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RESEARCH ARTICLE

Extended Model of Expectation Confirmation Model to Examine Users' Continuous Intention Toward the Utilization of E-Learning Platforms

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ABSTRACT The utilization of E-learning platforms has attracted considerable attention recently. Universities are increasingly adopting diverse E-learning platforms that offer a range of features to enhance student satisfaction and promote their sustained utilization of E-learning platforms. The task of consistently engaging and encouraging students to use E-learning platforms remains a persistent challenge. Many students tend to discontinue their participation in E-Learning platform courses, showing reluctance towards sustained engagement with the platform. Therefore, this research analyses the essential factors impacting students' inclination to sustain their utilization of the E-Learning platform. The present study uses the "Expectation Confirmation Model" (ECM) with four factors: "interactivity", "social influences", "computer self-efficacy", and "perceived enjoyment". A survey was administered to college students via online Google Forms, resulting in 362 respondents. The data analysis is conducted using the Smart-PLS 4 Programme. Based on its findings, the study presented a "conceptual framework" for the sustained utilization of E-learning platforms. Results show that perceived enjoyment, satisfaction, interactivity, computer self-efficacy, and social influences impact continuing intention. This research indicates that satisfaction has the most substantial consequence on students' intention to persist in utilizing E-Learning platforms. The model prediction power (R2) is 70 %, which can explain the users' continuous intention.

INDEX TERMS Continuous intention, E-learning platforms, interactivity, perceived enjoyment.

I. INTRODUCTION

The usage of E-learning platforms has experienced a considerable increase, primarily attributed to the worldwide impacts of COVID-19. In response to the education crisis, several e-learning platforms have been designed and used to address the closure of entire educational institutions [1]. In addition, the optimization of the E-learning platform's effectiveness requires the identification and resolution of challenges, as well as the anticipation of user motivation for future system utilization. There is a belief among researchers that the implementation of e-learning has the potential to facilitate the expansion of e-learning and training capabilities within educational institutions, hence enhancing students' skills [2], [3]. Nevertheless, implementing E-learning has brought up additional complexities that require careful consideration to maintain the effectiveness of the continued desire to utilize E-learning beyond the post-adoption phase [4]. These supplementary obstacles are occasionally associated with the personalization and aptitudes of students, factors that impact their inclination to sustain engagement with E-Learning. One of the primary challenges lies in ensuring students are motivated to utilize online learning systems. Thus, more research is necessary to analyze the variables that impact users' sustained intention and satisfaction [5]. Moreover, researchers in [6] state that a more comprehensive understanding of the

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factors hindering students' continuous adoption of E-learning is necessary, demanding heightened scrutiny.

Considering empirical data indicating a fall in attendance rates for lectures delivered using E-learning platforms and a decline in students' motivation to continue using these platforms [7], [8]. Several studies have reported a significant rise in the dropout rate for E-Learning compared to traditional learning [9], [10], [11]. Various factors influence students' inclination to prolong their usage of E-Learning platforms. According to [12], it has been argued that around 21% of students exhibit a willingness to discontinue their utilization of E-Learning platforms. Additionally, a significant proportion of 47% withdraw from such platforms due to a shortfall of motivation, while approximately 25% express a need for more self-confidence in their ability to navigate E-Learning platform courses effectively. In addition, it was found that around (30% - 50%) of E-Learning participants dropped out and could not finish their courses due to lack of interest, quality of E-Learning platforms, user behaviour, experience, and interaction [13]. According to [14], a high portion of the dropout rate required actions to motivate users to actively engage with and persist in utilizing E-Learning platforms. Furthermore, research has indicated that a considerable proportion, ranging from 30% to 50% of individuals engaged in E-Learning fail to complete their courses. This high dropout percentage can be attributed to diminished interest, inadequate quality of E-Learning platforms, user behaviour, experience, and engagement. The researcher in [15] proposed a range of elements that contribute to student attrition, encompassing adverse experiences, lack of desire, limited time availability, unstimulating course materials, and inadequate assistance.

Furthermore, to maintain the ongoing progress of the educational process and achieve the desired outcomes of their system, which is intended to attract students, academics and decision-makers must investigate students' continued intent to use the E-Learning platform. In addition, identifying the elements that impact users' intention to continue utilizing E-learning platforms will enable decision-makers to comprehend the factors that inhibit users' willingness to continue utilizing E-learning platforms and encourage them to develop solutions to address these obstacles.

Hence, this study will incorporate a conceptual framework to examine the elements that impact users' opinions regarding their inclination to continue using the E-learning platform.

II. LITERATURE REVIEW

The investigation of users' continuous intention to utilize an e-learning platform is a reliable indicator of the platform's viability. Therefore, more attention is given to examining users continuous intention [16]. Several theories and models have been utilized in prior research to analyze users' ongoing intentions concerning their acceptance, such as TPB, TAM, IS Success, UTAUT, and ECM [17], [18], [19]. Furthermore, the E-learning platform will likely generate greater user interest and engagement when it aligns with users' expectations and effectively fulfils their requirements [20]. Hence, examining users' determinations during the post-adoption phase requires focused research attention since the determination of the acceptance phase exhibits distinctions from the determination of the post-adoption phase [21], [22]. The ''Expectation Confirmation Model'' (ECM) is a famous framework for examining the continuous intention within the field of Information Systems (IS) as it developed to examine the post-adoption phase instead of the acceptance phase [23], [18], [24], [25]. According to [26] and [27], the ECM theory emphasizes the significance of user satisfaction in shaping the users' subsequent intentions toward using E-Learning. Therefore, this research utilizes the ECM in combination with (perceived enjoyment, computer self-efficacy, interactivity, and social influences) to explore users' continuous intentions and analyze these variables' influence on students' future intentions to sustain their usage of the E-Learning platform.

A. EXPECTATION CONFIRMATION MODEL (ECM)

The ''Expectation Confirmation Model'' (ECM) is a frequently utilized theoretical framework that aims to determine the likelihood of a user's continued usage of an information system rather than solely assessing their satisfaction [28]. The model proposed by [27] aims to analyze the post-adoption phase, encompassing four key variables: ''confirmation'', ''satisfaction'', ''perceived usefulness'', and ''continued intention''. The core development of the theory is about the post-adoption stage, in which user satisfaction is obtained after meeting the user's confirmation. Therefore, user satisfaction is the main factor that continuously motivates users to use the target information system [29]. According to the theory, satisfaction is the most influential factor toward continuous intention, and perceived usefulness directly affects satisfaction [30]. Figure 1 illustrates the ECM model and its various components.

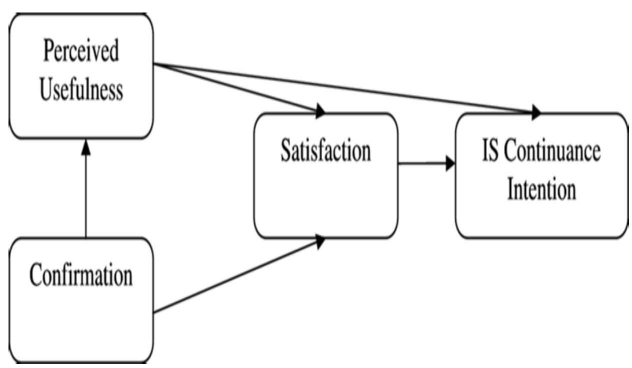

FIGURE 1. Expectation confirmation model [27].

B. CONTINUOUS INTENTION

A system's efficacy is contingent upon users' satisfaction and willingness to continue utilizing the Elearning platforms [31]. Therefore, the significance of continuous intention in assessing the efficiency of an information system (IS) after the acceptance stage is evident. The researcher in [32] claims that the system's actual usage and popularity can be concluded from the continuous intention to utilize the system. Therefore, examining students' ongoing intents concerning E-learning is essential to foster greater student participation. Furthermore, the ECM model examines the continuous intention of users to utilize E-Learning, as ECM primarily focuses on the post-adoption phase [28], [33]. Various examinations have been performed to explore the concept of continuous intention [7]. The researcher in [34] conducted a study whereby they combined the "Technology Acceptance Model" (TAM) and "Task Technology Fit" (TTF) framework to investigate the many aspects that influence users' intentions. Their findings indicate that social influence and convenience significantly motivate students to utilize E-learning platforms. Another investigation, conducted by [34], aimed to examine the factors that impact the sustained intention of students in Sri Lanka; the researchers employed an extended "Technology Acceptance Model" (TAM) and analyzed the data to achieve this. The study implied that "ease of use", "self-efficacy", "perceived usefulness", and "quality of the Learning Management System" (LMS) were influential determinants of continuous intention among students. Moreover, the researcher [35] put out a conceptual framework in their recent study, which seeks to merge two well-established theories, specifically "Social Cognitive Theory" and "Social Cognitive Career Theory". The study emphasizes the importance of personal and environmental factors in determining users' future willingness to utilize E-learning. In addition, the researcher in [36] presented an enhanced version of the "Unified Theory of Acceptance and Use of Technology" (UTAUT) paradigm proposed by [37], incorporating components specifically applicable to Learning Management Systems (LMS).

Other researchers have expanded upon the ECM model by incorporating additional components to examine the influences on users' continuous intentions. This approach allows for a broader examination of the elements that affect continuous intention and the ability to address the specific requirements of different domains or areas of study. The researchers in [38] examine the impact of quality elements, "information quality", "system quality", and "service quality" on the continuing intention to utilize "massive open online courses" (MOOCs) in the context of e-learning. The research extends the "expectation-confirmation model" (ECM) by incorporating these quality factors. [39] Incorporate the ECM model with three elements that reflect gamification (flow, perceived enjoyment, and engagement) to study the impact of these elements on students' continuous intention toward using E-Learning. Researchers in [40] investigated the relationship between task skill and task challenge as predictors of enjoyment leading to satisfaction. The researchers discovered a noteworthy impact of these elements on the utilization of e-learning platforms. In their study, [41] investigated several variables influencing students' sustained intention to utilize Learning Management Systems (LMS). To attain this, they integrated the "Expectation Confirmation Model" (ECM) with the "Technology Acceptance Model" (TAM) while incorporating two supplementary elements: subjective norms and hedonic value. Additionally, the researchers in [42] investigate users' continuous intention toward virtual online classes. Further, the researcher used the ECM (Expectation-Confirmation Model) and IS Success model to construct their theoretical framework, incorporating quality factors. Numerous research endeavors have investigated the key factors impacting users' continuous intention to utilize E-Learning platforms. Nevertheless, there is a need for more research to examine students' continuous intention towards utilizing E-learning platforms. According to [39], more attention is needed to investigate the continuous intention as it plays a crucial part in the success of IS. Different studies show that perceived enjoyment and interactivity factors can influence users' intent to continue using E-Learning platforms [14], [25], [43], and [44].

The literature above shows a need to examine the elements that affect users' continuous intention to demonstrate the long-term efficacy of information systems. However, aspects such as the level of interactivity with E-Learning platforms and the perceived Enjoyment of using e-learning platforms are given little consideration. Due to the limitation mentioned earlier, the present study suggests an integrated model that uses the ECM Model with four distinct characteristics to forecast students' sustained inclination towards utilizing the E-learning platform. This research examines the impact of Enjoyment, social influence, "computer self-efficacy", and interaction on students' intention to sustain the use of E-learning platforms.

III. METHODOLOGY

The research methodology employed in the study consists of several distinct stages. The initial phase of the research process involves data collection and analyzing data. Additionally, it is essential to choose the target sample and the appropriate size for the study. Next, develop the instrument that will be used for data collection from the designated participants. Subsequently, the questionnaires should be subjected to validation procedures, namely face and content validity assessments. In addition, pilot research is being conducted to detect any potential failures or inaccuracies that may arise while utilizing the initial instrument for assessing reliability and validity. Subsequently, the model undergoes measurement and structural assessments. The model's performance is evaluated following the methodologies and metrics suggested by prior scholarly investigations [45]. The Smart-PLS software is utilized to assess the measurement and structural models. Figure 2 depicts the evaluation procedure.

A. DATA COLLECTION

Data is gathered during the data collection phase through online Google forms and distributed to the intended responders by email or URL links. Moreover, the research focuses

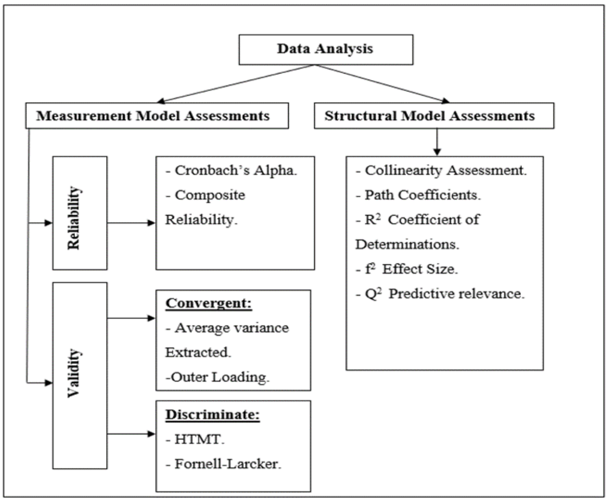

FIGURE 2. Data analysis process.

on university students' perspectives from Iraq and Malaysia regarding their continuous intention to use E-Learning platforms. To ensure that all targeted students have experience dealing with the E-Learning platforms, the data collection process was conducted after 2021, guaranteeing students' experience using E-Learning platforms. In the latter half of 2020, an entire shift in e-learning was implemented in both countries [46] and [47]. Ensuring the accuracy and reliability of the gathered data is a crucial factor when collecting data. Hence, participants are requested to provide feedback on their experiences with E-learning platforms. Therefore, individuals with no experience or less than three months of experience with E-learning platforms are instructed to submit their Google Form without considering their survey responses. Another challenge was to reduce the occurrence of missing data mistakes during the survey. Consequently, every survey item requires participants to answer all questions before proceeding to the next section. After eliminating unreliable responses, 362 respondents were selected to gather data from 412 original respondents, which was then analyzed using Smart-PLS 4.0.8.5 software.

B. TARGETED SAMPLE AND SIZE

The cohort population comprises college students (undergraduate and graduate) utilizing E-Learning platforms for their educational journey. Respondents are eligible if they employ E-learning platforms in their educational process. The scope of this investigation includes students graduate and post-graduate from Iraq and Malaysia. The data were collected from 362 students dealing with E-Learning platforms in their education process. Because the analysis results depend on selecting the appropriate sample size, the G* Power software is employed to find the adequate sample size based on the independent constructs [48]. The researcher in [49] asserts the following settings for the program (alpha a = 0.05, beta ß = 0.80, and effect size = 0.15) with seven predictor items. Then, the minimum number of respondents is 103. Out of the initial 412 primary respondents, a subset of 362 was chosen to participate in the data collection process. Table 1 displays participants' demographic details.

TABLE 1. Demographic details of respondents.

Variable	Type	Frequency	Percentage
Gender	Female	229	55.6%
	Male	183	44.4%
Age	Under 20	66	16%
	20 - 25	184	44%
	26 - 31	16	3.9%
	32 - 37	33	8%
	38 - 42	47	11.4%
	Over 42	66	16%
Education Level	Graduate	176	42.7%
	Post-graduate	236	57.3%

C. INSTRUMENT

The instrument developed in this analysis is primarily developed to measure students' continuous intention to utilize E-learning platforms. The questionnaires comprise three sections encompass inquiries regarding demographic information, open-ended questions to explore the user's familiarity and experience with E-learning, and questions designed to assess the user's perception of E-learning platforms. A five-point "Likert scale" is employed to assess users' perceptions regarding using E-learning platforms, ranging from "strongly disagree" to "strongly agree". The instrument comprises a total of thirty-eight questions, which represent eight constructs. These items have been adopted from prior studies and slightly revised to align with the specific context of our domain.

D. MEASUREMENT AND PRE-TEST

The model includes eight factors, and the interrelationships among them are investigated using thirty-six items. Prior research utilized items that were slightly modified in their wording to be consistent with the specific objectives of our study. The Likert scale is a commonly used tool in research for measuring the degree of agreement respondents express towards a specific topic. It comprises five response possibilities spanning from strongly agree to disagree strongly. Subsequently, the instruments undergo an evaluation process involving face and content validity to mitigate potential sources of measurement error. Hence, it is imperative to seek the expertise of professionals in Information Systems (IS) to assess and examine the survey thoroughly before its implementation. In addition, pilot research is carried out to mitigate the risk of encountering failures or errors before completing the primary survey [50]. The pilot survey is used to prevent unnecessary expenditure of time and resources. A sample of around 35 participants, constituting 10% of the overall survey population, was chosen to complete the pilot study. The validation and reliability evaluation standards for the pilot study are depicted in Table 2.

TABLE 2. Data reliability and validity standards.

Assessment	Measurement type	Criteria	References
Pilot study reliability assessment	Cronbach's Alpha	≥0.6 accepted ≥0.7 sufficiently good	(J. Hair & Alamer, 2022)
	Composite Reliability	≥0.6 accepted	
Pilot study validity assessment	Average Variance Extracted (AVE)	≥0.5 accepted	
	Heterotrait-monotrait (HTMT)	All items must be no higher than 0.85 to be accepted	

For measuring the reliability of the survey, two measurements are used: "Cronbach's Alpha" (CA) and composite reliability, and the recommended scores are 0.6 and ≥ 0.6, respectively [51]. Table 3 illustrates the assessment of "Cronbach's Alpha" and "composite reliability" for the survey items. Cronbach's Alpha assessment indicates that all the constructs have scores over the threshold value of 0.6. In addition, the Composite reliability assessment also confirms that all the items have scores over 0.6. Hence, the model exhibits a notable degree of reliability and consistency.

TABLE 3. Cronbach's alpha and composite reliability measurements.

Variable	Code	No. of items	Cronbach's alpha results	Composite reliability (rho_a)
Continuous intention	Ci	4	0.925	0.928
Confirmation	CONF	5	0.787	0.834
Computer Self-Efficacy	CSE	4	0.793	0.804
Interactivity	INT	8	0.837	0.874
Perceived Enjoyment	PENJ	5	0.926	0.931
Perceive Usefulness	PU	4	0.926	0.929
Satisfaction	SA	3	0.859	0.867
Social influence	Si	5	0.799	0.829

Assessing the validity of variables requires two distinct measurements: "discriminant" and "convergent validity". Convergent measurement employs the "Average Variance Extracted" (AVE) criterion, as proposed by [45], wherein no score is considered acceptable if it falls below the threshold of 0.5. Table 4 presents the results of the AVE measurement, wherein all items are above the established threshold of 0.5, Consequently, convergent validity has been attained, indicating substantial agreement among the constructs.

TABLE 4. Validity Measurement (AVE).

Variable	Code	No. of items	Average variance extracted (AVE)
Continuous intention	Ci	4	0.818
Confirmation	CONF	5	0.527
Computer Self-Efficacy	CSE	4	0.505
Interactivity	INT	9	0.577
Perceived Enjoyment	PENJ	5	0.772
Perceive Usefulness	PU	4	0.818
Satisfaction	SA	3	0.780
Social influence	Si	5	0.557

The Heterotrait-Monotrait Ratio (HTMT) is a measurement employed in discriminant assessment to ascertain the conceptual distinctiveness of a particular construct concerning others utilized within the study [45]. The cutoff score of 0.9 is essential, with no score above it, which suggests that validity exists among the two targeted constructs. Table 5 shows that items are above the cutoff score of 0.9 and cannot be accepted.

TABLE 5. Heterotrait-Monotrait Ratio (HTMT) 1ST round.

	CI	CONF	CSE	INT	PENJ	PU	SA	SI
CI								
CONF	0.693							
CSE	0.845	0.786						
INT	0.534	0.6	0.689					
PENJ	0.527	0.651	0.692	0.469				
PU	0.719	0.707	0.92	0.431	0.734			
SA	0.967	0.778	0.952	0.564	0.695	0.894		
SI	0.805	0.697	0.806	0.401	0.601	0.854	0.741	

Hence, scholars propose the exclusion of items that yield a score over the threshold of 0.9 (namely, PU4, CONF5, and SAT1), followed by a subsequent administration of the evaluation to ensure reliability [50], [51]. The results of the second round of the HTMT examination demonstrate that all items have scores below 0.9, affirming the HTMT ratio and establishing the discriminant validity. Table 6 displays the results of the second round of HTMT assessment.

Based on the Pre-test results that implement Cronbach's Alpha, composite reliability evaluate the instrument's reliability and Validity Measurement that uses both Average Variance Extracted and Heterotrait-Monotrait Ratio to evaluate the discriminate and convergent validity. It shows that the constructs are very reliable and consistent.

IV. CONCEPTUAL MODEL AND HYPOTHESES

The integrated study model was constructed based on the theory of ECM with four additional constructs: social influences,

TABLE 6. Heterotrait-Monotrait Ratio (HTMT) 2ND round.

	CI	CONF	CSE	INT	PENJ	PU	SA	SI
CI								
CONF	0.693							
CSE	0.845	0.786						
INT	0.534	0.6	0.689					
PENJ	0.527	0.651	0.692	0.469				
PU	0.659	0.707	0.871	0.408	0.728			
SA	0.899	0.714	0.88	0.488	0.658	0.704		
SI	0.805	0.697	0.806	0.401	0.601	0.846	0.636	

interactivity, computer self-efficacy and perceived enjoyment. This study considers eight variables and sixteen hypotheses to examine the elements impacting students' continued intention and enjoyment of using the E-learning platform. Model constructs and hypotheses are present in Figure 3.

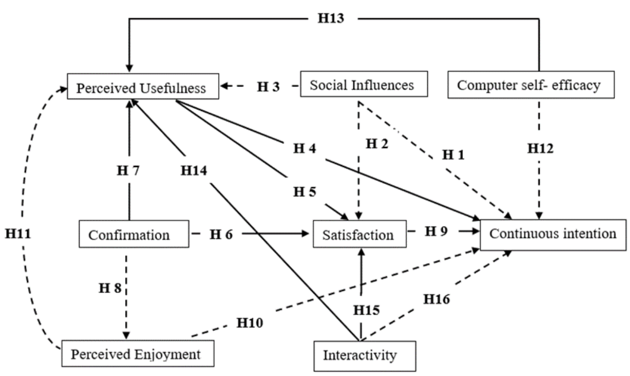

FIGURE 3. Suggested research model for the investigation of continuous intention.

All the proposed hypotheses are evaluated considering the existing body of research. Consequently, a total of sixteen hypotheses have been formulated to examine the proposed associations among the constructs of the model. The model contains 16 hypotheses demonstrating how the constructs may be related. H1, H2, and H3 illustrate the association between the independent variable social influences and the dependent variables' continuous intention, satisfaction, and perceived usefulness. In addition, Hypotheses H4 and H5 illustrate the associations between perceived usefulness and the dependent variables' Continuous intention and satisfaction, respectively. Three confirmation hypotheses are H6, H7, and H8, with H6 about the dependent variable of satisfaction, H7 toward the dependent variable of perceived usefulness, and H8 with the dependent variable of perceived enjoyment. In addition, there is only one hypothesis regarding satisfaction and the dependent variable, continuous intention H9. In addition, Hypothesis H10 demonstrates the association between the independent variable, perceived enjoyment, and the dependent variable, continuous intention.

In contrast, Hypothesis H11 demonstrates the relationship between perceived enjoyment and the dependent variable, perceived usefulness. The independent variable, computer self-efficacy, has two hypotheses regarding the dependent variables: continuous intention (H12) and perceived usefulness. (H13). Lastly, the independent variable interactivity has three hypotheses, H14, H15, and H16, characterizing the relationships with three dependent variables: perceived usefulness, satisfaction, and continuous intention.

V. EVALUATIONS AND RESULTS

The data analysis portion utilizes Smart-Pls software to assess the measurement and structural model of the proposed model. Smart-Pls is widely used by researchers for analysis because of its different features, ability to handle small sample sizes, and many visualization methods [52], [53]. Moreover, Smart-Pls is suitable for assessing the relationships between independent and dependent variables, and it is especially beneficial when the sample size is limited [54]. Smart-pls is selected when the study focuses on prediction and understanding the variability of essential target components utilizing different explanatory constructs.

Assessing the model consists of two stages: evaluating measurement and structural model. During the measurement model stage, it examines the association between the construct's variable and the "observed variables." Moreover, eight variables Among these variables, four are considered dependent variables, including continuous intention, "perceived usefulness", "perceived enjoyment", and "satisfaction". Furthermore, the study incorporates four distinct independent variables, including "computer self-efficacy", "confirmation", "interactivity", and "social influences". Furthermore, a thorough measurement model analysis allows for evaluating the accuracy with which the model variables are measured [54]. Given the reflective nature of the variables in this study, it is essential to run a series of tests to evaluate the measurement model's convergent validity, discriminant validity, and internal consistency [56], [57]. For the investigation of the measurement model, we need to investigate the reliability and validity of the model. In reliability measurement, "Cronbach's alpha" and composite assessments are used. Cronbach's alpha assessment shows that all items score above the suggested threshold value (0.7). In addition, the composite reliability test reveals scores more significant than the cutoff score (0.6). Consequently, the research demonstrated higher internal consistency and reliability in Table 7.

To evaluate the validity of the measurements, two commonly employed metrics are utilized: "Average Variance Extracted" (AVE) and outer loading are used to assess the model validity. Furthermore, the assessment known as the AVE test, employed to measure the convergent validity, suggests that any items with scores surpassing the predetermined threshold of 0.5 are deemed acceptable [50]. Table 8 presents AVE values for each item, revealing that all scores surpass the threshold of 0.5, proving convergent validity.

TABLE 7. Reliability measurements.

Variable	Code	No. of items	Cronbach's alpha results	Composite reliability (rho_a)	Composite reliability (rho_c)
Continuous intention	Ci	4	0.944	0.944	0.960
Confirmation	CONF	5	0.791	0.793	0.865
Computer Self-Efficacy	CSE	4	0.869	0.876	0.911
Interactivity	INT	8	0.900	0.902	0.919
Perceived Enjoyment	PENJ	5	0.922	0.923	0.942
Perceive Usefulness	PU	4	0.921	0.921	0.944
Satisfaction	SA	3	0.888	0.896	0.919
Social influence	Si	5	0.830	0.832	0.887

The second measure for evaluating convergent validity is the outer loading. Furthermore, according to [50], it has been suggested that an outdoor loading score of 0.7 or above is considered ideal. The assessment outcomes of the outer loading are given in Table 9, indicating that all items are above the predetermined threshold value of 0.7.

TABLE 8. Average Variance Extracted (AVE) test results.

Variable	Code	No. of items	Average Variance Extracted (AVE)
Continuous intention	Ci	4	0.856
Confirmation	CONF	5	0.615
Computer Self-Efficacy	CSE	4	0.718
Interactivity	INT	8	0.588
Perceived Enjoyment	PENJ	5	0.764
Perceive Usefulness	PU	4	0.808
Satisfaction	SA	3	0.694
Social influence	Si	5	0.663

Discriminant validity is employed to assess the association between measured constructs and other constructs and the number of items that pertain to a particular construct [55]. Likewise, the HTMT evaluation has been proposed to evaluate the discriminant validity by examining the extent to which a particular construct accounts for the variance in its indicators relative to the variance accounted for by other indicators [45]. Moreover, the HTMT assessment sets the threshold value at less than 0.85. Nevertheless, if potential similarities are observed among the constructs' indicators, the threshold might be raised to approximately less than 0.90 [50], [56]. The findings of the HTMT test for all items are presented in Table 10, indicating that the results scores are below the specified threshold of 0.90 [50].

The Fornell-Larcker Criterion, proposed by "Fornell and Larcker" (1981), is a method employed to measure the discriminant validity of constructs. The criteria involve comparing the square root of a construct's variance with the correlation between different constructs. Based on the results

TABLE 9. Outer loading assessment.

	CI	CONF	CSE	INT	PENJ	PU	SA	SI
CI1	0.910							
CI2	0.932							
CI3	0.934							
CI4	0.924							
CONF1		0.748						
CONF2		0.801						
CONF4		0.773						
CONF5		0.814						
CSE1			0.848					
CSE2			0.878					
CSE3			0.855					
CSE4			0.806					
INT2				0.746				
INT3				0.712				
INT4				0.772				
INT5				0.742				
INT6				0.819				
INT7				0.778				
INT8				0.771				
INT9				0.790				
PENJ1					0.842			
PENJ2					0.894			
PENJ3					0.916			
PENJ4					0.852			
PENJ5					0.863			
PU1						0.896		
PU2						0.922		
PU3						0.900		
PU5						0.876		
SA1							0.868	
SA2							0.720	
SA3							0.833	
SA4							0.879	
SA5							0.855	
SI2								0.820
SI3								0.855
SI4								0.801
SI5								0.778

TABLE 10. HTMT assessment results.

	CI	CONF	CSE	INT	PENJ	PU	SA	SI
CI								
CONF	0.758							
CSE	0.830	0.814						
INT	0.669	0.727	0.761					
PENJ	0.751	0.816	0.819	0.643				
PU	0.741	0.820	0.726	0.578	0.697			
SA	0.846	0.899	0.867	0.679	0.822	0.840		
SI	0.717	0.800	0.660	0.579	0.699	0.806	0.774	

displayed in Table 11, the significance of all construct values surpasses that of the "inter-construct correlation."

To assess the structural model, Upon the completion of the initial phase of model analysis, whereby the focus lies on verifying its reliability and validity, the subsequent stage entails the evaluation of its underlying structure. The researcher [50] suggests multiple assessments for evaluating the structure model, the links between model constructs, and the model's predictive capabilities. The initial evaluation consists of examining the collinearity statistics. Examine the path coefficients next. Then, evaluate the R2 evaluation to determine the model's "predictive capabilities." Additionally, research the influence size (f 2). At the conclusion, evaluate q2 and Q2.

TABLE 11. Fornell-Larcker assessment results.

	CI	CONF	CSE	INT	PENJ	PU	SA	SI
CI	**0.925**							
CONF	0.641	**0.818**						
CSE	0.757	0.663	**0.847**					
INT	0.619	0.599	0.673	**0.767**				
PENJ	0.702	0.681	0.739	0.586	**0.874**			
PU	0.691	0.684	0.652	0.529	0.643	**0.899**		
SA	0.777	0.742	0.767	0.613	0.747	0.763	**0.870**	
SI	0.636	0.634	0.566	0.502	0.612	0.707	0.67	**0.814**

The initial assessment involves collinearity statistics, which entails the examination of tolerance and the VIF factor (Variance Inflation Factor). According to [50], a threshold value of five is commonly recommended for assessing collinearity, where values beyond this threshold indicate the presence of substantial collinearity concerns. Table 12 illustrates the results of the collinearity assessment, in which all items' scores are below the cutoff score of 5.

TABLE 12. Collinearity assessment VIF.

	CI	CONF	CSE	INT	PENJ	PU	SA	SI
CI								
CONF					1	2.427	2.33	
CSE	3.274					2.869		
INT	1.951					2.006	1.649	
PENJ	2.805					2.725		
PU	2.925						2.497	
SA	3.923							
SI	2.264					1.892	2.212	

The second assessment involves determining if the proposed connections between components are evident in the collected data using path coefficients [57]. According to [54], the recommended path coefficient assessment score falls from −1 to 1. Coefficients nearer to 0 exhibit a weaker predictive relationship, while coefficients nearer to 1 exhibit a more substantial predictive potential concerning dependent constructs. The data obtained indicate acceptance of all hypotheses, except for two hypotheses with t values below the required cutoff of 1.96, as proposed by [57]. Table 13 presents the outcomes of the bootstrapping examination conducted to evaluate the hypotheses and ascertain the significance between the constructs.

Furthermore, this study employs a bootstrapping analysis to calculate the "P values" as a two-tailed test of hypotheses, which can be either directional or positive [45]. The path coefficient diagram is depicted in Figure 4.

TABLE 13. Assessment of the hypotheses.

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	Results
CONF -> PENJ	0.646	0.648	0.036	17.718	0	***
CONF -> PU	0.249	0.249	0.05	4.987	0	***
CONF -> SAT	0.319	0.319	0.045	7.158	0	***
CSE -> CI	0.259	0.258	0.063	4.097	0	***
CSE -> PU	0.205	0.203	0.061	3.342	0.001	***
INT -> CI	0.107	0.108	0.05	2.135	0.033	*
INT -> PU	0.012	0.013	0.054	**0.223**	**0.823**	**NS**
INT -> SAT	0.134	0.135	0.038	3.54	0	***
PENJ -> CI	0.114	0.113	0.054	2.119	0.034	*
PENJ -> PU	0.085	0.087	0.06	**1.41**	**0.159**	**NS**
PU -> CI	0.105	0.104	0.053	1.994	0.046	*
PU -> SAT	0.381	0.379	0.05	7.61	0	***
SAT -> CI	0.284	0.283	0.062	4.595	0	***
SI -> CI	0.105	0.106	0.05	2.094	0.036	*
SI -> PU	0.375	0.375	0.051	7.309	0	***
SI -> SA	0.134	0.135	0.048	2.801	0.005	***

CONF Confirmation PENJ Perceived Enjoyment PU Perceived Usefulness SAT Satisfaction CSE Computer self-efficacy CI Continuous intention INT Interactivity SI Social influences

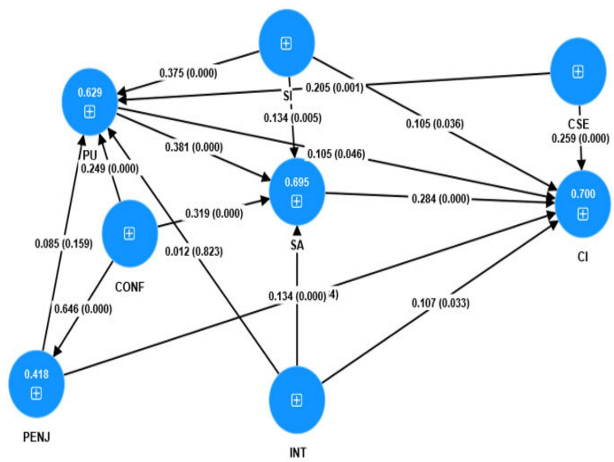

FIGURE 4. Path coefficient.

Examining and evaluating the structural model's predictive capability involves utilizing the R2 statistic, also known as the "coefficient of determination". The researchers in [51] state that the "coefficient of determination" is bounded by values ranging from 0 to 1. Furthermore, R2 assesses the influence of the independent variables on the dependent variable. In addition, it is worth noting that R2 values exceeding 0.66 have a "significant" level of explanatory power, while values of 0.333 and 0.19 are categorized as moderate and weak, respectively [58], [59]. In addition, the researchers in [59] argue that R2 must have a score of at least 0.05 to be considered significant.

Based on the findings of the R2 assessment, Table 14 demonstrates that the constructs of continuous intention and satisfaction exhibit a robust explanatory power, in contrast

TABLE 14. The results of R2.

Dependent variables	R-square	R-square adjusted	Explanatory level degree
CI	0.700	0.695	substantial
PENJ	0.418	0.416	moderate
PU	0.629	0.624	moderate
SA	0.695	0.691	substantial

to perceived enjoyment and usefulness, which provides a moderate predictive capability. In addition, the model demonstrates that a significant portion, precisely 70%, of the variability in continuous intention can be accounted for by factors such as computer self-efficacy, perceived usefulness, enjoyment, satisfaction, and involvement.

Another assessment method commonly utilized in research is the F2 Effect size, which serves as a quantitative metric to evaluate the relative impact of the independent variable on the dependent variable. The researcher in [58] states that the f2 statistic is employed to assess the influence of a specific "exogenous" latent variable on an "endogenous" latent variable by analyzing fluctuations in the R2 coefficient. Table 15 presents the findings of the F2 evaluation, which quantifies the effect size of each association and provides an estimation of the importance of that effect.

TABLE 15. Illustrate the f2 effect size assessment results.

Paths	Effect size	results
CONF → PENJ	0.718	Large effect
CONF → PU	0.072	Small effect
CONF → SA	0.144	Small effect
CSE → CI	0.068	Small effect
CSE → PU	0.040	Small effect
INT → CI	0.021	No effect
INT → PU	0.000	No effect
INT → SA	0.037	Small effect
PENJ → CI	0.017	No effect
PENJ → PU	0.008	No effect
PU → CI	0.013	No effect
PU → SA	0.189	Medium effect
SA → CI	0.070	Small effect
SI → CI	0.016	No effect
SI → PU	0.189	Medium effect
SI → SA	0.027	Small effect

The other metric employed to assess the structural model is Q2, which implies the model's predictive relevance. Furthermore, to determine the significance of quantifying predictive relevance, [57] argues that the Q2 value is employed as a metric to assess the predictive significance of a variable concerning the model.

Table 16 presents the q2 values and the corresponding effect levels of the independent variables on the dependent variables. The association between Confirmation (CONF)

TABLE 16. q2 predictive relevance measuring.

Dependent construct / Q2 score	Direction	q^2
PU = 0.500	PENJ → PU	0.004
	CONF → PU	0.04
	INT → PU	0
	CSE → PU	0.02
	SI → PU	0.116
PENJ = 0.338	CONF → PENJ	0.515
SA = 0.517	CONF → SA	0.068
	PU → SA	0.091
	INT → SA	0.014
	SI → SA	0.010
CI = 0.589	INT → CI	0.009
	CSE → CI	0.041
	SI → CI	0.009
	PENJ → CI	0.007
	SA → CI	0.041
	PU → CI	0.004

and Perceived Enjoyment (PENJ) has the most significant predictive significance among all other relationships, with a score of 0.515. Furthermore, the relationships between PENJ and INT (Interactivity) associations towards Perceived usefulness (PU) do not exhibit any statistically significant impact. Furthermore, the relationships from INT(Interactivity), SI (Social influence), PENJ (Perceived enjoyment) and PU toward the CI (Continuous intention) have no effect. The association between interactivity and perceived usefulness has been encountered to have no considerable impact. Moreover, the association between INT and SI regarding SA (Satisfaction) exerts a negligible influence. Ultimately, the correlations between Computer Self-Efficacy (CSE) and Self-Assessment (SA) with Computer Interaction (CI) demonstrate a minimal impact.

After completing measurement and structural model assessments, sixteen hypotheses were developed to investigate the association between the model components and determine their significance level. Moreover, the recommended hypotheses were assessed by the implementation of various measurements. Fourteen of the initial sixteen hypotheses were statistically significant, indicating a notable impact. Conversely, two hypotheses were determined to have insignificant effects. The final model is refined and introduced by eliminating insignificant assumptions to align with the measurement data. Figure 5 depicts the ultimate model after evaluating the measurement and structure models.

VI. DISCUSSION

This investigation aims to establish a conceptual model incorporating supplementary components into the ECM model to analyze the continuous intention of using E-Learning platforms. Additional factors that can be considered in the model are perceived enjoyment, computer self-efficacy, social influence, and interactivity. The investigation findings indicate a positive correlation between social influences and continuing

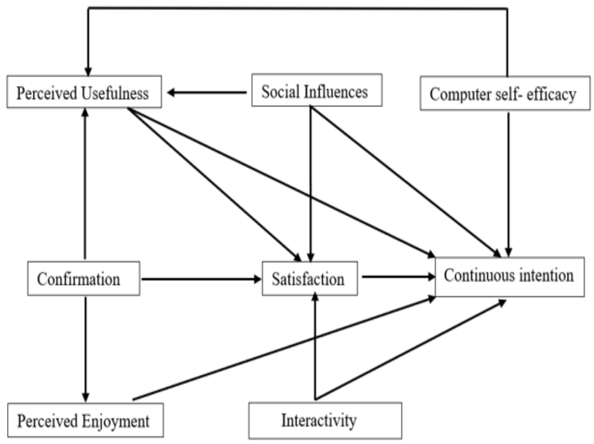

FIGURE 5. : Final model for students' continuous intention.

intention, in contrast to previous studies that have indicated a lack of substantial association between social influences and continuous intention [24], [60], [61]. Based on the analysis results, satisfaction is the key factor that determines the continuous intention of users when dealing with the E-Learning platform. Satisfaction has the highest value of R2, meaning that as long as satisfaction is high toward using the E-Learning platform, users will continue to use that platform. The model analysis results indicate that various elements, including interactivity, social influence, perceived usefulness, and confirmation, influence satisfaction. Furthermore, users' perception of the usefulness, elevated level of interactivity, and expectation of confirmation aligned with the actual usage of the E-Learning platform significantly contribute to a heightened level of satisfaction. Consequently, users are more likely to be positively motivated to use the E-Learning platform for an extended duration.

Long-term social factors can influence students' decision to utilize an e-learning platform. When students perceive that their peers either reject or adopt a specific system, their view about that system may transform. In addition, it is noteworthy that social influences substantially impact individuals' levels of enjoyment and perceived usefulness concerning their utilization of E-Learning platforms. In addition, students' perceptions may be positively influenced when the surrounding community is convinced of the benefits of the E-Learning platform.

Furthermore, it is observed that the "perceived enjoyment" favors the intention to continue using the platform. Therefore, when students have a positive and enjoyable experience while interacting with the platform, they are more likely to persist in using it. Thirdly, it is evident from empirical analysis that computer self-efficacy has a substantial role in shaping individuals' continuous intention, which aligns with previous studies conducted by [14] and [56]. Further, it is essential to point out that interactivity plays a crucial role in determining happiness levels among individuals while also exerting a favorable influence on their inclination to engage in continued interactions or activities. Despite receiving less attention in past studies, interactivity is an essential feature in implementing and utilizing information systems [18], [43].

Integrating the suggested elements with the ECM model has impacted users' continual intention to utilize E-Learning platforms. Therefore, it is imperative for decision-makers and developers of E-Learning platforms to duly acknowledge these factors as crucial drivers and incentives for sustaining students' engagement with E-Learning platforms. The results of this investigation substantially impact individuals involved in the design, decision-making, and research of E-Learning platforms. This study is the inaugural examination of users' sustained intention to utilize an E-learning platform that targets university students. This research considers the impact of three interactivity dimensions, active control, synchronization, and two-way communication, alongside subjective enjoyment.

A. THEORETICAL CONTRIBUTIONS

Constructing a complete model is crucial for expanding our knowledge of the continuous desire to utilize E-Learning platforms from a theoretical perspective. The offered approach is founded on the (ECM), a suitable framework for analyzing the continuous intention.

The initial theoretical contribution involves the integration of the ECM with variables such as perceived enjoyment, interactivity, "computer self-efficacy", and social influences. After an in-depth examination of the existing scholarly literature, it was ascertained that combining the four constituent elements within the proposed framework had yet to be employed in previous academic investigations. Furthermore, this study represents one of the initial investigations into the continuous intention to use E-Learning platforms.

Another contribution of this research is specifying elements that were seen to impact individuals' continuing intentions directly. These factors include perceived enjoyment, computer self-efficacy, interactivity, and social influences. Furthermore, it is worth noting that computer self-efficacy exhibits a noteworthy positive correlation with continuous intention. Additionally, enjoyment, interactivity, perceived utility, and social effects contribute positively to the continuous intention.

One notable contribution is the analysis of the extended model, which demonstrates a higher predictive capacity (R2) of 70% compared to the original model proposed by [27], which achieved an estimated value of 41%. The notable rise in figures demonstrates a considerable improvement in the model's efficacy. As a result, the proposed factors, substantiated by empirical evidence, provide advantages for decision-makers and researchers operating within the domain of the study. Moreover, empirical evidence has demonstrated that student satisfaction substantially influences their inclination to persist in utilizing E-Learning platforms. This result is compatible with prior research studies conducted by [14], [20], [43], [63], [64], and [65]. Furthermore, learners who experience satisfaction are more inclined to persist in using the E-learning platform in subsequent instances. Furthermore, it is worth noting that the perception of enjoyment has a favorable effect on the intention to continue, aligning with prior studies conducted by [41], [43], and [66].

B. PRACTICAL CONTRIBUTIONS

This research delivers valuable understanding for decision-makers and designers of E-learning platforms. It sheds light on the key aspects that led to the continuous intention to use e-learning platforms in educational journey. The model could help stakeholders understand effective platform design strategies for student attraction and reduction of dropouts. In addition, the survey instruments developed during this study can be utilized by other researchers to assess user satisfaction, which leads to continuous use of the E-Learning platform. Furthermore, the research has provided insights into overlooked elements by platform designers, perhaps aiding them in developing more engaging and dynamic platforms in subsequent endeavors.

This study highlights the need to incorporate interactivity in educational design, specifically concentrating on the interaction between learners and technology. These two key aspects should be considered by designers to effectively motivate students and encourage their active participation in the learning process. Therefore, designing interactive features increases users' engagement with the platform and improves users' willingness to continue using the platform. To increase users engagement with the platform, E-Learning platforms should consider adding interactive features such as: discussion rooms, user' assistance services, voting, and submitting forms.

Additionally, it has been demonstrated that the perception of enjoyment positively affects the continuous intention to utilize the E-Learning platform. Consequently, it is imperative to focus more on developing platforms that offer an Enjoyable learning experience by adding enjoyment features, such as gamification, learning puzzles, and badge giving. Study results show that computer self-efficacy is an essential determinant of continuous intention toward using E-Learning platforms. Thus, to boost students' computer self-efficacy in utilizing E-Learning platforms, providing clear instructions for completing specific tasks and guidance for resolving any challenges is crucial.

These strategies would boost students' confidence in educational platforms and help their overall academic development. According to the research findings, social variables support students' tendency to continue using E-learning platforms [26], [41]. Therefore, it is crucial to consider the potential influence of students' immediate environment on their tendency to continue using the platforms when developing the E-learning platform.

C. LIMITATIONS AND FUTURE RESEARCH

This study is subject to certain constraints. Firstly, this research principally concentrated on the students' perspectives concerning their intention to sustain their usage of the E-Learning platform. Thus, it is advised that prospective examinations concentrate on examining educators' perspectives and ascertaining whether various cohorts hold comparable views towards a given E-Learning platform. Further investigation is necessary to analyze the effects of moderating factors, such as gender, age, experience, or learning habits. Secondly, the investigation did not consider psychological dimensions such as attitude, motivation, or mental state. Thus, prospective research is advised to investigate the influence of these variables on students' inclination to sustain their usage of E-Learning platforms. Furthermore, there was a lack of experts in Iraq who could assess the survey items, as the complete transition to E-learning in Iraq only occurred after the onset of the COVID-19 pandemic. Therefore, future research efforts should consider broadening their study scope to include more countries to capitalize on the experience of professionals from those regions. They may also extend their data collection period to ensure a sufficient number of experts for their research. Furthermore, this study aims to determine the primary factors influencing users' continuous intention to utilize E-Learning platforms. Hence, to gain a deeper understanding of the impact of these factors, future studies should investigate the utilization of qualitative research methodologies. Furthermore, as the study is predicated on examining a specific time frame, students' opinions may evolve over time. Longitudinal research may look at their perspectives over time to track students' intentions and behavior regarding using E-learning platforms.

VII. CONCLUSION

This research aims to develop a conceptual framework that can be used to examine the various aspects that affect the continuous intention of users on E-Learning platforms. The impact of a complete transition to E-Learning environments presents new possibilities for investigating other variables that may influence students' opinions regarding their ongoing utilization of E-Learning platforms. Therefore, interactivity, social influences, computer self-efficacy, and perceived enjoyment have been selected to expand upon the ECM model. The outcomes of the suggested hypotheses and model analysis demonstrate that these variables affect individuals' intention to persist in using E-Learning platforms. While fourteen of the proposed hypotheses are accepted and demonstrate a significant effect on continuous intention, the remaining two are rejected. Therefore, the model's predictive power is 70% vital. Furthermore, the analysis findings suggest that decision-makers and platform developers should consider these four constructs during the planning and design phases of E-Learning platforms.

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