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Research Article

Exploring E-Learning Systems' Usability through the Modified Technology Acceptance Model: An Empirical Study at Albaha University Students in Saudi Arabia

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Abstract:

In Saudi Arabia, the acceptance of e-learning is rapidly increasing, especially since its benefits were recognised during the COVID-19 pandemic, and hence, has continued since then. Although some research has been carried out on the mechanisms of e-learning acceptance using models such as the Technology Acceptance Model (TAM), however, this research aimed to evaluate the applicability of a modified TAM to Behavioural Intentions (BI) and the actual adoption of e-learning by computing and information technology students at Albaha university in Saudi Arabia. One hundred students were recruited for this study and conducted an online survey using items related to demographics and the items of the modified TAM. The responses were analysed for demographics and descriptive statistics, correlations and regression. The study showed a high correlation (r=.591) between the intention and actual adoption of e-learning by the surveyed students. Intention was significantly related to all variables (r values: .311 to .737) except perceived anxiety. The relationship between perceived anxiety and BI was non-significant (-r=.195). Actual adoption of e-learning was positively related to all variables except perceived anxiety (r values: .317 to .591). Perceived anxiety was negatively related (r=-.234, p=.05) to actual adoption of e-learning. Other significant negative relationships were between anxiety with peer influence and between anxiety with effort expectancy. Non-significant relationships were obtained for anxiety with enjoyment, effort expectancy, facilitating conditions and perceived usefulness. Perceived usefulness, facilitating conditions and adoption explained 60.5% of the variation in the intention to use e-learning. These three variables accounted about 95% of the variation in intention, with their effects decreasing in the order of perceived usefulness, adoption of e-learning and facilitating conditions.

1. Introduction

In modern times, e-learning has become a common practice. E-learning helped in the continuity of education during the COVID-19 pandemic. The advantages of e-learning became evident, and e-learning has continued post-COVID. E-learning offers flexibility, accessibility, and scalability, making it a popular choice for both academic and professional development. Learners can access learning materials and activities at their convenience from anywhere, anytime, provided there is a good internet connection. Learning management systems is easier and more efficient for both educators and learners. It is cost-effective, engaging and provides personalised education. These benefits have led to a large-scale acceptance of e-learning.

In Saudi Arabia, the adoption of e-learning has witnessed significant growth, although certain traditional groups may express reservations toward unfamiliar technologies due to cultural value or resistance to change. To date, much research has been done on the mechanisms of e-learning acceptance, especially using the Technology Acceptance Model (TAM), however, no experimental evidences on the modified TAM with computing and information technology students at Albaha university.

The Technology Acceptance Model (TAM) was developed by Davis [1]. The model was proposed to explain the reasons for people accepting or rejecting information systems and how the user

acceptance behaviour determines the features of the system. It explains the causal relationships among system design features, perceived ease of use (PEOU) and perceived usefulness (PU). TAM was the result of integrating management information systems (MIS) attitude research, MIS laboratory research and human-computer interactions. A diagram of the model is given in Fig. 1. According to the model, our attitudes towards technology are shaped by two key factors: perceived usefulness and perceived ease of use. Perceived usefulness is the level at which we think that utilising technology will improve our performance or help us reach our objectives, whereas perceived ease of use is the extent to which we believe that using technology will be simple and uncomplicated. These two aspects are key factors influencing our intention to use a technology, which subsequently forecasts our actual behaviour in using it. In summary, if we find a technology both beneficial and user-friendly, we are more inclined to embrace and utilise it.
To provide the background for this research, recent studies are reviewed in the following section.

2. Literature Review

In order to explore the main factors that affect higher education students' behavioural intentions to adopt metaverse technology for education, Al-Adwan et al. (2023) used a modified version of TAM by incorporating technological, personal, and inhibiting/enabling factors [2]. A survey of 574 students showed perceived usefulness, personal innovativeness in IT, and perceived enjoyment as key enablers of students' behavioural intentions to adopt the metaverse. Perceived cyber risk was an extra inhibiting factor of students' metaverse adoption intentions. There was no effect of perceived ease of use on metaverse adoption intentions. Self-efficacy, personal innovativeness, and perceived cyber risk determined perceived usefulness and perceived ease of use. The TAM version they used is shown in Fig. 2. The additional elements and the hypothesised relationships are clear. Self-efficacy and personal IT innovativeness substitute for external factors of the original model. Perceived enjoyment and perceived cyber risks are the influencing factors. They all lead to behavioural intention. Actual use is excluded from the model.

As ChatGPT is gaining popularity, its use among 156 Pakistani university management students was assessed by Saif et al. (2024) using TAM [3]. Results showed that students' stress contributed to the emergence of anxiety, which in turn, motivated the adoption of Chat-GPT for efficient completion of assignments within their deadlines, as they could work through any device from anywhere. This led to a perceived ease of use and usefulness associated with Chat-GPT's AI-generated text and favourable attitudes toward using Chat-GPT. The ease of tasks reduced their stress levels. The students developed a positive attitude, which acted as a driving force to engage with Chat-GPT through the ubiquitous learning (UL) procedure. All these led to an increased actual usage of Chat-GPT. Thus, this research demonstrates the contribution of TAM to the social exchange process.

TAM was applied by Alsyouf et al. (2023) to predict patient usage of their health record systems [4]. The authors surveyed 389 Saudi patients, and the data were analysed using structural equation modelling–partial least squares (SEM-PLS4). PHR system usage was influenced by three factors, including PEOU, PU and security towards intention to use. PHR PEOU and PHR's intention to use were moderated by privacy. Privacy positively moderated PHR PEOU, and intention and usability negatively moderated them. The authors' version of TAM is shown in Fig. 3. As is shown in the model and by the findings, three items of privacy are added to the external variables. Four items of usability and security moderate the relationship between privacy, PHR PEOU and PHR PU and the intention to use PHR by the patients. This led to a 3-item actual usage. Using a similar approach to the social media addiction of 217 Malaysian higher education students, Paiman and Fauzi (2023) showed that their addiction to social media was determined by their habit of use and the TAM variables [5]. The utility of TAM to predict addictions is a step towards evolving strategies to reduce addictions to various things among citizens.

Jan, Alshare, and Lane (2024) conducted a meta-analysis of 22 papers (1989 to 2018) on the direct, moderating, and mediating role of Hofstede's cultural dimensions in TAM [6]. The possibility of relationships between Hofstede's national cultures [7] and technology adoption has already been established. The masculinity dimension did not affect the technology acceptance models. Also, power distance and masculinity had weak moderating effects. Out of 22 papers, nine dealt with students. None of them dealt with student satisfaction with e-learning. Hofstede [7]defined six cultural dimensions with their descriptions as follows: Power Distance, related to the different solutions to the basic problem of human inequality, Uncertainty Avoidance, related to the level of stress in a society in the face of an unknown future, Individualism versus Collectivism, related to the integration of individuals into primary groups, Masculinity versus Femininity, related to the division of emotional roles between women and men, Long-term versus Short-Term Orientation, related to the choice of focus for people's efforts: the future or the present and past, and Indulgence versus Restraint, related to the gratification versus control of basic human desires related to enjoying life. He showed how national cultures can be characterised using these dimensions.)

Sina, Sabzian, Moeini, and Yakideh (2023) used TAM, along with factor analysis, to assess 143 learners' satisfaction with the university of King Khalid university LMS during the pandemic [8]. The proposed TAM-based scale successfully explained factors predicting learners' satisfaction. PEOU was influenced by technical knowledge. PU was related to attitude and behavioural intention. Attitude was related to technical knowledge, PU and behavioural intention. Behavioural intention was related to learner satisfaction. Facilitating conditions were related to PU and PEOU. PEOU and PU were interrelated. The TAM version used by the authors is shown in Fig. 4. A modified version of TAM was used by Aljader (2023) to explain the e-learning behaviour of 270 undergraduate Iraqi students [9]. E-learning information quality positively influenced students' adoption of e-learning. Both PU and PEOU influenced attitudes towards e-learning and information quality. Attitude influenced behavioural intention. PU and PEOU were mutually related. The TAM version used by the author is shown in Fig. 5.

Using both the Theory of Planned Behaviour (TPB) and an extended TAM, Ullah, Hoque, Aziz, and Islam explored what shapes a student's intention and actual response to online classes, and how it affects satisfaction and academic performance [10]. The authors collected data from 214 Bangladeshi undergraduate students from multiple sources and periods. The response of students to online classes was influenced by their intentions and other external antecedents. Both determined their satisfaction. However, student satisfaction and performance were not related. Their research model and framework are shown in Fig. 6. Using a survey of 724 Jordanian university students, Masadeh, et al. (2023) tested a TAM to evaluate their satisfaction with the system during the COVID-19 pandemic [11]. PU of information systems, user training, system quality, and management support positively influenced their behavioural intention. However, PEOU did not have any such effect. Behavioural intention positively influenced information systems use, use on student satisfaction, and the latter on student loyalty. Machine Learning (ML) methods, with their highest correlation, were the best predictors of behavioural intention from input factors and student loyalty derived from student satisfaction. Thus, ML emerged as a promising e-learning technology to forecast future targets from independent input factors.

Using a survey of 500 Saudi university students, Saqr, Al-Somali, and Sarhan (2023) explored the influence of different AI-based social learning networks, personal learning portfolios, and personal learning environments on Saudi university students' perceived usefulness and ease of use regarding AI-driven platforms (Blackboard, Moodle, Edmodo, Coursera and edX) [12]. Social learning networks, electronic personal learning portfolios and online personal learning environment influenced PU and PEOU. Both PU and PEOU influenced student satisfaction and attitude. PEOU influenced PU. Satisfaction and attitude led to a higher intention to use e-learning. Intention to use e-learning was moderated by readiness for self-directed learning, self-efficacy, personal innovativeness, readiness for self-directed learning x satisfaction, self-efficacy x satisfaction and personal innovativeness x satisfaction. The theoretical framework of this research is shown in Fig. 7. Using a mixed model of TAM and the Unified Theory of Acceptance and Use of Technology (UTAUT), Yang and Qian (2025) showed that attitude, subjective norms and facilitating conditions influenced the behavioural intentions of Chinese physical education students to use e-learning [13]. A survey of 504 students was conducted in this study.

Using an extended TAM (added innovation, social and organisational characteristics) and a survey of 932 Iranian participants, including faculty members, postgraduates, and undergraduates, Mastour, Yousefi, and Niroumand (2025) showed PU and PEU to be the most important in influencing e-learning acceptance. Participants' intention to engage with e-learning platforms was notably affected by their attitude towards e-learning, with perceived ease of use (PEU) identified as the most significant factor [14]. Perceived usefulness (PU) had a more considerable effect on faculty and undergraduate students, whereas postgraduate students placed less value on its usefulness. Organisational factors influenced e-learning acceptance indirectly, through individual traits. System quality, information quality and service quality were added to the TAM in the studies of Xiang [15]. A survey of 500 Chinese college students showed that the qualities of the system and information greatly affect how useful it is perceived to be. The perception of ease of use and the perception of usefulness notably impact one's self-learning attitude. The perception of ease of use significantly affects the perceived usefulness and perceived enjoyment. The perception of usefulness has a considerable effect on behavioural intention. Conversely, service quality does not significantly affect perceived usefulness. In addition, there is an online survey was carried out by Fareed and Kirkil [16] involving 232 students who utilised the Khas Learn system at Kadir Has University in Turkey. The primary factors influencing students' success (SS) include behavioural intention, ease of use, usefulness, visual design, and learner interface interactivity, which accounted for 53.6% of the perceived success in using the system. The key predictors of behavioural intention (BI) are facilitating conditions, effort expectancy, ease of use, and usefulness, explaining 71% of the variance in the intentions to continue using e-learning. This study employed an integrated model of the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). In a different study, Yangbaixue (2025) surveyed 500 Chinese students majoring in painting, merging the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [24]. The most substantial influence on behavioural intention was perceived usefulness. Additionally, perceived ease of use had a significant effect on perceived usefulness. Both reliability and responsiveness considerably affected the quality of e-learning. Furthermore, hedonic motivation, facilitating conditions, social influences, and the quality of e-learning influenced behavioural intention. Furthermore, a survey conducted with 200 Indian postgraduate students revealed that perceived ease of use (PEOU), perceived usefulness (PU), and perceived enjoyment (PE) are key factors in predicting students' behavioural intention to engage with e-learning (BI). This, in turn, influences actual usage (AU), ultimately leading to the adoption of e-learning as a sustainable solution (ELSS). Additionally, while PEOU does not have a significant effect on BI, both PU and PE have a significant impact on BI [17]. The finding of TAM-based survey of 125 students of English and Information Technology in Oman showed that gameplay engagement influenced students' readiness to adopt technology. Thus, new insights were gained on the intersection of gaming, education, and technology adoption. The results showed the potential of digital games as a leisure activity and a useful tool to promote technology acceptance through perceived usefulness. The factors connected to PU (technology integration and perceived ease of use) were effectively integrated in educational Settings [18]. From a survey of 316 students [19] obtained a positive effect of intrinsic motivations, relatedness, and autonomy to enhance perceptions regarding the ease of use and usefulness of Massive Open Online Courses (MOOCs) and, hence, on the BI to use MOOCs. The study integrated TAM with self-determination theory. In a systematic review of 67 studies, Sumi (2024) observed that the majority of them utilised an extended version of the Technology Acceptance Model (TAM) [20]. Elements such as self-efficacy regarding technology/internet and computers, the interactivity of e-learning, perceived enjoyment or playfulness, subjective or social norms, student experiences, and the quality of content/courses/information tend to have the most significant influence on students' acceptance of e-learning. Personal innovativeness and perceived fear associated with COVID-19 also demonstrate positive effects, whereas computer/internet anxiety, perceived risks, and costs negatively affect the intention to adopt e-learning among students. In a case-control study of 75 first-year Indian medical students each, blended learning with a digital library was compared with the traditional method of lecture classes. TAM was used as the research framework. The influence of PE (perceived ease of use) on PU, PU on BI and BI on AU (Actual use) was proved. Poor internet connectivity, time management, user experience and connectivity problems were some challenges experienced [21]. Using a VR (Virtual Reality) TAM framework, a survey of 512 secondary students by Man, Fang, Chan, & Han (2025) showed language learning anxiety (LLA) as an important factor for their acceptance of technology through respect for viewpoints, mutual respect, academic support from teachers and interactions [22]. PEOU positively impacted PU. PEOU and PU together influenced their attitudes towards using VR. Academic support and mutual respect negatively impacted language learning anxiety. Attitude towards academic support and PU students' willingness to use VR. The results of a survey of 73 postgraduate students by Rukmana, Bactiar, and Akbar (2025) showed that perceived anxiety and perceived enjoyment influenced perceived ease of use and perceived usefulness, all leading to the adoption of e-learning [23]. Perceived enjoyment was a positive factor influencing and a predictor of students' acceptance of e-learning, as was shown in a systematic review of 67 papers by Sumi [20]. Thus, both perceived anxiety and perceived enjoyment influence acceptance of e-learning by students. Although anxiety can be a negative factor, the reviewed papers showed its influence to be positive. The above reviews of papers show that TAM can be used to study the effect of external variables like peer influence, PU, PEOU, and other mediating and moderating variables on the outcomes of behavioural intention to use e-learning, leading to its actual adoption. This study aimed to investigate the applicability of TAM to explore satisfaction and attitudes toward using e-learning technologies among the students at Albaha University. A research framework was developed on this basis as shown in Fig. 8. According to this model, if students perceive an enjoyment in using e-learning, they will exhibit a positive behavioural intention leading to actual adoption of the technology. Perceived enjoyment is driven by the expectancy of the desired performance. The desired performance comes from the effort needed to use the technology. Students will make efforts to use the technology if they perceive its usefulness for e-learning and facilitating conditions (internet, etc) are available. These two are driven by peer influence, relative advantage and perceived anxiety about the technology.

3. Methodology

This research has relied on a methodology to investigate the applicability of the modified Technology Acceptance Model (TAM) to understand the behavioural intentions and actual adoption of e-learning technologies among students at Albaha university. This section has been structured to provide the research design, sampling methods, data collection processes and analytical techniques to evaluate the modified TAM constructs set-up.

A quantitative research design has been used in the study, having an impugned online survey methodology to gather primary data from the participants. The underlying theory of this study has been explained by the research framework and its description above.

A sample of 100 undergraduate students from Albaha University, particularly from Computing and Information programs, participated in the study. This selection of participants was an outcome of a convenient sampling technique befitting attributes regarding accessibility and availability of the targeted population within the institution. Given the usual time and research constraints outlining academic research works, this sampling method was crucial for collecting appropriate data in an economic and time-bound manner.

Informed consent for voluntary participation was obtained from all participants after explaining the project and answering their doubts, guaranteeing their privacy and confidentiality of their responses and informing them of their right to withdraw from the study at any time without the need for any explanation. The participants were requested to give their honest and unbiased responses to the survey items.

An online questionnaire was structured, which was divided into 11 segments corresponding to different TAM constructs and demographic information. Altogether 54 items with Likert-type scales were incorporated in the questionnaire, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), to measure perceptions of the participants and their attitudes towards e-learning technologies. Factors such as demographic details, peer influence, relative advantage, perceived anxiety, perceived enjoyment, performance expectancy, effort expectancy, facilitating conditions, perceived usefulness, behavioural intention to use e-learning and actual adoption of e-learning technologies were incorporated.

To have an understanding of external and inhibiting factors influencing the TAM's core variables, the sections viz. "Peer Influence" and "Perceived Anxiety" were designed. Additionally, sections on "Behavioural Intention to Use E-Learning" and "Adoption of E-Learning" were designed to focus on the practical aspects of the TAM framework in the context of e-learning.

Descriptive statistics, to summarise demographics and item responses, were provided due accordance in the analytical framework, which facilitated assessment of patterns and trends within the dataset. Also, correlation analysis was used to establish preliminary evidence of relationships between TAM constructs with a specific focus on the strength and direction of these relationships while employing Pearson correlation coefficients.

Further, this study also incorporated Regression analysis to explore the predictive capacity of specific TAM variables about behavioural intention and actual adoption. Thus, the key determinants among the TAM constructs were identified and the findings indicated that a significant portion of the variance, with intention to use e-learning technologies, was explained by factors such as perceived usefulness, facilitating conditions and adoption.

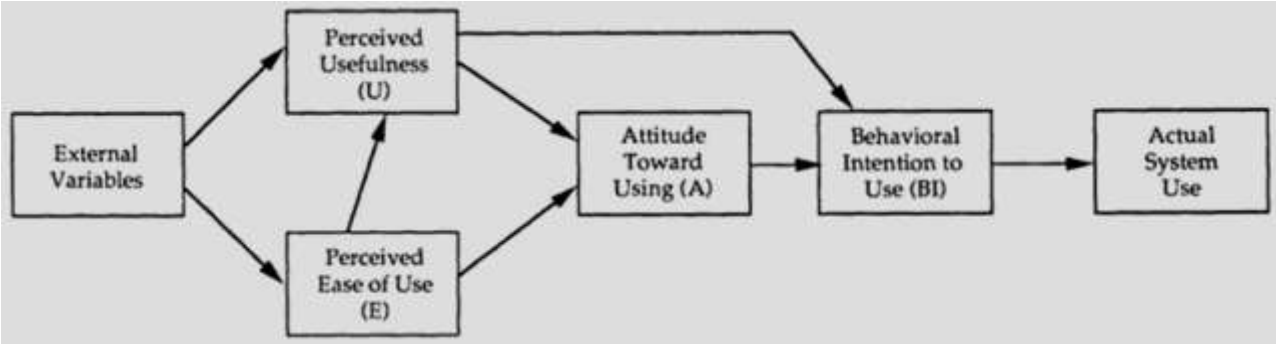

Figure 1 *Technology Acceptance Model [1]*

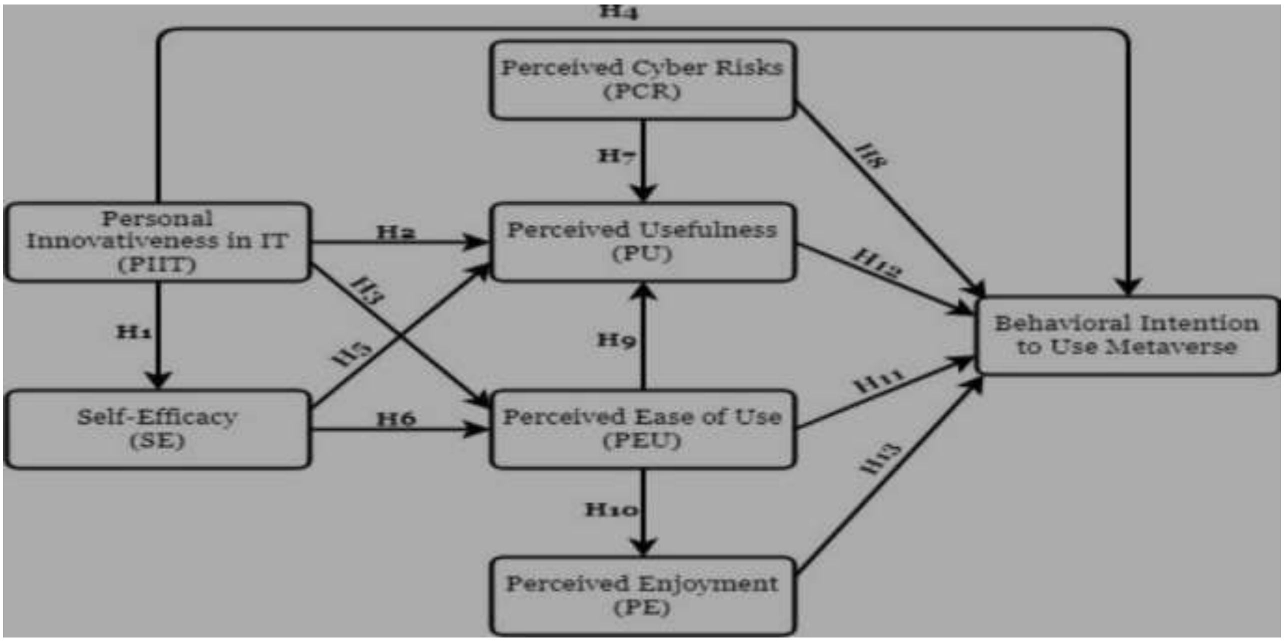

Figure 2 *TAM version used by Al-Adwan et al. [2].*

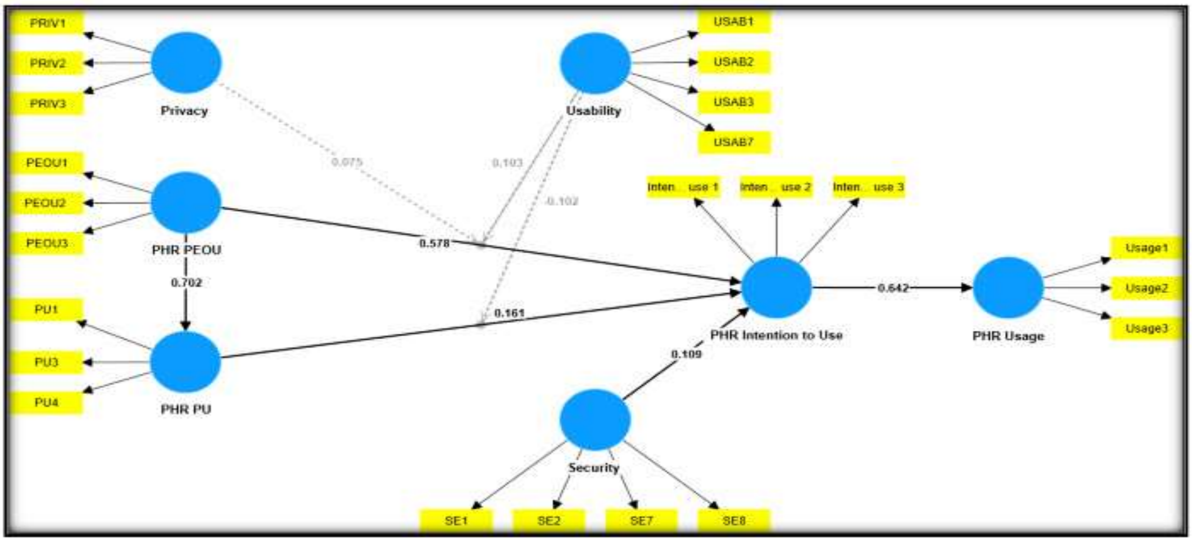

Figure 3 *TAM version of Alsyouf [4].*

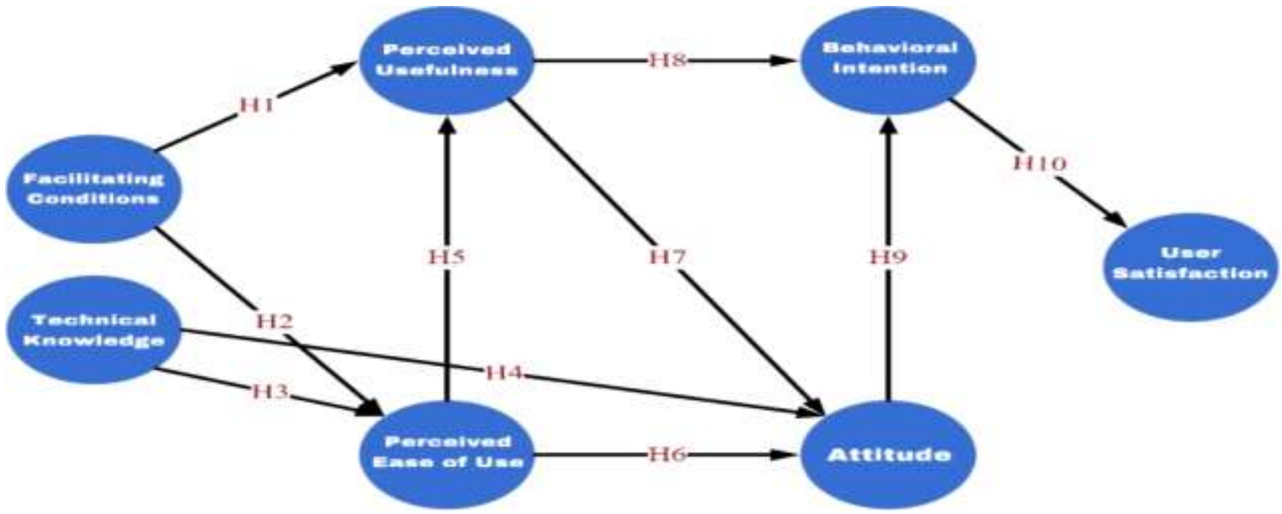

Figure 4 *TAM version of Sina, Sabzian, Moeini, and Yakideh [8].*

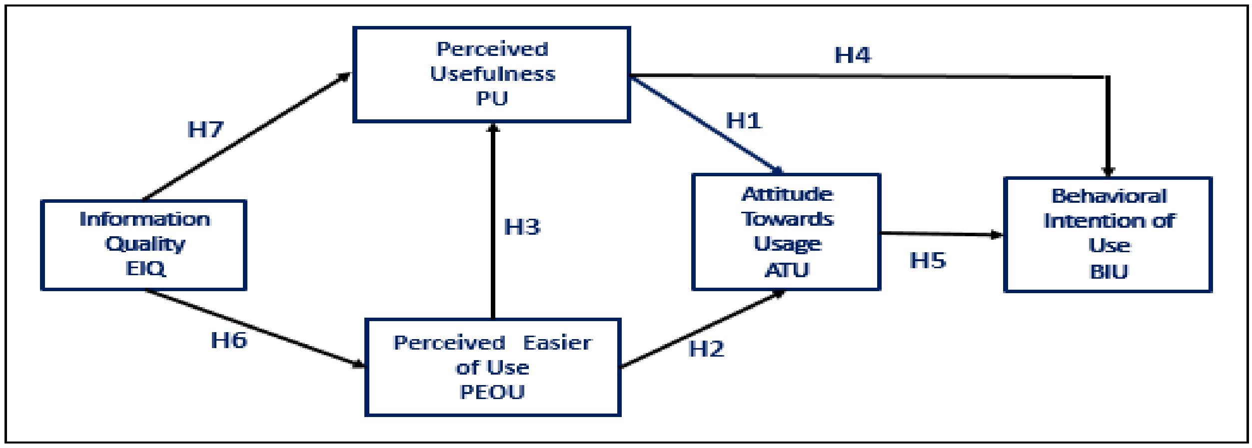

Figure 5 *The TAM version of Aljader [9].*

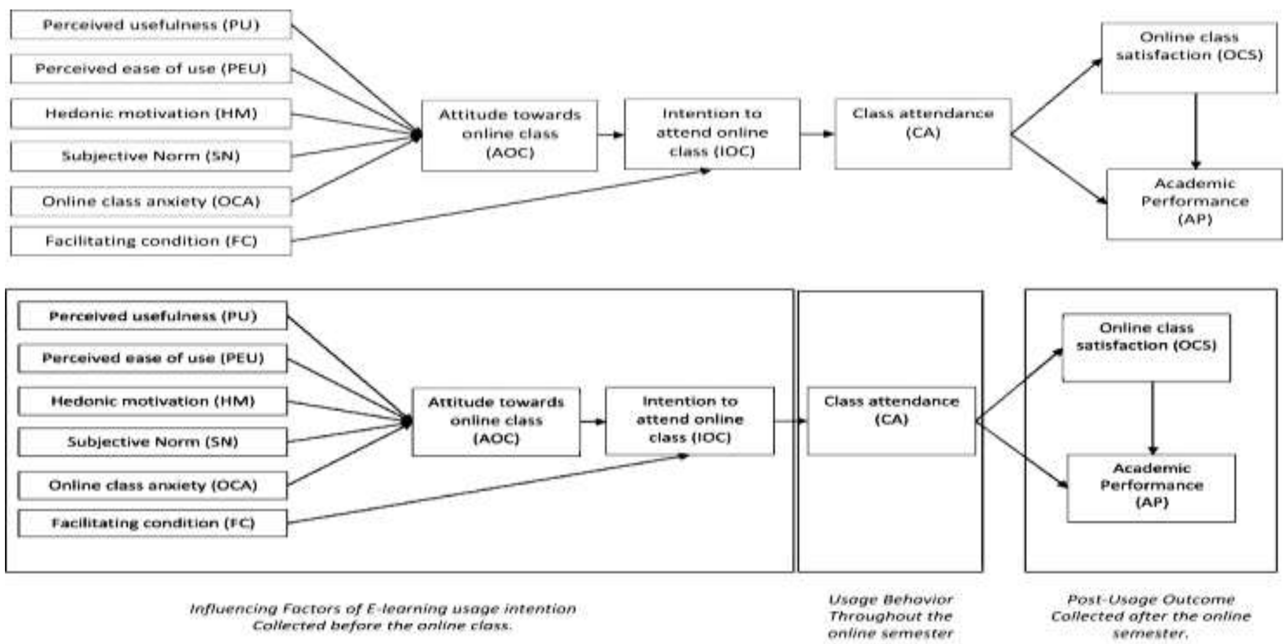

Figure 6 *The research model and framework of Ullah, Hoque, Aziz, and Islam [10].*

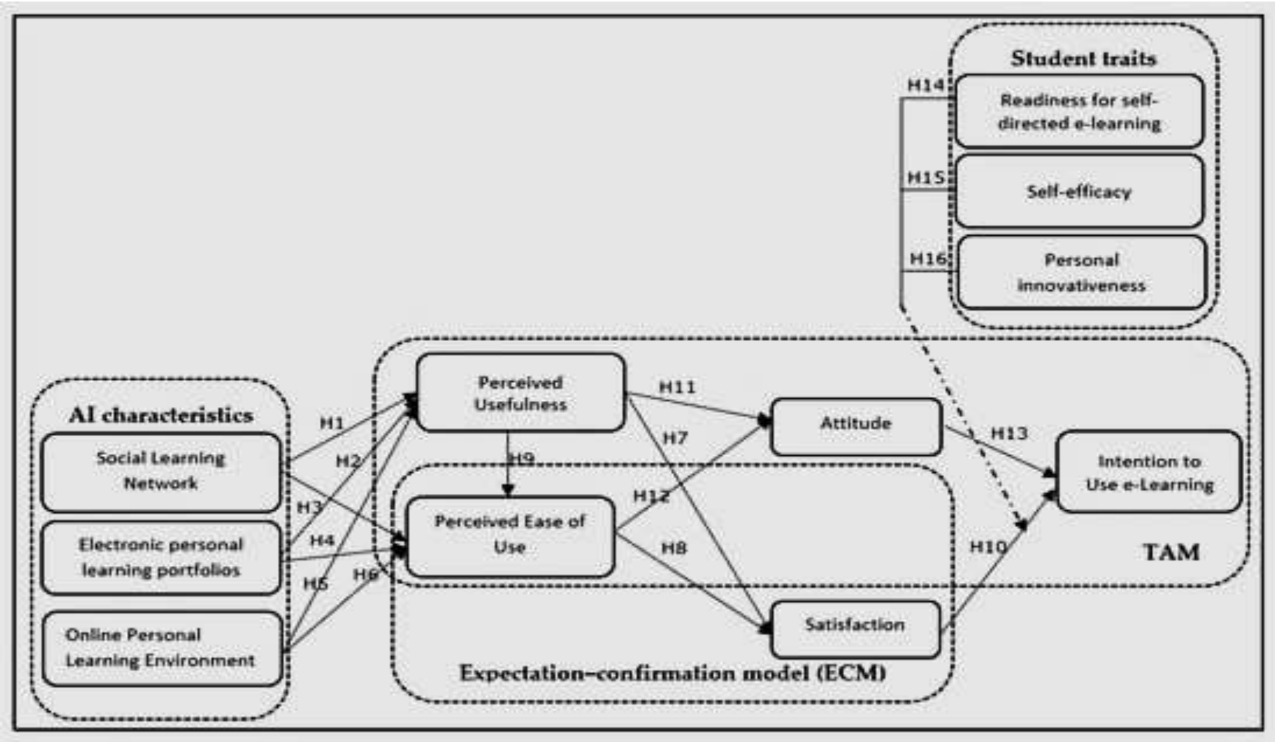

Figure 7 *Theoretical framework of Saqr, Al-Somali, and Sarhan [12].*

4. Results

This section presents the results derived from the application of the methodology described in the previous section. The findings are organized to address the research objectives and questions in a structured manner. Quantitative data are analyzed to identify key patterns, trends, and insights that emerged from the study. The results are supported by relevant tables, figures, and descriptive summaries where appropriate, to enhance clarity and understanding. This section does not interpret the results but rather focuses on presenting the data as objectively as possible, laying the foundation for the subsequent discussion and analysis.

Demographics

The frequencies and percentages of demographic variables of the survey participants are presented in Table 1.More than half (n=55) of the participants in this survey were female students. Majority of the students were younger (18-21 years= 88%). All were studying the Computer & Information course. Most of them (65%) were in their second year. There were 20 final-year students. The course and year of study patterns show their competence in answering e-learning-related questions of the survey.

TAM Variable Scores

The survey items related to the TAM variables are given in Table 2.

The mean scores of all variables were above 4.0, except for perceived anxiety (1.79) and facilitating conditions (3.96). That means, facilitating conditions were medium and the perception of anxiety by the students was low. The latter is a good indication.

Correlation Analysis

The correlation coefficients of all possible relationships between the study variables are presented in Table 3.

Correlations were significant at p=.05 level and negative for the relationships between perceived anxiety and peer influence, effort expectancy and perceived anxiety and adoption of e-learning and perceived anxiety.

At p=.01 level, positive correlations were obtained for the relationships for Perceived Enjoyment (PE), Performance Expectancy (PEX), Facilitating Conditions (FC), Perceived Usefulness (PU), Effort Expectancy (EEX), Behavioural Intention to Use E-Learning (BIFC) and Adoption of E-Learning (AFC) with Peer Influence, for Relative Advantage with all others except Perceived Anxiety (which was negative and significant), for Perceived Enjoyment with Performance Expectancy (PEX), Facilitating Conditions (FC), Perceived Usefulness (PU), Effort Expectancy (EEX), Behavioural

Intention to Use E-Learning (BIFC) and Adoption of E-Learning (AFC), for Facilitating Conditions (FC), Perceived Usefulness (PU), Effort Expectancy (EEX), Behavioural Intention to Use E-Learning (BIFC), Adoption of E-Learning (AFC) with Perceived Enjoyment, for Perceived Usefulness (PU), Effort Expectancy (EEX), Behavioural Intention to Use E-Learning (BIFC), Adoption of E-Learning (AFC) with Facilitating conditions (FC), for Effort Expectancy (EEX), Behavioural Intention to Use E-Learning (BIFC), Adoption of E-Learning (AFC), for Behavioural Intention to Use E-Learning (BIFC), Adoption of E-Learning (AFC) with Effort Expectancy (EEX),for Behavioural Intention to Use E-Learning (BIFC) with Adoption of E-Learning (AFC), Negative relations at p=.01 were obtained for Perceived Anxiety vs Perceived Advantage and Perceived Usefulness vs Perceived Anxiety, no significance was obtained for Perceived Enjoyment, Performance Expectancy and Facilitating Conditions with Perceived Anxiety.

Significant positive correlations: Peer influence versus all others, except the negative correlation with perceived anxiety; Relative advantage versus all, except the negative correlation with perceived anxiety; Perceived anxiety negatively correlated with perceived usefulness, effort expectancy and adoption of e-learning; Perceived enjoyment, performance expectancy, facilitating conditions, perceived usefulness and effort expectancy correlated positively with other variables. Behavioural intention is positively correlate with actual adoption. The highest correlation was obtained for perceived usefulness versus behavioural intention. The lowest significant correlation was obtained for peer influence versus behavioural intention (r=0.311, p=0.01). The lowest non-significant correlation was obtained for perceived anxiety versus perceived enjoyment (r= -0.171).

Regression Analysis

Behavioural Intention to use E-Learning (BIFC) Score was taken as the dependent variable to undertake regression analysis. Under the aegis of TAM constructs, factors such as perceived usefulness and perceived ease of use often influence the behavioural intention, which is an outcome factor. This also reflects the intention of students to engage with e-learning technologies. The rest of the variables were taken as independent variables in a stepwise regression.

As evidenced by an R value of .778, a strong overall fit to the data was demonstrated by the regression model (Table 4). This implied that a high degree of correlation between the independent variables (Perceived Usefulness, Adoption of E-Learning and Facilitating Conditions) and the dependent variable (Behavioural Intention to Use E-Learning) was present. Further, the R Square value of .605 indicated that approximately 60.5% of the variance in behavioural intention could be explained by the model, which integrates these influential factors as a whole. An unstandardized coefficient (B) of .555 and a standardised coefficient β=0.518, p<0.001) PU emerged as the most significant predictor of behavioural intention. This indicates that for every unit increase in perceived usefulness, the behavioural intention to use e-learning increases by approximately .555 units. The t-value of 6.088 (higher side) and the p-value of .001 (very low) indicate that the impact is strong and statistically significant.

Also, with a B value of .215 and a (β .217, p=0008) Adoption of e-learning has been observed as a significant predictor. This indicates a positive relationship where a .215-unit increase in behavioural intention is obtained by each unit increase in the adoption score. The predictor's significance is affirmed by the t-value of 2.713 and a p-value of .008.

The B value of .182 and a (β of .180, p=0.019) have been observed, which indicate that facilitating conditions contribute positively to the behavioural intention. Statistical significance of this relationship is reflected by a t-value of 2.390 and a p-value of .019, suggesting the importance of an environment that supports e-learning as a factor in shaping students' intentions. Other variables such as Relative Advantage (ADV), Perceived Anxiety (PA), Perceived Enjoyment (PE), Performance Expectancy (PEX) and Effort Expectancy (EEX), have been observed but, it was found that they did not exhibit significant predictive power in the regression model, even though they exhibit significant correlations with behavioural intention (except for PA). This indicates that though these factors may correlate with students' intentions, they do not independently contribute to predicting it like other key factors, such as PU, AFC and FC.

5. Discussions

This study aimed to investigate the applicability of TAM to explore satisfaction and attitudes toward using e-learning technologies among the students at Albaha University. The results of the analysis of a survey of 100 students of Albhah University were presented in the Results section above. The analyses included demographic variables, descriptive analysis of TAM items, correlations and regression analysis. These results are interpreted in this section with the support of the literature.

The research framework of this study modified the original TAM of Davis by replacing PEOU with facilitating conditions. The external variables are peer influence, relative advantage and perceived anxiety. Effort expectancy, performance expectancy and perceived enjoyment mediate the relationship between PU and Facilitating conditions and BI and then to actual use. Thus, there are three mediating variables compared to none in the original TAM. Attitude towards using the technology in the original TAM is not considered in this model.

TAM is a widely used model for research on e-learning acceptance. Most papers reviewed above had used TAM [3,4,8], extended [10] modified TAM [2,9,14] or a combination of TAM with UTAUT [13,16,24]. Thus, the literature supports the adoption of TAM for this research work.

The demographic characteristics of the participants indicate their competency in answering the survey questions adequately, as all of them were studying a computing and information course, and most of them were senior students.

Descriptive scores of TAM variables showed the mean scores of most items nearer to the maximum score of 5 (4.06 to 4.41). Their levels of anxiety were low, with a mean score of 1.79, a good indication as a supporting variable. In the studies of Saif et al. (2024), it was found that stress contributed to anxiety, which, in turn, motivated the students to adopt Chat GPT [3]. Among external factors, perceived anxiety influenced attitude, leading to the intention to use online classes in the studies of Ullah et al. [10]. Anxiety was a factor influencing behavioural intention in the study of Sumi [20].

A score of 3.96 for facilitating conditions indicates a medium level of their perceptions about the conditions under which their e-learning is facilitated. In the studies of Sina et al. [8], facilitating conditions influenced both perceived usefulness and perceived ease of use. Both, in turn, influenced attitude, behavioural intention and user satisfaction. According to Ullah et al. [10] and Yang and Qian [13], facilitating conditions influenced attitudes leading to behavioural intention. In the studies of Fareed and Kirkil [16], facilitating conditions predicted behavioural intention. According to Yangbaixue (2025), facilitating conditions influenced behavioural intention [24]. Man et al. (2025) found language learning anxiety to be an important determinant of acceptance of technology [23].

Significant effect of perceived enjoyment on perceived ease of use and behavioural intention was noted by Al-Adwan et al. [2]. Perception of ease of use influenced perceived enjoyment in the studies of Xiang [15]. In this study, the mean response of 4.12 for perceived enjoyment indicates its strong influence on behavioural intention.

Most variables were correlated with one another. The highest correlation (r=.737) was obtained for the relationship between PU and BI, which is a direct effect of two important TAM variables. Negative correlations of PA with PI, EEX with PA and PA with AFC were also found. Anxiety decreasing with increasing peer influence is a useful finding, as it can be used to reduce anxiety among these students when e-learning is implemented. Anxiety decreases with increasing effort expectancy is also useful if those e-learning elements which increase their efforts can be reduced. If the students are more anxious about e-learning, they may not adopt it. Therefore, the negative relationship between the two is favourable for more students adopting e-learning. The reviewed papers did not use correlations in their studies. All correlations were significant at the 0.01 level in the studies of Paudel and Acharya (2024), who studied on the BI to use ChatGPT by 215 Nepalese university students [25]. The variables were PU, hedonic motivation, privacy, social influence and system quality. System quality had the highest correlation coefficient and contributed the highest (45.8%) to BI.

The regression analysis indicated that the combined variance explained by PU, AFC, and FC on BI was 60.5%. Together, these three were used for the predictive regression modelling. The highest contribution of 55.5% was for PU, followed by 21.5% by AFC and 18.2% by FC. Thus, only 95% of the total variation of BI was accounted for by these three variables. Notably, the constant was not significant. Since none of the reviewed papers used predictive regression analysis, these results are yet to be supported by other researchers. In the studies of Fareed and Kirkil [16], BI was jointly predicted by PU and PEOU (negative), accounting for 68.9% variation in behavioural intention. Thus, PU contributed the most in their study. Since PEOU was not a part of the research model in this study, PU, along with AFC and FC, explained only 60.5% variation in BI, with PU contributing the most.

Thus, many papers supported some of the relationships obtained in this study. However, this study did not include many of the variables they studied. On the other hand, some variables included in this study were not part of the study by these researchers. All these mean, a comprehensive study including all possible variables is required.

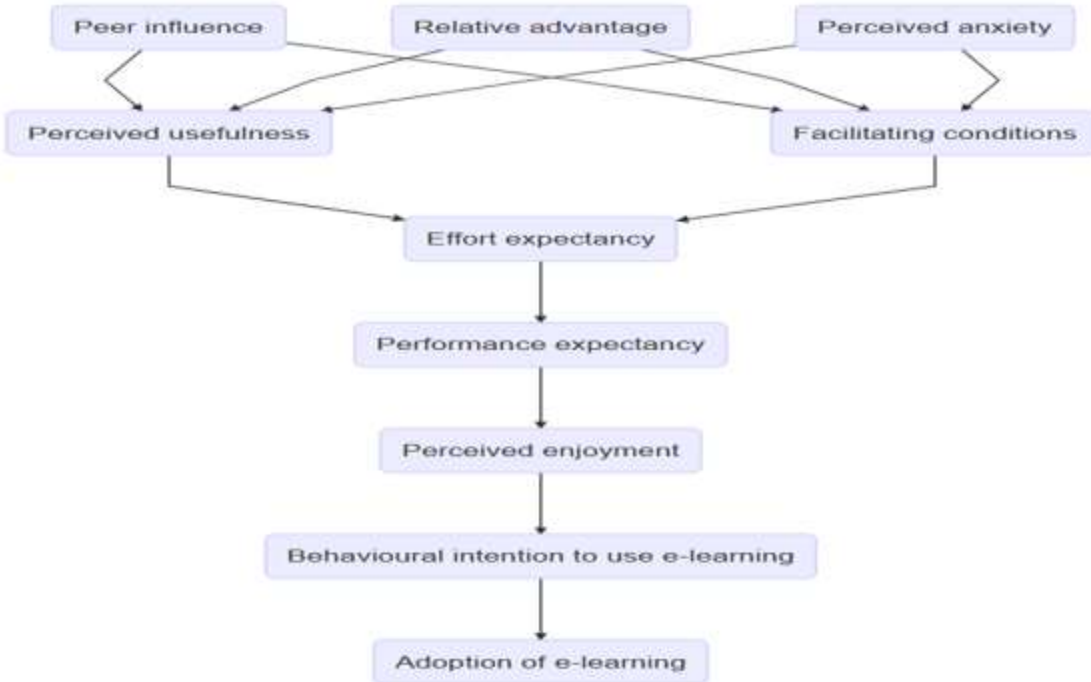

Figure 8. *The theoretical framework of this study.*

Table 1. *Frequencies and percentages of demographic variables.*

Variable	Classes	Frequency	Percentage
Gender	Female	55	55
	Male	45	45
	Total	100	100
Age	18-21	88	88
	21-25	12	12
	Total	100	100
Field of study	Computing & Information	100	100
Year of Study	1st Year	2	2
	2nd Year	65	65
	3rd Year	13	13
	4th Year	20	20
	Total	100	100

Table 2. *Descriptive statistics of TAM variables.*

	Min.	Max.	Mean	SD
Peer Influence (PI) Score	1.80	5.00	4.06	.64
Relative Advantage (ADV) Score	3.00	5.00	4.41	.53
Perceived Anxiety (PA) Score	1.00	4.20	1.79	.76
Perceived Enjoyment (PE) Score	2.40	5.00	4.12	.63
Performance Expectancy (PEX) Score	2.20	5.00	4.23	.57
Facilitating Conditions (FC) Score	1.60	5.00	3.96	.65
Perceived Usefulness (PU) Score	2.20	5.00	4.31	.61
Effort Expectancy (EEX) Score	2.33	5.00	4.25	.56
Behavioural Intention to Use E-Learning (BIFC) Score	2.00	5.00	4.35	.65
Adoption of E-Learning (AFC) Score	2.20	5.00	4.40	.66

Table 3. *Correlation coefficients across the study variables.*

	Peer Influence (PI) Score	Relative Advantage (ADV) Score	Perceived Anxiety (PA) Score	Perceived Enjoyment (PE) Score	Performance Expectancy (PEX) Score	Facilitating Conditions (FC) Score	Perceived Usefulness (PU) Score	Effort Expectancy (EEX) Score	Behavioural Intention to Use E-Learning (BIFC) Score
Relative Advantage (ADV) Score	.484**								
Perceived Anxiety (PA) Score	-.211*	-.447**							
Perceived Enjoyment (PE) Score	.463**	.572**	-.171						
Performance Expectancy (PEX) Score	.373**	.510**	-.191	.690**					
Facilitating Conditions (FC) Score	.422**	.385**	-.196	.556**	.503**				
Perceived Usefulness (PU) Score	.373**	.612**	-.293**	.692**	.630**	.509**			
Effort Expectancy (EEX) Score	.317**	.376**	-.243*	.622**	.617**	.578**	.539**		
Behavioural Intention to Use E-Learning (BIFC) Score	.311**	.443**	-.195	.614**	.577**	.529**	.737**	.498**	
Adoption of E-Learning (AFC) Score	.317**	.465**	-.234*	.477**	.374**	.396**	.585**	.357**	.591**

*. Correlation is significant at the .05 level (2-tailed).

**. Correlation is significant at the .01 level (2-tailed).

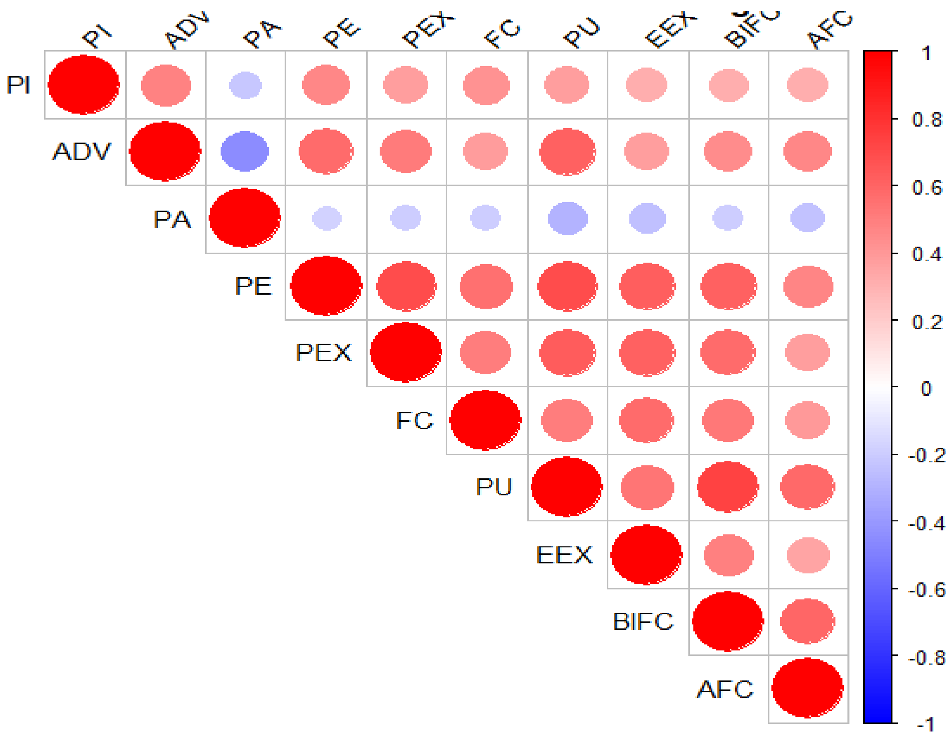

Figure 9. *Correlation coefficients across the study variables.*

Table 4. *The Regression Model.*

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	β		
(Constant)	.284	.344		.826	.411
Perceived Usefulness (PU) Score	.555	.091	.518	6.088	<.001
Adoption of E-Learning (AFC) Score	.215	.079	.217	2.713	.008
Facilitating Conditions (FC) Score	.182	.076	.180	2.390	.019
a. Dependent Variable: Behavioural Intention to Use E-Learning (BIFC) Score					

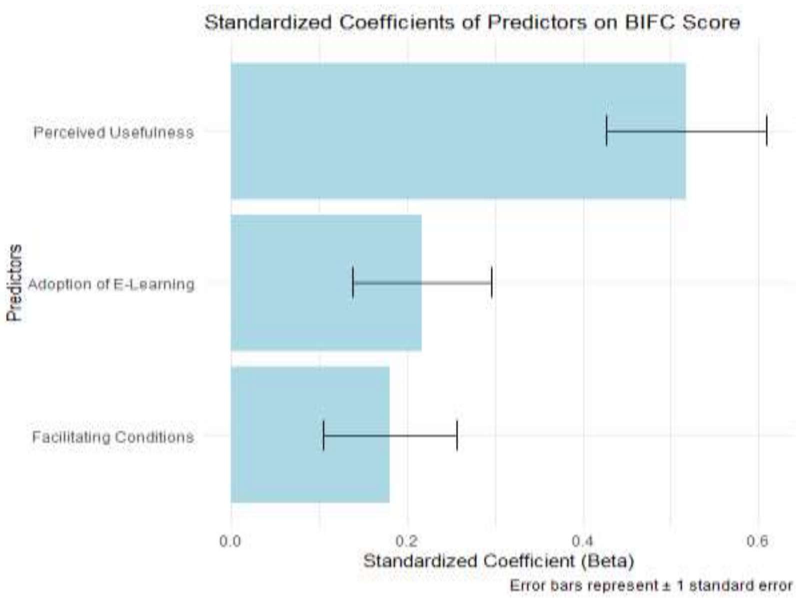

Figure 10 *Diagram explaining the relationship between standardised coefficients and predictors*

4. Conclusions

The aim of this study was partially achieved by the results obtained. TAM was modified by adding some variables and excluding some variables from the original version of Davis. The variables used in this study were Relative Advantage (ADV), Perceived Anxiety (PA), Perceived Enjoyment (PE), Performance Expectancy (PEX), Facilitating Conditions (FC), Perceived Usefulness (PU), Effort Expectancy (EEX), Behavioural Intention to Use E-Learning (BIFC), Adoption of E-Learning (AFC).
BI and actual adoption were highly correlated. BI and actual adoption were also correlated with all variables, except perceived anxiety, which was negatively correlated with actual adoption. Other significant negative relationships were between anxiety with peer influence and anxiety with effort expectancy. Non-significant relationships were obtained for anxiety with enjoyment, effort expectancy, facilitating conditions and perceived usefulness.
Perceived usefulness, facilitating conditions, and adoption explained 60.5% of the variation in the intention to use e-learning. About 95% of the variation in intention was accounted for by these three variables, with their effects decreasing in the order of perceived usefulness, adoption of e-learning and facilitating conditions.
This study also has some limitations. The sample size of 100 may be low for the generalisation of the findings. The study was focused only on one university in Saudi Arabia. Results might have been different if sampling had been done from many universities. The study was limited to Saudi students. Saudi Arabia has certain specific sociocultural environment. Hence, the findings may not apply to other countries with different sociocultural environments. Perceived ease of use is an important element in TAM. Exclusion of this variable from this research model might have affected the results. Satisfaction and performance outcomes were not included.
It is recommended that further investigation is needed. Since PU and FC emerged as the most important predictors of BI and actual adoption, universities can improve the conditions to motivate more students to use e-learning and more the use of e-learning by those already using it. These conditions include high-speed internet accessible always, infrastructure in the university to facilitate the students to use the technology safely. Support from top management and the faculty needs to be ensured. All the required conditions for students to enjoy e-learning without any anxiety need to be provided.
The deanship of E-learning at Albaha university can arrange training programmes for university faculty members on e-learning technologies and methods to teach with the aid of e-learning. The Ministry of education via The National eLearning Center (NeLC) can also initiate programmes to promote e-learning in more universities and other educational institutions. The Saudi government can provide policy, strategy and resource support for these efforts of the Ministry.
Rather than using a single model, combinations of models such as TAM and UTAUT seem to provide better results. Hence, future research should combine suitable models in its studies. Studies on e-learning are limited to certain countries such as middle east countries ,therefore, future research should consider other developing countries which not been studied so far. Studies comparing different universities in the same countries and those in different countries may provide useful findings. Instead of using survey only, mixed methods combining surveys with qualitative methods like interviews will provide more depth to the findings.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

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- **Author contributions:** The authors declare that they have equal right on this paper.

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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