialto ensuring the study accomplishes its objectives and identifies the research gap. The other SLR processes included paper selection, quality article evaluation, data, and synthesis. Chapter 2 presented the articles evaluated and critical assessment of the papers; the subsequent chapters detail the SLR process. The research philosophy in the framework Figure2 guides how the research will be conducted.

Research Philosophy and Strategies

Figure. 2



The study aims to contribute to a deeper understanding of fundamental aspects, observable facts, and processes related to a specific phenomenon (Hammad et al., 2022; Sekaran & Bougie, 2016). Figure 3 provides an overview of this thesis's research design and methodology.

Paper Selection Process

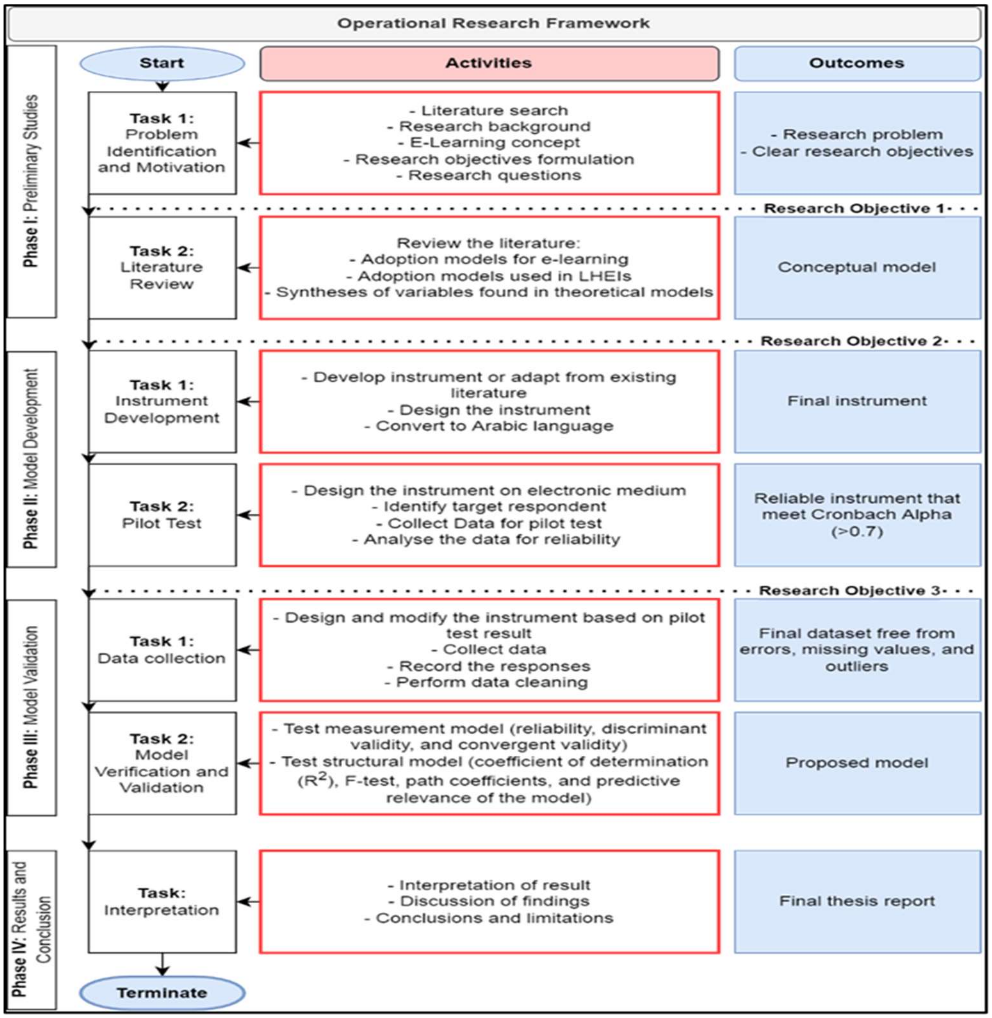
The first phase of our analysis focused on the articles the query returned. Seventy-four paperswere retrieved based on the relevance of titles and abstracts. Their full text was assessed for eligibility. These papers excluded textbooks, theses, reports, or duplicates. Scopus-indexed publications, JCR Journal articles, conference papers, and review articles were all considered in the selection process. In identifying and selecting the full text of thesepapers, methods consistent with previous research were employed (Bukar et al., 2020; Qasemet al., 2019). Finally, the full text of forty-six articles was selected for the review, as shown in Figure 4.

Data Extraction and Synthesis

The retrieved empirical papers were classed based on their contributions. The empirical studies were in the context of traditional technology acceptance or adoption theories. A thematic analysis was used to synthesize the summary of each article.

Research Operational Framework

Figure 3



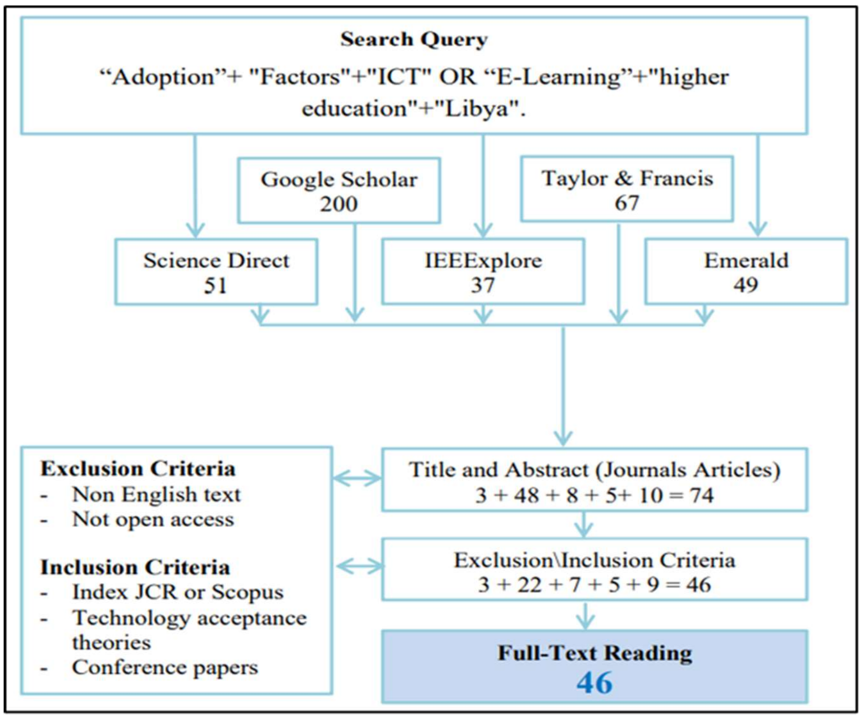
Sampling Design Process

It has been established that the students of HEIs constitute the primary audience for the various departments. The literature has demonstrated that these groups of people are crucial to the success of e-learning in Libya because they are the system's users. Studies

showed that successful e-learning relies on students' perceptions and satisfaction with the system (Ghawail et al., 2021; Lahrash et al., 2021; Ramadan et al., 2019). Therefore, academics will benefit from a better grasp of the variables impacting the uptake of e-learningin Libyan HEIs if they become familiar with these demographic subgroups. There are two sampling approaches: probability and non-probability sampling (Goldstein & Reinert, 1997) In statistical research, probability random sampling techniques are utilized to choose a representative sample from a population (Etikan & Bala, 2017; Selamat et al., 2020). As opposed to this, non-probability sampling chooses a sample from the population using non- random or subjective criteria. As each member of the target population has an equal chance of being chosen, probability sampling was used for this thesis. There are four types of sampling in probability: stratified, cluster, simple, and systematic.

The Search and Selection Proces

Figure 4



This thesis seeks to understand the ways in which different factors impact Libyan students' decisions to accept and use e-learning. Students from diploma, bachelor's, master's, and doctorate programs will participate in this study. This research aims to improve our understanding of students' decision-making processes by looking at how students' interests and learning styles, as well as their cultural origins and socioeconomic situations, affect howthey use e-learning.

Libyan students will be surveyed quantitatively, and the main study methodologies will be individual and group interviews. Additionally, a survey will be used to collect data on the demographics, e-learning proficiency, and efficacy perceptions of the students. With an emphasis on the objectives, difficulties, and approaches that students use to interact with e-learning, this study aims to offer a thorough grasp of how these elements influence students' e-learning decisions and experiences in Libya. To choose participants from the designated target demographic, a random sample technique was employed, guaranteeing that every member of the population had an equal chance of being chosen. Students from Higher Education Institutions (HEIs) across all faculties in Libya were the target population in this case. A complete list of all HEIs in Libya was obtained by the researcher in order to carry outthe simple random sample. The sampling frame was this list. The HEIs that satisfied the inclusion criteria for the study made up the sampling frame. A representative sample of HEIswas chosen to take part in the study from this sampling frame.

By guaranteeing that each HEI had an equal chance of being chosen, this strategy produced a sample that was representative of the total number of HEIs in Libya. The results might be extrapolated to the nation's HEI population due to the random sampling technique. This approach also offered a fair mix of accessibility and representation because it featured HEIs from various Libyan faculties and locations. The target population for this research, which consists of HEIs in Libya, informed the design of the sampling frame. A complete list of all the HEIs that satisfy the study inclusion requirements is included in the sample frame. To identify every HEI, data will be obtained from multiple sources, including the Ministry of Education in Libya, in order to create the sampling frame.

Simple Random Sampling

The target population should be accurately reflected by a realistic target sample size. Furthermore, it will yield more precise outcomes in accomplishing the goals of this thesis. Every person of the population has an equal and fair chance of being selected to take part in the study when using this sample strategy (Acharya et al., 2013; Sharma, 2017, Alhoot et al.,2021, Selamat et al., 2021). Additionally, this method aids in minimizing or doing away withbias.

Sample Size

Achieving the goals of this thesis and obtaining more precise statistical results depend on choosing the right sample size. Thompson's (2012) equation was used to calculate the samplesize needed for this study. The purpose of this study is to identify what criteria students believewill influence their acceptance and use of e-learning, which in turn will influence their educational experiences. Libya is home to roughly fourteen state universities. Only seven of the nation's 19 private institutions hold full accreditation from the National Center for Quality Assurance. According to the most recent data available from the Ministry of Education officein Libya, there were roughly 402,392 university students enrolled in the 2020–2021 academicyear, with 52.7% of them being female. The intended study population for this research was represented by the projected 402,392 student population.

The sample size calculation equation is displayed as follows:

$$n = \frac{N \times P(1-P)}{N - 1 \times (d^2 \div z^2) + P(1-P)}$$

Where:

n = sample size N=population size

Z= 1.96 for a confidence level (α) of 95%,P = Probability (50%)

d=Error proportion (0.05)

$$n = \frac{402{,}392 \times 0.5(1-0.5)}{402{,}392 - 1\times(0.05^2 \div 1.96^2) + 0.5(1-0.5)}$$

= 384 Students

From the formula, n represents the sample size, N is the population size, and e is the level of precision.Using this formula, a sample size of 384 was obtained. This reflects the minimum sample size for the study (Aburagaga *et al.*, 2020).

Sampling Technique

Probability sampling is handled in a way that is separate from non-probability sampling (Goldstein & Reinert, 1997). However, in quantitative research, the reasonably large number of units from a community to represent is often selected by probability random sampling procedures so that all population members may be reliably ascertained. An example of a non-probability sampling strategy is selecting outliers or outlying instances where biases or personal interests can influence decision-making. On the other hand, probability sampling strategies need to choose samples focusing on specific questions (Etikan & Bala, 2017).

Non-probability sampling, sometimes known as "outlier sampling," is not permissible in this study. Researchers here use a technique of statistical analysis called probability sampling as a direct outcome of this. In addition, there are four alternative approaches to data collection when using a probability-based sampling technique. Because it is straightforward and may select individuals at random from the entire population, simple random sampling was used for this thesis (Goldstein & Reinert, 1997; Etikan & Bala, 2017).

Data Analysis Process

To analyze the goals and hypotheses of the research, data analysis entails a number of steps. Following data cleaning and assumption verification, Partial Least Squares Structural Equation Modeling (PLS-SEM) with Smart PLS 3.0 is used for the analysis, following the methodology of a related study by Sarwar & Azam (2019), Neni et al., (2020), Alsoud et al., (2021), and Abdeljaber et al., (2021).

Utilizing metrics like composite reliability, factor loadings, and average variance extracted, the analysis focuses on analyzing the measurement model and determining the validity and reliability of constructs. To assess the resilience and strength of the measurement model, convergent and discriminant validity are looked at. Testing the structural model becomes the priority after the measurement model has been confirmed. To assess the connections between latent components and verify the study hypotheses, this entails closely examining path coefficients, significance thresholds, and effect sizes. The importance and intensity of these associations provide information about the variables affecting how engaged students are with e-learning in LHEIs.

Data Collection

Empirical research is essential to obtaining reliable evidence for a particular question. The components of the study paradigm serve as the framework for the questionnaire. Right now, the main goal is to gather information that can be used to investigate possible relationships between various aspects. The components of the conceptual model were discovered through the online survey. For clarity, every response was noted on paper.

Measurement and Structural Models

The PLS-SEM will be used to assess the data received from respondents, using reasons from the literature (Hair et al., 2019; Rigdon, 2016; Sarstedt et al., 2016). First, Hair et al. (2019) proposed using PLS-SEM to examine a theoretical framework from a prediction standpoint. Thus, this thesis aims to predict and assess e-learning adoption and utilization predictors in LHEIs. Second, this research employed the UTAUT theoretical perspective and will test hypotheses. Hence, PLS-SEM is appropriate for testing a theoretical perspective and provides a prediction perspective (Rigdon, 2016). Finally, the thesis's small population necessitated the using smaller sample sizes, and PLS-SEM helps analyze smaller samples (Sarstedt et al., 2016; Rigdon, 2016).

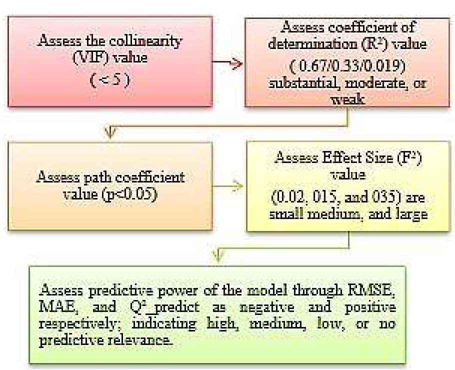
The SEM method will test the priori-specified hypotheses based on the relationships between observed and latent (unobserved) variables (Mueller & Hancock, 2019). The structural model has several connections between the dependent and independent variables (inner model). A well-defined measurement model for each independent variable is required. Structural equation models combine measurement and structural models (Frederik & Ahlemann, 2010).

Measurement Model Assessment

The structural model assessment will be done after successfully validating the measurement model. The procedure will be carried out in line with the recommendations of Ramayah et al. (2018) using SmartPLS3. The procedure for assessing the structural model is illustrated in Figure 5.

The procedure of Structural Model Assessment

Figure 5



Pilot Test and Reliability Procedure

The initial test of the study serves as an early evaluation of the reliability of the research tool. As advocated by Saunders et al. (2019), conducting a pilot study is recommended to pre-test the research instrument to gauge the feasibility of the primary study—an approach adopted by various studies, including Thinagar et al. (2021). The assessment of the study instrument's reliability will involve the utilization of Cronbach's alpha. Furthermore, the consistency of the survey items will be examined. More confidence in the measurement is achieved when both the survey and its items effectively measure the same construct.

RESULTS AND DISCUSSION

The data includes 398 students' responses to various factors affecting the usage of e-learning and their mediating effects. There are ten factors related to Perceived Ease of Use (PE1-PE10), eight factors related to Perceived Enjoyment (EE1-EE8), ten factors related to Self-efficacy (SI1-SI10), nine factors related to Teacher's Attitude (TA1-TA9), ten factors related to Perceived Usefulness (PU1-PU10), nine factors related to Perceived Interest (PI1-PI9), 11 factors related to Facilitating Conditions (FC1-FC11), nine factors related to Behavioral Intention (BI1-BI9), nine factors related to Actual Use (AU1-AU9), and eight factors related to Perceived Barriers (PB1-PB8).

Each factor is measured on a 7-point Likert scale, with one being "strongly disagree" and seven being "strongly agree." The mean scores for all factors are above the midpoint of 4, indicating that students generally agree with the statements related to the factors affecting the usage of e-learning and their mediating effects.

The standard deviation scores indicate variations in students' responses to the factors. Perceived Enjoyment (EE1-EE8) has the highest standard deviation scores, indicating that students have a more comprehensive range of responses to these factors. The valid N (listwise) is 398, indicating that all 398 students' responses were used in the analysis. Overall, the descriptive statistics provide a general overview of the data and indicate that students generally agree with the factors affecting the usage of e-learning and their mediating effects. However, there is some variation in students' responses, indicating that there may be individual differences in how students perceive and use e-learning.

Demographic analysis

Based on the provided data, here are the descriptive statistics:

Gender:

The total number of respondents is 400, with 185 (46.3%) female and 215 (53.7%) male. All 400 respondents have valid responses for gender.

Age:

The total number of respondents is 400, with 127 (31.7%) aged between 18-26, 87 (21.8%) aged between 27-35, 102 (25.5%) aged between 36-44, 66 (16.5%) aged between 45-53, and 18 (4.5%) aged 54. All 400 respondents have valid responses for age.

Education:

The total number of respondents is 400, with 114 (28.5%) having a bachelor's degree, 48 (12%) having a Diploma, 86 (21.5%) having an MA, and 152 (38%) having a PhD. All 400 respondents have valid responses for education.

Region:

The total number of respondents is 400, with 49 (13.2%) being international students and 351 (86.8%) being Libyan students. All 400 respondents have valid responses for the region. As presented in table and table 3.

Years of Experience:

The total number of respondents is 400, with 55 (12.6%) having less than 2 years of experience, 128 (32%) having 2-5 years of experience, 107 (26.8%) having 6-9 years of experience, 39 (9.8%) having 14-17 years of experience, and 71 (17.8%) having 10-13 years of experience. Most of the respondents have more than 2 years of experience.

Field of Study:

The total number of respondents is 400, with 139 (34.8%) studying in the East, 102 (25.5%) studying in the South, and 159 (39.7%) studying in the West. Most of the respondents are studying in the West.

Structural Equation Modeling (SEM) discussion

SEM typically involves confirmatory factor analysis (CFA) and structural equation modeling. In the CFA step, the researcher specifies the relationships between the observed variables and the underlying latent factors. The validity and reliability of the study's measurements are evaluated in this step. The researcher defines the linkages between the latent components and examines the relationships between the factors hypotheses in the structural equation modeling process.

The ability to estimate both direct and indirect effects between variables is one of SEM's benefits. This is especially helpful for this study because the investigator wants to find out which factors mediate the relationship between e-learning uptake and usage.

The study's 10 items had a high degree of internal consistency and reliability, as evidenced by the Cronbach's Alpha rating of 0.801. This indicates that the measurement of the items is consistent and measures the same construct. The items are suitable for the study and can be utilized to make meaningful inferences about the assessed construct, according to the high reliability coefficient.

For the study, the 400-person sample size is also appropriate since it provides sufficient power to detect small to moderate effect sizes. Only complete cases are included in the study when listwise deletion is used for missing data, which can help to lessen bias and increase the accuracy of the findings.

Demographic analysis

Table 3

Gender				
	Frequency	Percent	Valid Percent	Cumulative Percent
Male	215	53.7	53.7	53.7
Female	185	46.3	46.3	46.3

Total	400	100.0	100.0	100.0

Age

	Frequency	Percent	Valid Percent	Cumulative Percent
18-26	127	31.7	31.7	31.7
27-35	87	21.8	21.8	53.5
36-44	102	25.5	25.5	79.0
45-53	66	16.5	16.5	95.5
54	18	4.5	4.5	100.0
Total	400	100.0	100.0	

Education

	Frequency	Percent	Valid Percent	Cumulative Percent
Bachelors	114	28.5	28.5	28.5
Diploma	48	12.0	12.0	40.5
MA	86	21.5	21.5	62.0
PhD	152	38.0	38.0	100.0
Total	400	100.0	100.0	

Region

Frequency		Percent	Valid Percent	Cumulative Percent
International	49	13.2	13.2	13.2
Libyan	351	86.7	86.7	100.0
Total	400	100.0	100.0	

Years_of_Experience

Frequency		Percent	Valid Percent	Cumulative Percent
23 years	1	.1	.1	.1
14-17 years	39	9.8	9.8	9.8
10-13 years	71	18.8	18.8	18.8
6-9 years	107	26.8	26.8	26.8

2-5 years	128	32	32	32
Less than two years	54	12.6	15.9	100.0
Total	400	100.0	100.0	

Field_of_study

	Frequency	Percent	Valid Percent	Cumulative Percent
East	139	34.8	34.8	34.8
South	102	25.5	25.5	25.5
West	159	39.7	39.7	39.7
Total	400	100.0	100.0	

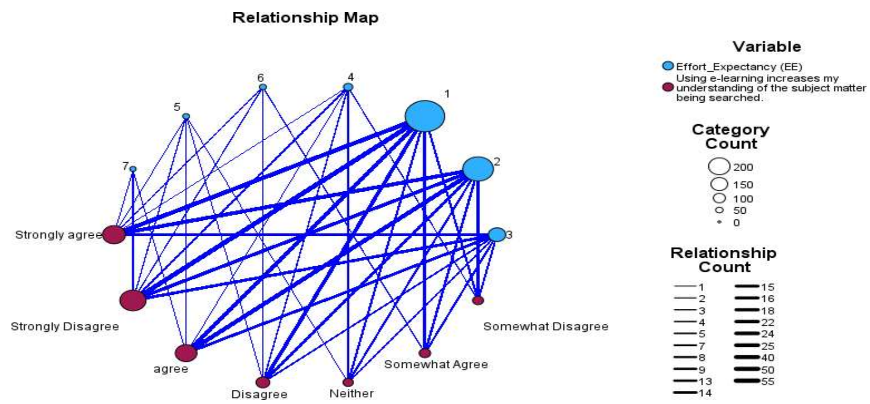
The two variables show a positive correlation; that is, the more strongly one agrees with the statement "My interactions with the e-learning systems available in my institution are clear and understandable," the more strongly one agrees with the statement "Using an e-learning system will increase my chances of getting benefits." According to this, students are more likely to think that adopting an e-learning system will help them if they find the systems used by their school to be clear and intelligible.

This finding is in line with earlier studies that have shown how important it is for e-learning systems to be user-friendly and usable in order to influence students' attitudes toward and willingness to utilize them. Institutions can boost students' confidence in adopting e-learning systems and their perception that they would be beneficial by making them transparent and understandable.

In addition, a moderate association between the two variables is suggested by the intensity of the correlation, meaning that they are related but not perfectly correlated. This implies that additional elements, such as motivation, past e-learning experience, and the accessibility of resources and support, may have an impact on students' views toward and desire to use e-learning. Figure 5 presents the association.

Relation Map

Figure 5



Validity and Reliability

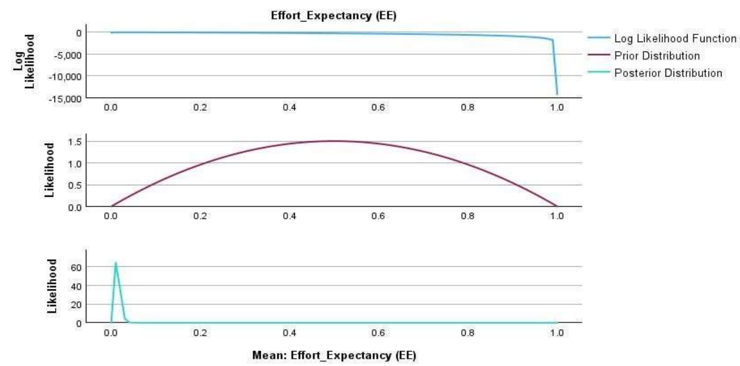
When examining the results of a structural equation modeling (SEM) investigation, validity and reliability—two fundamental principles in research and measurement—become especially pertinent. In this talk, we'll examine the reliability and validity of the SEM analysis's constructs using the data displayed in the image. A measure is said to be valid to the extent that it accurately captures the idea being measured. There exist multiple categories of validity, such as It possesses discriminant and convergent validity.

Convergent Validity

The degree to which several measures of the same construct are connected is known as convergent validity. Convergent validity would be shown in the context of the figure if there is a positive correlation between the two items that measure the construct of e-learning benefits (i.e., "Using an e-learning system will boost my chances of receiving rewards" and "My interactions with the e-learning systems available in my institution is clear and understandable"). A moderately positive correlation between the two questions is seen in Figure 6, supporting convergent validity and suggesting that the two are measuring the same construct. 0.51% as the correlation coefficient. Convergent validity is demonstrated by this, indicating that the two items may be measuring the same underlying construct.

Mean Effort Expectancy EE

Figure 6

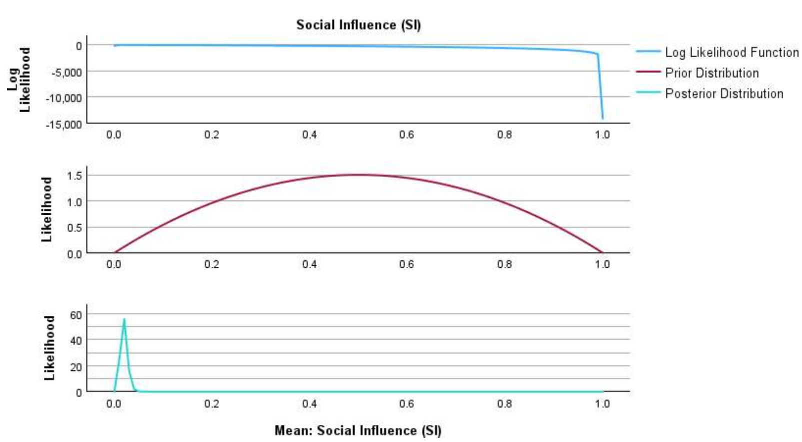


Discriminant Validity

Discriminant validity is the degree to which various notions are distinct.. In the context of the figure, discriminant validity would be demonstrated if the two items used to measure the construct of e-learning benefits were not correlated with other constructs in the SEM model. Based on the data presented in Figure 7, it is impossible to assess discriminant validity directly, as the correlations The relationship between the e-learning benefits construct and the other constructs in the model is not specified. However, discriminant validity can be assessed by comparing the correlations between the e-learning benefits construct and other constructs in the model with the correlations between the e-learning benefits construct and itself. If the correlations between the e-learning benefits construct and other constructs are significantly lower than those between the e-learning benefits construct and itself, then discriminant validity is demonstrated.

Social influence

Figure 7



Structural Models- Stage 2 of SEM

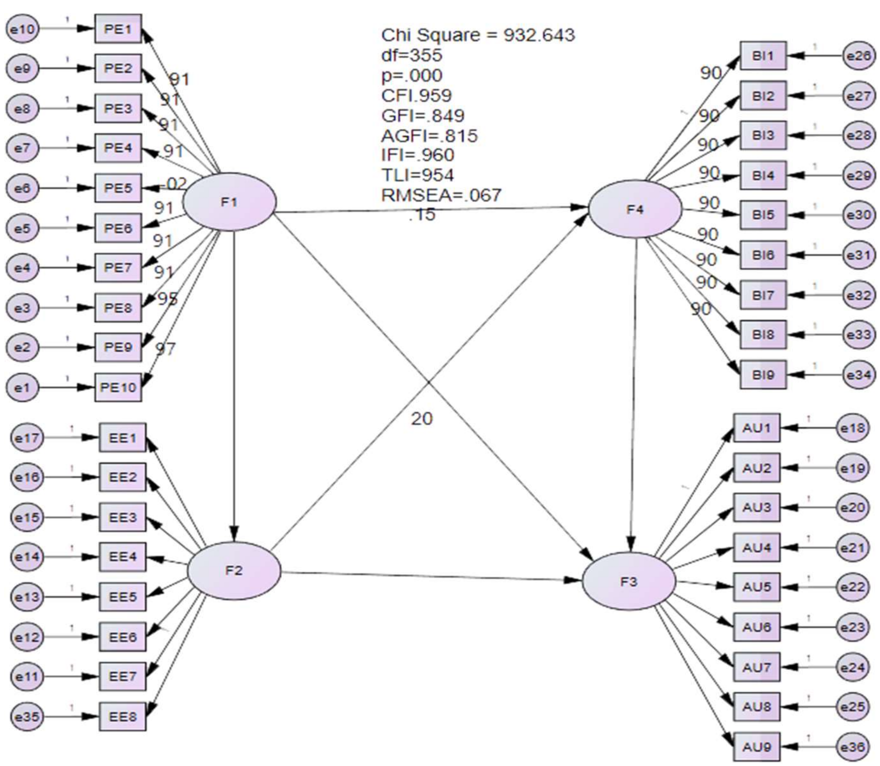
The second stage of structural equation modeling is used to test the significance of hypothesized relationships. The model provides coefficients, p-values, and t-statistics, which are compared to benchmarks to determine the significance of the relationships. This section will test the hypotheses that performance expectancy, effort expectancy, social influence, technology awareness and anxiety, and personal innovativeness impact behavioral intention and actual usage of e-learning. Structural equation modeling will determine if these hypothesized relationships are statistically significant.

Direct Effects of the Variables

In this section, direct relationships will be assessed. The hypothesis under assessment is: (H1, H8), (H2, H8), (H3, H8), (H4, H8), (H5, H8), (H6, H8). Based on the assessment, the AMOS diagram is to determine the relationship between these hypotheses and whether there is an impact of H1, H1, H1, H1, H1, and H1 on behavioral intentions and actual usage of eLearning in Libyan higher learning. Test Effort Expectancy (EE), Behavioral Intentions (BI), Social Influence (SI), Actual Usage (AU). As presented in Figure 8.

AMOS Graph of Structural Model 1

Figure 8

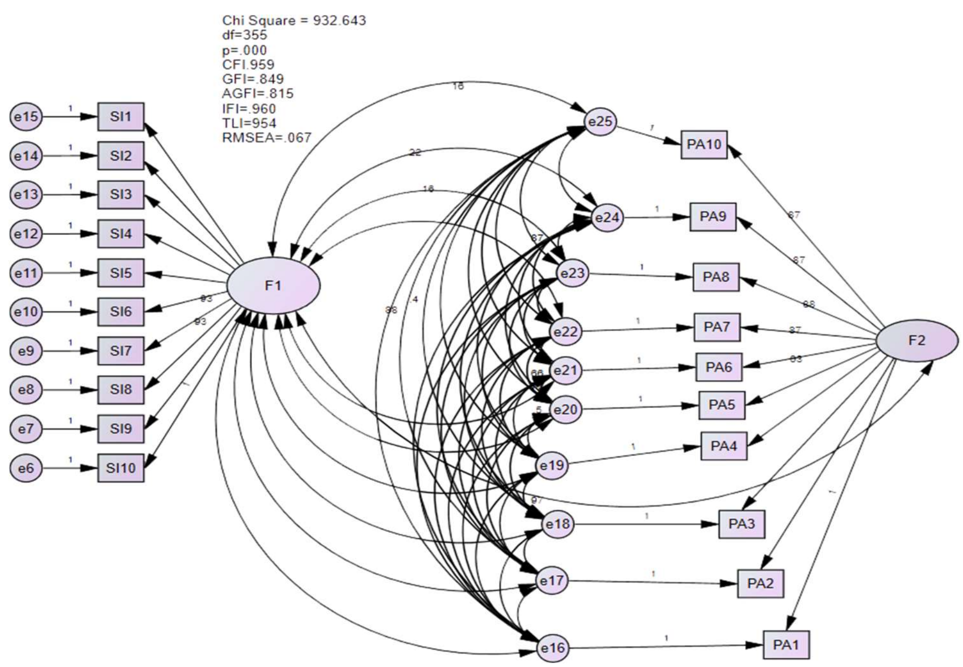


Upon evaluating the model titled "The Factors Affecting the Usage of E-learning and Their Mediating Effects Among Students of Libyan Higher Education Institutions," we determine that the values of the model exhibit a suitable match. This analysis was done initially when the measurement model was provided. Furthermore, several research assess the model fit values at various stages of the structural model creation process as a precaution. The Chi-Square Test, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) are the standards for all indices, as was previously mentioned in the section on the measurement model. To verify the accuracy and applicability of the model, these indices and the thresholds that go along with them were carefully studied.

In order to show a satisfactory fit, the TLI and CFI indices need to be higher than 0.90. Excellent match is indicated by values greater than 0.95. For a good fit, the RMSEA value should be less than 0.08, and for an exceptional fit, it should be less than 0.06. In order to signify a successful match, the SRMR score must be less than 0.08. These indices were all within reasonable bounds, suggesting that the model does a good job of fitting the information obtained by LHEIs. This assessment of perfect fit aligns the model with the requirements set by the literature, ensuring that the factors impacting e-learning usage and their mediating effects are adequately accounted for. The model fits well, as evidenced by the confidence that all fit metrics are adequate.

Path model for categorizing variables according to personal and social influence

Figure 9.

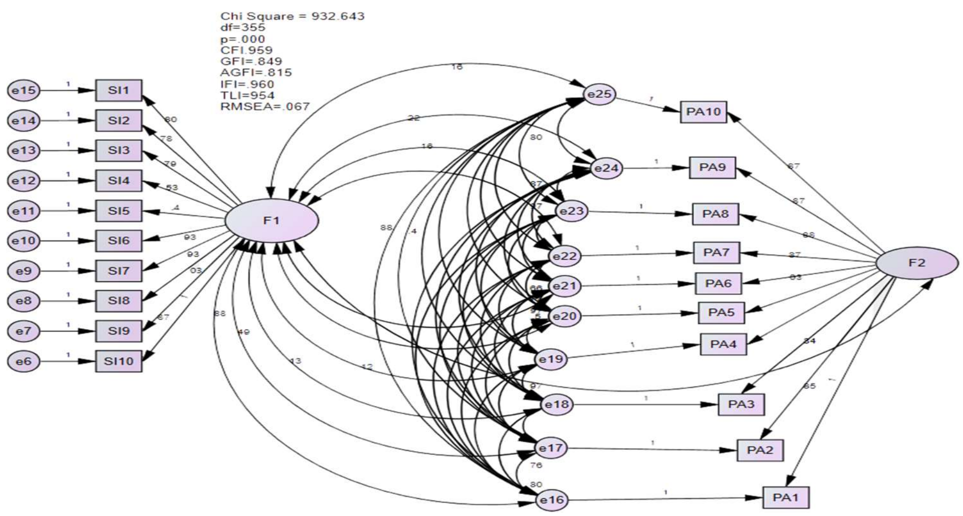


The outcomes of a regression analysis that looked at the variables influencing how much students in Libyan universities used e-learning. For each factor, the unstandardized and standardized estimates, P value, C.R. (critical ratio), and hypothesis outcomes are displayed in the table. Included in the analysis are the following variables:

- PE: Performance Expectancy
- EE: Effort expectancy
- SI: Social influence
- TA: Technology Awareness
- TAX: Technology Anxiety
- PI: Personal Innovativeness
- FC: Facilitating conditions

This is a path model for categorizing variables according to experience and social influence.

Figure 10



Positive Relationships:

Performance Expectancy (PE): The utilization of e-learning and perceived ease of use are positively correlated statistically significantly ($p < 0.006$). This implies that learners are more likely to participate if they believe e-learning is simple to use.

Effort Expectancy (EE): A statistically significant positive correlation ($p < 0.22$) has been observed between EE and e-learning utilization. This suggests that e-learning users are more likely to be students who think it takes less work.

Technology Awareness (TA): The use of e-learning and administrative trust are positively correlated statistically. $P < 0.0000$. This shows that e-learning tools are more likely to be used by students who have faith in the administration to administer them.

Technology Anxiety (TAX): Use of e-learning and perceived usefulness have a statistically significant positive correlation. $P < 0.013$. This suggests that students are more inclined to interact with e-learning if they believe it will help them learn.

Personal Innovativeness (PI): There is a statistically significant positive correlation between the use of e-learning and subjective pleasure. ($p < 0.043$). This implies that e-learning is more likely to be used by students who appreciate it.

Facilitating Conditions (FC): There is a statistically significant positive correlation ($p < 0.0000$) between the use of e-learning and the facilitating conditions. This suggests that e-learning is more likely to be used by students who have access to the right tools and technology.

Negative Relationship:

Social Influence (SI): There is a statistically insignificant negative The link between social influence and e-learning usage ($p > 0.909$). This indicates that the influence of others on student's e-learning usage is not significant.

Overall Findings

The findings suggest that various factors play a role in determining the usage of e-learning among Libyan students. Notably, perceived ease of use, effort expectancy, trust in administration, usefulness, enjoyment, and facilitating conditions are positively related to e-learning usage.

Further Analysis

Mediating Effects: Investigate whether any of these factors mediate the relationship between other factors and e-learning usage.

Moderating Effects: Exploring if other variables moderate the relationships observed in the table.

CONCLUSION

This report provided the findings of the normalcy test, outlier analysis, and demographic Analysis for paper on the factors influencing students' use of e-learning platforms in Libyan higher education institutions. The normality test results showed that the majority of variables were not normally distributed, as evidenced by p-values less than 0.05 in the Shapiro-Wilk test. Therefore, appropriate non-parametric tests should be used in the data analysis stage. The outlier analysis was conducted using univariate and multivariate methods. The univariate outliers were identified using boxplots, and the multivariate outliers were identified using the Mahalanobis distance method. After removing the outliers, the final sample consisted of 390 students. The demographic analysis showed slightly more male students (53.8%) than female students (46.3%) in the sample. The students ranged from 18 to 54 years, with a mean age of 28.5. Most of the students were from the West region (39.8%), followed by the East (34.8%) and the South (25.5%). The students' years of experience in using e-learning platforms varied, with the majority having 2-5 years of experience (32.0%). The study area also varied, with most students studying in the Faculty of Education (28.5%). Overall, the normality test results, outlier analysis, and demographic analysis provide essential information for the data analysis stage helps assure the validity and trustworthiness of the paper findings.

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