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Investigation A Technology Acceptance Model (TAM) of E-Learning in Higher Education Institutions (HEIs)

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Abstract

In recent years, the integration of e-learning, which refers to using electronic technology to aid and enhance learning processes, has received substantial attention in Higher Education Institutes (HEIs). This study explores the adoption and acceptance of e-learning in Higher Education Institutes (HEIs) using the Technology Acceptance Model (TAM) framework. The research investigates the influence of external variables on the acceptance of e-learning, specifically focusing on Mobile Friendliness (MF), LMS Replacement (LMSR), Job Insecurity (JIS), and Job Switching (JS). The study utilizes survey-based empirical research, collecting responses from 407 participants out of 500 academics from Saudi public and private sector HEIs and colleges in the Southern region. The survey instrument was designed based on established measures of the TAM constructs, including Attitude and Behavioral Intention. Additionally, items were included to assess MF, LMSR, JIS, and JS external variables. Participants were asked to rate their perceptions and experiences related to e-learning adoption using a Likert scale. Data analysis involved descriptive statistics, bivariate correlation, and multiple regression analyses. The findings indicate a significant relationship between the external variables and the acceptance of e-learning. Mobile Friendliness, LMS Replacement, Job Insecurity, and Job Switching influenced participants' attitudes and behavioral intentions toward e-learning. These results have important implications for policy and practice in the HEI context. Policymakers should prioritize the development of mobile-friendly e-learning platforms and provide support for replacing outdated Learning Management Systems. Additionally, efforts to address job insecurity and minimize job switching among faculty members are crucial for fostering a positive attitude toward e-learning. This study contributes to the existing knowledge on e-learning adoption by examining the role of external variables within the TAM framework. The findings offer insights into the factors influencing the acceptance of e-learning and provide a basis for future research in this area. Moreover, the study underscores the importance of considering external variables when designing and implementing e-learning initiatives in HEIs.

Keywords: E-learning, Technology acceptance model, External variables, Mobile friendliness, LMS replacement, Job insecurity, Job switching, HEIs

1. Introduction

Human life is revolutionized by new technologies and actual use of the system and behavioral intention to use new technology is the main challenge. Digitalization has modified the education system in recent years. The use of electronic technology and the internet to transmit educational information and support learning remotely is referred to as e-Learning, sometimes known as electronic learning or online learning. It entails the use of digital technologies, resources, and platforms to make educational content, interactive activities, and assessments.

It provides several advantages over traditional-based learning in terms of personalization and adaptability to meet individual needs and preferences, provide educational contents by delimiting the geographical barriers, enhance learner engagement by introducing interactive features[1].

However, it is also important to remember that e-Learning has issues that must be handled to be adapted in Higher Education Institutes (HEIs) at vast level. E-Learning deployment requires 24/7 reliable Internet connectivity, access to appropriate equipment, and technical assistance[2]. Inadequate infrastructure can obstruct access and reduce the efficacy of online learning sessions[3]. Learners must have fundamental digital literacy abilities in order to navigate online learning platforms, interact with digital information, and communicate and cooperate successfully in virtual settings. It is critical to provide help and training to learners who may lack digital abilities in order for them to succeed in e-Learning.

Online learning may not always give the social contact and networking possibilities that traditional education does. This difficulty may be addressed by cultivating a feeling of community, promoting peer-to-peer interactions, and introducing collaborative activities into e-Learning experiences. It is critical to maintain high quality standards in e-Learning[4]. Institutions must guarantee that learning material, assessments, and experiences are rigorous, engaging, and aligned with learning objectives. Accreditation systems and quality assurance mechanisms tailored to online education are critical to building trust[5, 6]. However, it is important to foster a culture of acceptance, enhance collaboration, and improve overall performance of the e-learning system in the HEIs by addressing the issues like resistance to change which requires effective communication, engagement, and addressing concerns and fears of the employees, ensure clarity of the roles and procedures, establishing effective communication channels to foster a collaborative environment, developing strong leadership skills and acknowledge achievements on the basis of regular feedback, aligning the goals with broad organizational culture.

Therefore, this research seeks to investigate the external factors and main challenges and limitations that have affected the acceptance and adoption of eLearning systems in HEIs. This study introduces external factors like Job Insecurity (JIS), Learning Management System Replacement (LMSR), Mobile Friendliness (MF) and Job Switching (JS) to integrate with Technology Acceptance Model (TAM)[7] for significant findings based on empirical data analysis. The remainder of the paper is structured as follows. In Section 2, we mention the background of our research work. Section 3 explains our research methodology. Section 4 presents the results and discussion. In the last section, we illustrate the conclusion, the limitations of this study, and propose future work.

2. Literature Background

The advancement of Information and Communication Technologies (ICT) has transformed education by increasing access, improving learning experiences, and altering old educational methods. It has had a huge influence on education, revolutionizing how education is offered, accessed, and experienced. Resultantly, several systems like Virtual Learning Environments (VLE), Computer-based Training Systems (CBTs), Learning Management Systems (LMSs) and e-Leaning have been emerged in the recent times for improving the education standards in Higher Education Institutes (HEIs) to meet rapid emerging challenges in education sector[8, 9]. This emphasizes the need of defining the parallels between freshly developing concepts in online learning[10].

The term “eLearning” is so wide that it might apply to nearly any platform that delivers elementary education to students via an online platform i.e. LMS and VLE. E-Learning refers to the use of electronic technologies and digital platforms for delivering educational content and facilitating learning experiences. Technology Acceptance Model is a theoretical framework that describes how people acquire and accept new technology. TAM, as applied to e-Learning, tries to comprehend the elements that influence users' adoption and utilization of e-Learning systems. In underdeveloped and developing countries, eLearning raises the level of education, literacy and economic development [11]. This is especially true for countries where technical education is expensive, opportunities are limited and economic disparities exist. E-Learning can be highly beneficial to both students and institutions if properly implemented. The impact of eLearning and internet technology on the quality of education in the institutions of higher education in Saudi Arabia in particular has predominantly influence the current studies [12].

The acceptance and adoption of technologies have been studied using a variety of theories and models including Diffusion of Innovation theory (DOI)[13] ,the Theory of Reasoned Action (TRA) [14] Uses, Gratification Theory (U&G)[15], Theory of interpersonal behavior (TIB)[16], The Model of PC Utilization (MPCU)[17], Theory of Planned Behavior (TPB)[18], Decomposed Theory of Planned Behavior[19], the Technology Acceptance Model (TAM)[20], Technology Acceptance Model 2 (TAM2)[21], External Variable Technology Acceptance Model (TAM3)[22], Social Cognitive Theory (SCT)[23], Motivational Model (MM)[24], Unified Theory of Acceptance and Use of Technology[25], Compatibility UTAUT[26]. Figure 1 depicts the Evolution of Technology Acceptance Theories Chronological TimeLine graph.

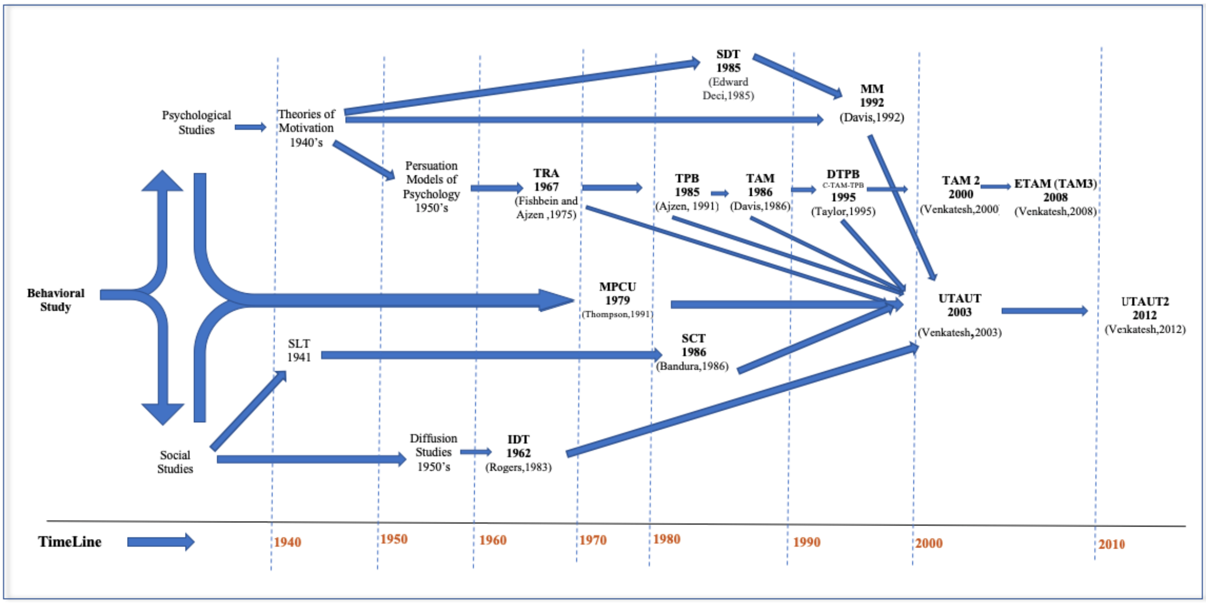

Figure 1: Chronological TimeLine graph for the Evolution of Technology Acceptance Theories [27]

The basic Technology Acceptance Model (TAM) presented in Figure 2 below, has been introduced by [28] for adaption of the Theory of Reasoned Action that was specifically geared for studying user adoption of information systems and technology and then has been expanded and modified by the researchers since then. The model is intended to illustrate the methods in which users embrace and apply technology. The theoretical foundation of the model is based on the aspects that users consider when encountering new technology.

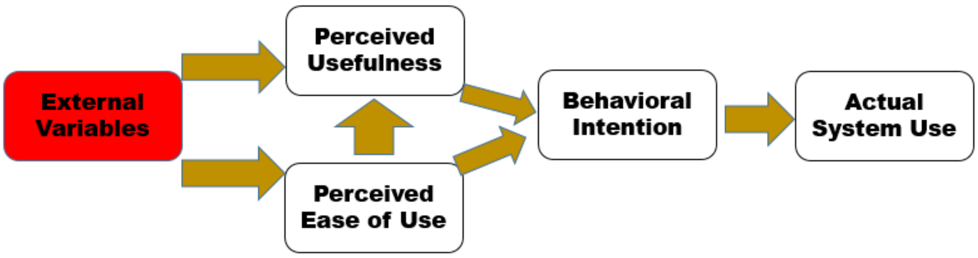

Figure 2: Technology Acceptance Model [15]

However, researchers frequently integrate external variables in the TAM to strengthen its explanatory power and account for other factors that may influence technology acceptance.

These external variables can include factors such as organizational context, social influence, system characteristics, and individual characteristics. Such like the authors of studies TAM2 [21] and TAM3 [22] have introduced external variables likewise perceived organizational support, perceived system quality, subjective norms, facilitating conditions, and personal innovativeness into the TAM to provide a more comprehensive understanding of technology acceptance. Due to the flexibility of TAM [29] and the inefficiency of perceived ease of use and perceived usefulness constructs [30, 31], and because specific external factors incorporated in the TAM may differ depending on the research context and study objectives, we introduced four (4) external factors in this study, namely Mobile Friendliness (MF), Job Insecurity (JIS), Job Switching (JS), and Learning Management System Replacement (LMSR) to meet our particular objectives to observe the usefulness of these factors for TAM to enhance e-Learning infrastructure in Higher Education Institutes (HEIs). These aspects are explained in further sub-sections for the researchers' knowledge while extending TAM and adapting in e-Learning.

2.1. Mobile Friendliness (MF)

In a Technology Acceptance Model (TAM), Mobile Friendliness (MF) refers to how much a team's members embrace and use mobile technology for communication, collaboration, and job execution. Mobile devices, such as smartphones and tablets, have become essential tools for many individuals, including team members in various professional contexts, in today's fast-paced and highly connected world. Following aspects might be addressed while establishing a TAM for MF:

- Accessibility
- Usability
- Collaboration
- Communication
- Security
- Training and Support

2.2. Learning Management System Replacement (LMSR)

When replacing a Learning Management System (LMS) in a Technology Acceptance Model (TAM), a new platform for managing and delivering educational or training content inside a team or organization is implemented. However, following factors might be considered while developing a TAM for LMS Replacement (LMSR). Teams may ease a faster transition, ensuring the new system fits their learning goals, and drive more adoption and acceptance among team members.

- Need Assessment (Requirements, Functionalities, and Features for learning)
- User Experience (Intuitive and user-friendly interface)
- Integration and Compatibility
- Customization and Flexibility
- Data Security and Privacy
- Evaluation and Feedback
- Training and Support

2.3. Job Insecurity (JIS)

Job insecurity can have a significant impact on team acceptance and the overall dynamics within a team. Organizations should address the following job insecurity concerns to develop a healthy team atmosphere and assist team members in steering difficult times in order to promote acceptance, cooperation, and productivity within the team.

- Resilience and Adaptability
- Job Redesign and Flexibility
- Team collaboration and support
- Career development and Advancement opportunities
- Performance feedback and recognition
- Empathy and support
- Skill development and training
- Communication and Transparency

2.4. Job Switching (JS)

Within a Technology Acceptance Model (TAM), job switching refers to the process of team members migrating from one role or position within the team or organization to another. It can have positive or negative impact on organizations. It may assist organizations in a variety of ways, including knowledge transfer, improved cooperation, and talent development. To prevent any possible obstacles or bad repercussions, organizations must carefully manage the process, give support to staff during transitions, and guarantee successful knowledge transfer. Following factors are considered important in terms of ensuring job switching in or out of organizations:

- Transparent communication
- Clarity of roles and expectations
- Skill development and training
- Recognition and reward
- Team integration and collaboration
- Continuous learning and adaptability

2.5. Attitude towards use of Technology

In a Technology Acceptance Model (TAM), attitude towards the usage of technology refers to the team members' general views, perceptions, and sentiments about the adoption and utilization of technology in their work environment. It includes their perspectives on the advantages, usability, efficacy, and influence of technology on their work processes and outputs. When Assessing attitude towards technology in a TAM, following factors needs to be given importance in order to promote decision acceptance and effective use of technology within the team.

- Perceived usefulness
- Perceived ease of use
- Impact on job performance
- Organizational culture and leadership
- Perceived risks and concerns
- Peer influence and social norms
- Feedback based continuous improvement

2.6. Behavioral Intention (BI)

Behavioral Intention (BI) is important in the context of a Technology Acceptance Model because it frequently precedes actual behavior adoption. In a TAM, BI refers to an individual team member's preparedness and desire to engage in a certain behavior connected to the acceptance or adoption of a new technology, procedure, or change within the team. It indicates their intentional intention or decision to engage in the aforementioned behavior. It is impacted by following elements that alter people's views and attitudes towards the behavior. Understanding and forecasting behavioral intentions can assist organizations in determining the likelihood of effective implementation and acceptance of desired team behavior.

- Attitude towards the behavior
- Subjective norms
- Perceived behavioral control
- Self-efficacy

2.7. Hypotheses Development

In the Extended Technology Acceptance Model, hypothesis creation entails creating explicit assertions that suggest links between variables (MF, LMSR, JIS, and JS) inside the model. These hypotheses form the basis for empirical investigation and testing to confirm or deny the hypothesized links. Based on theoretical framework presented in Figure 1 below, we have developed the following hypothesis to empirically investigate the impact / influence of mentioned factors while extending Technology Acceptance Model (TAM) and adapting e-Learning infrastructure in Higher Education Institutes (HEIs).

The presence of factors (MF, LMSR, JIS, and JS) positively influence the technology acceptance and adaptation in e-Learning in Higher Education Institutions

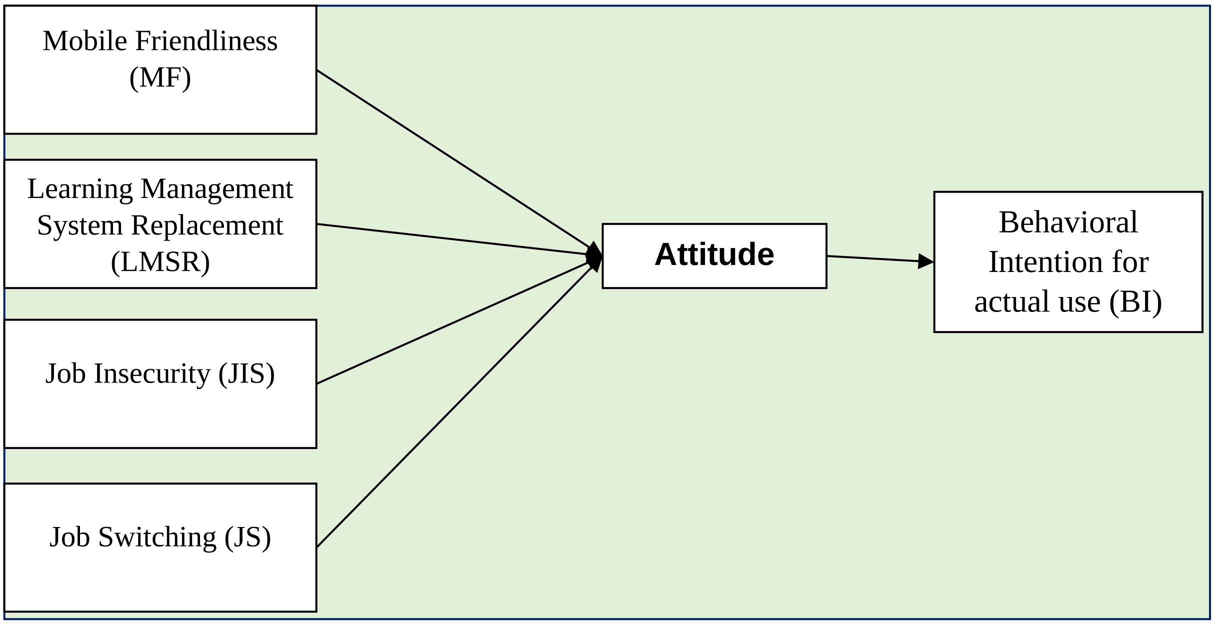

Figure 3: Proposed Theoretical Framework

3. Research Methodology

The overarching strategy or framework that specifies how a research study will be done is referred to as the research design. It includes the methodology, data collection methods, and analytic techniques used to address the study questions or objectives. A well-designed research study guarantees that the information gathered is valid, trustworthy, and pertinent to the research objectives. After carefully exploration of the literature regarding external factors influencing e-Learning in HEIs, we have used cross-sectional design to collect data while utilizing questionnaires from past studies. The study's population included all academics teaching at Saudi public and private sector higher education institutions and colleges in the southern area. The sample size 500 was determined using a non-probability convenience sampling approach[32]. After distributing the questionnaires among the specified population, we have received 407 responses thus yielded 81.4% response rate. The data is analyzed using SPSS and smart PLS-SEM statistical tools. Furthermore, Herman Single Factor Analysis (HSFA) is used to examine Common Method Bias (CMB). Meanwhile, skewness and kurtosis are used to assess data normality. Besides, in order to ensure ethical considerations, prior to data collection, consent was obtained from the relevant officials as well as from the respondents. Respondents were assured that their information would only be utilized for academic purposes and that their names would be kept private.In order to test the hypotheses bivariate correlation and multiple regression analyses were run to find the best fit model. In PLS-SEM confirmatory factor analysis (CFA) was run to test the reliability, convergent and discriminant validity.

4. Results and Analysis

This section has addressed data analysis and interpretation. Data was collected online through Google forms and was downloaded in the form of an MS Excel (.CSV) file and then entered into SPSS version 25. While collecting the data, we have used demographic factors but strict to ethical considerations, The Table 1 below shows the generic information for reliability of the collected data through respondents. Majority of the respondents are females 246 (60.4%) and followed by their male counter parts 161 (39.6%) of the sample size. In addition young respondents with age group of 30-40 years 200(49,.1%) participated in the study followed by those having age of 40-50 years 184 (45.2%) and 16 respondents belong to age group of 25-30 years and only 7 belong to age more than 50 years. Moreover, there were more non-Saudi faculty members participated in the study 334 (82.1%) and only 73 Saudi i.e. (17.9%) have taken part in the survey. Regarding language 283 (69.5%) were non Arabic speakers and 124 (30.5%) were Arabic speakers. Majority of the respondents belong to HEIs 405 (99.5%). Likewise, majority of the participants were on contract 364 (89.4%) followed by permanent employees 32 (7.9%) and only were visiting and 4 were daily wages employees. In the same way respondents were asked about designation in which majority of lecturers participated 227 (55.8%) followed by instructors 143 (35.1%) and assistant professors 37 (9.1%) respectively. Regarding field of education most of the respondents belong to natural sciences field 175 (42.75%) and 122 belong to humanities and social sciences and 61 belong to applied sciences and remaining 49 belong to other fields. It is evident from the findings that majority of the respondents were holding master degrees i.e. 363 (89.2%) and 44 were having Ph.D. degrees.

Most of the lecturers were having experience of between 4 to 10 years i.e. 146 and majority of the respondents working at current positions at least 5 years or above and between 1 to 3 years were 113 and 100 respectively.

Table 1: Demographic Information of the Respondents

Variables	Attributes	n	%
Gender	Male	161	39.6
	Female	246	60.4
Age	25-30 Years	16	3.9
	30-40 Years	200	49.1
	40-50 Years	184	45.2
	Above 50 Years	7	1.7
Nationality	Saudi	73	17.9
	Non-Saudi	334	82.1
Language	Arabic	124	30.5
	Non-Arabic	283	69.5
HEIs Employee	Yes	405	99.5
	Others	2	0.5
Job Nature	Permanent	32	7.9
	Contract	364	89.4
	Visiting	7	1.7
	Daily Wages	4	1.0
Designation	Assistant Professor	37	9.1
	Lecturer	227	55.8
	Instructor	143	35.1
Field of Education	Applied Sciences	61	14.98
	Humanities & SS	122	29.97
	Natural Sciences	175	42.75
	Others	49	12.03
Education	Ph.D.	44	10.8
	Master	363	89.2
Length of Service	< 1 year	84	20.6
	Between 1 & 2 years	78	19.2
	Between 2 &4 years	61	15
	Between 4&10 years	146	35.9
	Above 10 years	38	9.3
Work with current Institution	<1 year	103	25.3
	Between 1 &3 years	100	24.6
	Between 3&5 years	91	22.4
	Above 5 years	113	27.8

In the next step after raw data collection, by following the guidelines provided in [33] regarding effects of missing values, We utilized Google forms and made all questions obligatory; responders were not permitted to progress unless they answered the questions. As a result, there were no missing data in this study. The normality of data is evaluated in the next stage. Skewness and kurtosis can be used to determine data normality that indicate the data's normal distribution and the results are presented in Table 2 below:

Table 2: Data Normality values

Variables	N	Skewness		Kurtosis	
		Stat	**S.E**	**Stat**	**S.E**
MF	407	-012	.121	-0.165	.242
LMSR	407	-0.038	.121	-0.200	.242
JIS	407	-0.062	.121	-0.237	.242
JS	407	0.023	.121	-0.105	.242
Attitude	407	-0.037	.121	-0.142	.242
BI	407	-0.024	.121	-0.183	.242
MF= Mobile Friendliness, **LMSR**= Learning Management System Replacement, **JIS**= Job Insecurity, **JS** = Job Switching, and **BI** = Behavioral Intention for actual use					

Further analysis was carried out the difference in the mean scores on the basis of gender presented in the Table 3 below:

Table 3: Compare means on the basis of Gender

Gender		MF	LMSR	JIS	JS	Attitude	BI
Male (161)	*Mean*	**4.22**	**2.28**	**2.72**	3.03	**4.19**	**4.13**
	n	161	161	161	161	161	161
	S.D	0.450	0.588	0.569	0.311	0.320	0.441
Female (246)	*Mean*	4.11	2.43	2.62	**3.06**	4.14	4.08
	n	246	246	246	246	246	246
	S.D	0.567	0.783	0.709	0.422	0.443	0.495
Total (407)	*Mean*	4.16	2.37	2.66	3.05	4.16	4.10
	n	407	407	407	407	407	407
	S.D	0.526	0.715	0.659	0.382	0.399	0.474

From the above Table 3, we have found that that on the basis of gender male (161) respondents had score high mean values on MF, LMSR, JIS, Attitude, and BI (4.22, 2.28, 2.72, 4.19, and 413) as compared to their female counter parts. Males have more intention towards learning mobile friendliness application, job insecurity (due to family responsibilities), attitude and intention to sue such applications while female (246) respondents have score high mean values on JS (3.06). It means that female participants have more intention towards job switching as compared to their male colleagues.

Cronbach's alpha is an internal consistency reliability metric that is often used in research to evaluate the reliability or consistency of a scale or questionnaire. Cronbach's alpha measures internal consistency and runs from 0 to 1, with higher values suggesting stronger internal consistency and number of 1 denotes complete internal consistency, which means that all items on the scale are closely connected and assess the same underlying construct. The study[34] stated that in order to have unbiased results and findings it is mandatory to have well developed, reliable and valid scales. For this purpose, reliability of the questionnaire and each construct was assessed in PLS-SEM. The value of 0.70 is acceptable level below this 0.6 is questionable and 0.5 is considered is very poor. The authors in [35]has recommended criteria for item total correlation (ITC) as 0.40. If any item does not meet the criteria, that item can be excluded to improve the reliability of the overall construct. Convergent validity is assessed through AVE and CR. In the study[36], the researchers recommended AVE >0.50 and CR>0.70. The convergent validity is investigated whether item used to measure the concept represents the same construct or not. In Table 4 it is obvious that all construct and their respective alpha values, AVE and CR met threshold values. Therefore, it is considered that scales used in the study are reliable and valid.

Table 4: Reliability Analysis (Cronbach's Alpha)

Variables	Cronbach's Alpha	CR	AVE
ATTITUDE	0.876	0.909	0.668
BI	0.910	0.930	0.690
JIS	0.817	0.891	0.731
JS	0.874	0.908	0.665
LMSR	0.843	0.905	0.761
MF	0.853	0.895	0.632
CR **= Composite Reliability,** AVE = **Average Extracted**			

The Table 5 shows the factor loadings of each item. In Partial Least Square Structural Equation Modeling (PLS-SEM), factor/items loadings are assessed through outer loadings. According to [36] loadings of 0.50 is acceptable but factor loadings of 0.7 and above is a perfect factor loading. Moreover, according to [35] in SPSS factor loadings of 0.40 are also acceptable but as PLS-SEM is more robust statistical software and is designed to refine the accuracy of construct that is why criteria recommended by [36] is taken as benchmark in the current study. If such cut off level is not met by any item it is recommended to exclude it from the analysis. Table 4.15 shows that all items met the threshold and no items are excluded, further analysis of results revealed that all items have VIF less than 5 [36]. Therefore, it is assumed that there is no issue of multicollinearity in the data.

Table 5: Exploratory Factor Analysis (EFA)

Variables	Items	Loadings	VIF
Mobile Friendliness (MF)	MF1	0.705	1.511
	MF2	0.812	1.957
	MF3	0.827	2.081
	MF4	0.837	2.126
	MF5	0.786	1.811
Learning Management System Replacement (LMSR)	LMSR1	0.879	2.027
	LMSR2	0.865	1.972
	LMSR3	0.874	2.026
Job Switching (JS)	JS1	0.810	1.990
	JS2	0.788	1.865
	JS3	0.858	2.365
	JS4	0.791	1.895

	JS5	0.829	2.076
Job Insecurity (JIS)	JIS1	0.845	1.764
	JIS2	0.860	1.893
	JIS3	0.861	1.785
Attitude	ATT1	0.821	2.079
	ATT2	0.803	1.948
	ATT3	0.836	2.118
	ATT4	0.805	1.908
	ATT5	0.820	2.046
Behavioral Intention (BI)	BI1	0.806	2.113
	BI2	0.851	2.538
	BI3	0.825	2.229
	BI4	0.836	2.365
	BI5	0.831	2.354
	BI6	0.835	2.341

In this study, while analyzing the data, we have used bivariate correlation analysis with 2-tailed test. Correlation coefficients vary from -1 to +1. A correlation value of -1 denotes a completely negative connection. A correlation value of 0 shows that there is no relationship between the variables. A weak association is indicated by correlation coefficients between 0.1 and 0.3 (or -0.1 and -0.3). A moderate relationship is indicated by correlation values between 0.3 and 0.5 (or -0.3 and -0.5). A significant relationship is indicated by correlation values between 0.5 and 0.7 (or -0.5 and -0.7). Correlation values of 0.7 to 1 (or -0.7 to -1) imply a very strong or almost perfect relationship[35, 37, 38, 39]. A positive sign indicates that both variables are moving in the same direction (increase or decline), whereas a negative sign indicates that one construct is increasing while the other is decreasing.

Table 6: Bivariate Correlation Analysis

Variables	**1**	**2**	**3**	**4**	**5**	**6**
Mobile Friendliness	1					
LMS Replacement	.802**	1				
Job Insecurity	.705**	.778**	1			
Job Switching	.678**	.692**	.692**	1		
Attitude	.654**	.621**	.627**	.804**	1	
Behavioral Intention	.679**	.688**	.753**	.749**	.860**	1

Based on the results presented in above Table 6, Mobile Friendliness (MF) has strong positive correlation with LMSR and JIS (0.802**& 0.705**) while it has shown moderate correlation with JS, Attitude, and BI (0.678**, 0.654**, and 0.679**). Learning Management System Replacement (LMSR) has moderate positive correlation with MF (0.802**), strong positive relation with JIS and JS (0.778**& 0.692**), and weak positive correlation with Attitude, and BI (0.621**, & 0.688**). Job Insecurity has strong positive correlation with MF, LMSR, and BI (0.705**, 0.778**, and 0.753**) while it has moderate positive correlation with JS and Attitude

(0.692** & 0.627**) respectively. Job Switching (JS) has strong positive correlation with MF, LMSR, and BI (0.768**, 0.692**, and 0.749**) and moderate positive correlation with Job insecurity and Attitude (0.692**, & 0.804**). The variable Attitude has shown moderate correlation with MF, LMSR, and JIS (0.654**, 0.621**, and 0.627**) and strong positive correlation with JS and BI (0.804**, & 0.860**). Behavioral Intention (BI) has shown moderate positive correlation with MF and LMSR (0.679**, and 0.688**) while strong positive correlation with JIS, JS and Attitude (0.753**, 0.749**, and 0.860**) respectively.

4.1.Regression Analysis

Correlation is utilized to look at certain simple linear relationships. Regression analyses are used to explore complicated models. Multiple regression analyses helps in the investigation of the influence of predictors on criterion variables. Simple linear regression (effect of one variable on another) and multiple regressions (all predictors entered into regression equation at once) has been used in this study. A statistical metric that measures how well an observed data set matches an expected or theoretical model is called goodness of fit. It assesses how well the observed data matches the predicted pattern based on the model's parameters and assumptions. We have used goodness of fit tests to assess if the observed data deviates considerably from the predicted values, suggesting a poor match in light of guidelines stated in [35] presented in Table 7 below:

Table 7: Goodness of Fit

R	**-1 to +1**	R^2	**0-1**
F	0 to ∞	**β**	0-1
t	1.96 and above	**p**	<0.05

The under given Table 8 presents the influence of predicting variables on behavioral intention. In model 1 mobile friendliness explained 46.1% variance upon BI. R^2= 0.461, goodness of fit or model fitness F= 346.299, p<0.01, is also found significant. Unit of change β=0.679, p<0.01 explained that one percent change in MF could possibly bring 67.9% change in behavioral intention. In model 2 LMSR explained 47.4% variance upon BI with R^2= 0.474. Model fitness was assessed by F= 364.506, p<0.01. It was found that there is positive significant impact of LMSR on BI (β = 0.688, p<0.01). LMSR was found 68.8% responsible to bring change in behavioral intention. Model 3 explained positive and significant impact of job in security on behavioral intention. Coefficient of determination R^2= 0.566, JIS explained 56.6% variance upon behavioral intention. Model fitness F= 529.255, p<0.01. Moreover behavioral intention could be 75.3% change due to one percent change in job in security. Model 4 includes job switching (JS) and its impact on behavioral intention (BI). It was assessed that 56.1% variance was explained by JS on BI with F= 194.220, p<0.01; β= 0.749**. Behavioral intention could be increased or decreased up to 74.9% if there is one percent change in job switching.

Table 8: Linear Regression Analysis on Behavioral Intention

D.V	I.V	R	R^2	F	B	β	p
BI(Model1)	Constant	0.679	0.461	346.299	1.785		0.000
	MF					0.679	0.000
BI(Model2)	Constant	0.688	0.474	364.506	1.969		0.000
	LMSR					0.688	0.000
BI(Model3)	Constant	0.753	0.566	529.255	1.460		0.000
	JIS					0.753	0.000
BI(Model4)	Constant	0.749	0.561	194.220	1.512		0.000
	JS					0.749	0.000

Table 9: Multiple Regression Analysis on Behavioral Intention

D.V	I.V	R	R^2	F	B	β	p
BI	Constant	0.822	0.676	210.023	0.604		0.000
	MF					0.140	0.005
	LMSR					0.022	0.699
	JIS					0.374	0.000
	JS					0.380	0.000

The above Table 9 presents findings of multiple regression analysis. It is evident that MF, LMSR, JIS and JS explained R2= 0.676; 67.6% variance upon behavioral intention. Goodness of fit F= 210.023, p<0.01 was also significant. Moreover, it was found that MF, JIS and JS have significant impact upon behavioral intention (0.140^{**}, 0.374^{***}, 0.380^{***}) but LMSR does not have significant impact on behavioral intention (0.022, p>0.05). MF is responsible to bring 14% change, JIS brings 37.4% change and JS possible bring 38% change in behavioral intention on the contrary there is no significant change in Bi due to LMSR.

The Table 10 below shows attitude is taken as criterion and MF, LMSR, JOS, and JS are taken as predictors to instigate the individual effect upon attitude. Model 1 presented the impact of MF on attitude with variance R^2= 0.427, i.e. 42.7% model is found fit F= 302.408, moreover one percent change in MF could possibly bring 65.4% change in attitude of respondents (0.654^{***}, p<0.01). Model 2 presented findings of role of LMSR on attitude, analysis of findings revealed that LMSR accounts for 38.6% variance upon attitude with F= 254.440, p<0.01 and (0.621^{***}, p<0.01) it implies that on percent increase or decrease in LMSR could change attitude of respondents up to 62.1%. Furthermore, job in security (JIS) explained 39.3% variance upon attitude with model fitness found F = 261.772, p<0.01, and (0.627^{***}, p<0.01); 62.7% change is possible in attitude with one unit change in job in security. Moreover, job switching (JS) also explained 64.6% variance upon attitude with F= 738.368, p<0.01 level, and impact of JS upon attitude is also found significant (0.804^{***}, p<0.01) it means 80.4% change is possible in attitude due to change in job switching. Being scored high beta value by job switching has emerged as most dominant variable in this model.

Table 10: Linear Regression Analysis on Attitude

D.V	I.V	R	R^2	F	B	β	p
Attitude (Model 1)	Constant	0.654	0.427	302.408	2.022		0.000
	MF					0.654	0.000
Attitude (Model 2)	Constant	0.621	0.386	254.440	2.432		0.000
	LMSR					0.621	0.000
Attitude (Model 3)	Constant	0.627	0.393	261.772	2.241		0.000
	JIS					0.627	0.000
Attitude (Model 4)	Constant	0.804	0.646	738.368	1.285		0.000
	JS					0.804	0.000

Table 11: Multiple Regression Analysis on Attitude

D.V	I.V	R	R^2	F	B	β	p
Attitude	Constant	0.818	0.669	203.566	0.843		0.000
	MF					0.196	0.000
	LMSR					-0.041	0.464
	JIS					0.070	0.151
	JS					0.650	0.000

The above Table 11 explains combine effects of all predicting variables i.e. MF, LMSR, JIS and JS upon attitude. All predictors explained R2= 0.669, 66.9% variance upon attitude with goodness of fit F= 203.566, p<0.01 and impact of MF and JS was found significant upon attitude (0.196^{***}, 0.650^{***}, p<0.01); on the other hand, LSMR and JIS does not have significant role upon attitude (-0.041, 0.079, p>0.05). In the above regression equation MF is found 19.6% responsible to bring change in attitude while job switching 65% change in attitude. Thus again job switching is again emerged as most dominant variable.

5. Discussion

Based on the findings of regression analyses (Model 1, Model 2, Model 3, Model 4) using Behavioral Intention (BI) as the dependent variable and independent variables (MF, LMSR, JIS, and JS) in each model (given in Table 8). We must infer that the constant term in Model 1 has a value of 0.679. The standardized coefficient (β) of the "MF" (Mobile Friendliness) is 0.679, and the p-value is 0.000. The R2 value is 0.461, suggesting that the model explains 46.1% of the variation in the dependent variable. The F-statistic is 346.299, and the p-value is 0.000, indicating that the model is statistically significant. Similarly, the constant term in Model 2 has a value of 0.688. The standardized coefficient (β) of the "LMSR" (LMS Replacement) is 0.688, and the p-value is 0.000. The R2 value is 0.474, suggesting that the model explains 47.4% of the variation in the dependent variable. The F-statistic is 364.506, and the p-value is 0.000, indicating that the model is statistically significant. The constant term in Model 3 has a value of 0.753. The standardized coefficient (β) of the "JIS" (Job Insecurity) is 0.753, and the p-value is 0.000. The R2 value is 0.566, suggesting that the model explains 56.6% of the variation in the dependent variable. The F-statistic is 529.255, and the p-value is 0.000, indicating that the model is statistically significant. Finally, the constant term in Model 4 has a value of 0.749. The standardized coefficient (β) of the "JS" (Job Switching) is 0.749, and the p-value is 0.000. The

R2 value is 0.561, suggesting that the model explains 56.1% of the variation in the dependent variable. The F-statistic is 194.220, and the p-value is 0.000, indicating that the model is statistically significant. Hence, these findings shed light on the link between the independent variables (MF, LMSR, JIS, and JS) and the dependent variable (BI).

Similarly, the findings in Table 10 are obtained by utilizing regression analysis with Attitude as the dependent variable and the independent variables MF, LMSR, JIS, and JS as the independent variables. We therefore conclude that the constant term in Model 1 is 0.654. The standardized coefficient (β) of the independent variable "MF" (Mobile Friendliness) is 0.654 and the p-value is 0.000. The model explains 42.7% of the variation in Attitude, according to the coefficient of determination (R2). The F-statistic is 302.408, and the p-value is 0.000, indicating that the model is statistically significant. The constant term in Model 2 has a value of 0.621. The standardized coefficient (β) of the independent variable "LMSR" (LMS Replacement) is 0.621 and the p-value is 0.000. The model explains 38.6% of the variation in Attitude, according to the coefficient of determination (R2). The F-statistic is 254.440, and the p-value is 0.000, indicating that the model is statistically significant. Model 3 has a standardized coefficient (β) of 0.627 and a p-value of 0.000 for the independent variable "JIS" (Job Insecurity). The model explains 39.3% of the variation in Attitude, according to the coefficient of determination (R2). The F-statistic is 261.772, and the p-value is 0.000, indicating that the model is statistically significant. Model 4 consists of the standardized coefficient (β) of the independent variable "JS" (Job Switching) is 0.804 and the p-value is 0.000. The model explains 64.6% of the variation in Attitude, according to the coefficient of determination (R2). The F-statistic is 738.368, and the p-value is 0.000, indicating that the model is statistically significant. These mentioned findings give information regarding the relationship between the independent variables (MF, LMSR, JIS, and JS) and the dependent variable (Attitude)

6. Conclusion

The purpose of this study was to determine the effect of external factors (mobile friendliness, LMS replacement, job insecurity, and job switching) on e-Learning adoption at Higher Education Institutes (HEIs). The study specifically attempted to explore how these characteristics affected the adaption of web-based educational technologies and their efficiency in supporting learning activities and boosting faculty members' teaching experiences. The survey comprised 500 academics from both public and private sector HEIs and colleges in Saudi Arabia's southern region. The study's findings, based on 407 responses, provide insight on the relationships between external variables and e-Learning adoption, shedding light on their relevance and influence in the context of the targeted sample. The study also indicates that in the future, this research might be expanded to other areas or nations to analyze the influence of the identified parameters, as well as investigate the introduction of new variables that may be significant in other cultural and contextual circumstances. The proposed external variables namely Mobile Friendliness (MF), LMS Replacement (LMSR), Job Insecurity (JIS), and Job Switching (JS) impact e-learning adoption at Higher Education Institutes (HEIs). These criteria have policy implications for encouraging and enabling the effective implementation of e-learning projects. These variables in the Technology Acceptance Model that have policy implications for adopting e-learning include developing an enabling environment that helps faculty members in effectively accepting and using e-learning technology. To guarantee the successful integration of e-learning at HEIs, policies should address technological infrastructure, training and support, job security, and professional growth. Future research can give a more thorough knowledge of the elements driving e-Learning adoption and customize treatments and tactics accordingly by taking into consideration the individual requirements and cultural features of diverse groups. In general, this study adds to the current literature on e-Learning acceptance in HEIs and underscores the need for more research in other contexts to improve our understanding of the variables driving technology uptake and adaption in education. HEIs are taking keen interest to adopt new models, methods, procedures and approaches in e-learning in Saudi Arabia. TAM is getting momentum and got noticed in e-learning in recent years by academicians and practitioners in Saudi Arabia. The current study has offered new insights form the TAM perspective by keeping in mind the Saudi HEIs demands to survive in the market and produce talented and hardworking motivated workforce.

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