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Synthesizing Determinants of E-Learning Continuance Intention: A Meta-Analysis and Weight Analysis

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ABSTRACT

Understanding the factors influencing students' intention to continue using e-learning platforms is critical for sustaining digital education, especially in the post-pandemic era. While individual studies provide varying insights, a comprehensive synthesis is needed to clarify the most influential predictors of E-Learning Continuance Intention (ECI). This study conducted a systematic meta-analysis and weight analysis of 14 predictor variables related to ECI. Relevant peer-reviewed quantitative studies published between 2005 and 2022 were retrieved from Google Scholar. Inclusion criteria focused on empirical studies reporting correlation coefficients between ECI and its predictors. Meta-analysis was performed using Comprehensive Meta-Analysis Software, while weight analysis was applied to assess predictor significance based on frequency and strength of tested relationships. The findings identified *Perceived Usefulness*, *Satisfaction*, and *Perceived Playfulness* as best predictors, supported by both high correlation values and consistent significance across studies. Experimental predictors such as *User Perception* and *Utility Value* showed strong correlations but limited testing frequency. Four predictors, including *Attitude* and *Social Influence*, demonstrated lower predictive strength. Notably, *Experiential Learning* showed no significant correlation with ECI in either analysis. This study contributes to theoretical development by confirming and refining key constructs within the Expectation-Confirmation Model (ECM) in the e-learning context. The results provide practical implications for designing effective e-learning environments and highlight areas for future research, including underexplored or context-dependent predictors.

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1. INTRODUCTION

The rapid advancement of information and communication technologies has fundamentally transformed the landscape of higher education, positioning e-learning as a central component of contemporary instructional delivery. As universities increasingly rely on digital platforms to support teaching and learning, understanding the determinants of students' continued use of these systems has become a critical research priority. While initial adoption of e-learning technologies is important, their long-term success ultimately depends on users' intention to continue using them. In this regard, the Expectation-Confirmation Model (ECM), originally proposed by Bhattacherjee (2001), provides a robust theoretical foundation for examining continuance intention in information systems (IS).

The ECM is grounded in the Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1980) and Expectation Confirmation Theory (ECT) (Oliver, 1980). Whereas ECT explains post-consumption satisfaction as a function of the confirmation or disconfirmation of prior expectations, ECM extends this logic to the context of information systems by emphasizing post-adoption behavior. Specifically, the model posits that users form expectations prior to initial use, compare these expectations with actual system performance, and develop satisfaction judgments based on the degree of confirmation. Satisfaction, together with perceived usefulness, subsequently shapes continuance intention. In the IS context, continuance intention refers to a user's intention to persist in using a system after initial experience (Bhattacherjee, 2001; Lin et al., 2017). Over the past two decades, ECM has evolved into a well-established framework for explaining sustained technology use across diverse domains (Cheng, 2019; Hsu et al., 2017; Venkatesh et al., 2016).

The post-adoption perspective embedded in ECM is particularly relevant for e-learning environments, where user expectations, learning needs, and technological competencies may change over time. Unlike one-time transactions, e-learning systems require repeated and sustained engagement. Thus, examining factors that influence E-Learning Continuance Intention (ECI) is essential for ensuring the effectiveness and sustainability of online education initiatives. Prior research has extensively applied ECM to e-learning contexts, demonstrating that satisfaction and perceived usefulness play central roles in shaping students' intention to continue using online learning platforms (Hung et al., 2011; Larsen et al., 2009; Tao et al., 2012). Beyond these core constructs, scholars have incorporated additional variables to better capture the complexity of e-learning experiences.

The global COVID-19 pandemic further underscored the strategic importance of e-learning. The abrupt transition from face-to-face instruction to fully online modes of delivery accelerated digital transformation in higher education and revealed both the potential and limitations of online learning systems. E-learning offers flexibility, accessibility, and opportunities for skill development, while fostering resilience in times of crisis (Vlachopoulos, 2020). It has reshaped interactions between students, instructors, and technology, altering pedagogical practices and learning behaviors (Sangrà et al., 2012). However, the long-term viability of e-learning depends not merely on emergency adoption but on students' willingness to continue using these platforms beyond mandatory requirements. Consequently, identifying the determinants of ECI remains a pressing issue for both researchers and practitioners (Al-Rahmi et al., 2020).

Among the determinants of continuance intention, satisfaction occupies a central position within ECM. Satisfaction reflects users' affective evaluation of their prior experiences with the system and is shaped by the confirmation of expectations. Empirical evidence consistently demonstrates that higher levels of satisfaction lead to stronger continuance intention in e-learning settings (Bhattacherjee, 2001; Cheng, 2020). In addition to satisfaction, perceived usefulness—defined as the extent to which users believe that a system enhances their performance—has been identified as a direct predictor of continued usage. When learners perceive that an e-learning system improves their academic performance or facilitates goal attainment, they are more inclined to persist in its use (Ashrafi et al., 2020; Wang et al., 2021).

Attitudinal factors also contribute to continuance decisions. Drawing on the Theory of Planned Behavior (TPB) (Ajzen, 1991), attitude represents an individual's overall positive or negative evaluation of performing a behavior. A favorable attitude toward e-learning is associated with stronger behavioral intentions, including the intention to continue using online platforms (Cheng et al., 2019). Similarly, perceived value—users' overall assessment of the benefits relative to the costs of using a system—has been shown to influence ECI. When learners perceive that the educational, functional, and emotional benefits outweigh the time, effort, or monetary costs, their likelihood of sustained use increases (Dağhan & Akkoyunlu, 2016).

Intrinsic motivational factors further enrich our understanding of continuance behavior. Perceived enjoyment, defined as the extent to which using a system is enjoyable in its own right, plays a significant role in fostering continued engagement (Davis et al., 1992; Ashrafi et al., 2020). Closely related is perceived playfulness, which captures the degree of cognitive spontaneity and pleasure experienced during system interaction. Systems perceived as enjoyable and playful are more likely to maintain user engagement and promote sustained usage (Chang et al., 2013; Roca & Gagné, 2008). These constructs highlight the importance of designing e-learning environments that are not only functional but also engaging.

Task-technology alignment and practical relevance also shape continuance intention. Perceived fit, derived from the task-technology fit perspective (Goodhue & Thompson, 1995), reflects the extent to which an e-learning system aligns with learners' needs and learning tasks. A higher degree of fit enhances users' perceptions of system effectiveness and encourages continued use (Lin, 2012). Utility value, referring to the perceived practical applicability of acquired knowledge and skills, similarly reinforces continuance intention when learners recognize the system's relevance to real-world goals (Hong et al., 2017). Experiential learning components that integrate theory with hands-on practice further strengthen engagement and satisfaction, thereby promoting sustained system use (Huang et al., 2009; Kattelmann & Krause, 1998).

Perceived ease of use, a core construct from the Technology Acceptance Model (Davis, 1989), remains influential in post-adoption contexts. When an e-learning system is perceived as effortless to use, users experience fewer barriers and are more likely to continue engaging with the platform (Roca & Gagné, 2008). In addition, perceived behavioral control (PBC), reflecting individuals' perceived ability to perform a behavior, contributes to continuance intention by enhancing users' confidence in their capacity to use the system effectively (Cheon et al., 2012; Lee, 2010).

Social factors further shape e-learning continuance decisions. Social influence, encompassing the impact of peers, instructors, and broader societal trends, can significantly affect students' intention to persist with online learning platforms (Zhou, 2017). Subjective norm, defined as perceived social pressure to perform or refrain from a behavior, similarly influences continuance intention, particularly in collectivist or collaborative learning environments (Ajzen, 1991; Cheng, 2014). Finally, user perception—encompassing evaluations of system quality, interface design, and content—affects satisfaction and, consequently, the likelihood of continued use (Zhuang et al., 2016).

Although numerous empirical studies have examined these determinants, findings often vary across contexts, institutions, and technological platforms. To address issues of inconsistency and generalizability, this study employs meta-analysis and weighting analysis to synthesize existing empirical evidence. Meta-analysis enables the integration of quantitative findings across studies, providing more precise estimates of effect sizes and clarifying the relative importance of different predictors (Eden, 2002; Patil et al., 2018; Tamilmani et al., 2019). By systematically aggregating prior research, this study offers a comprehensive and evidence-based understanding of the factors that influence E-Learning Continuance Intention.

The contributions of this study are twofold. Theoretically, it extends the ECM framework by consolidating diverse determinants of ECI into an integrated model, thereby enhancing conceptual clarity and cumulative knowledge development. Practically, the findings provide actionable insights for e-learning platform developers, instructional designers, and higher education administrators

seeking to foster sustained student engagement. By identifying the most influential factors driving continuance intention, stakeholders can design more effective, engaging, and user-centered e-learning environments that support long-term educational success. Figure 1 illustrates the proposed research model.

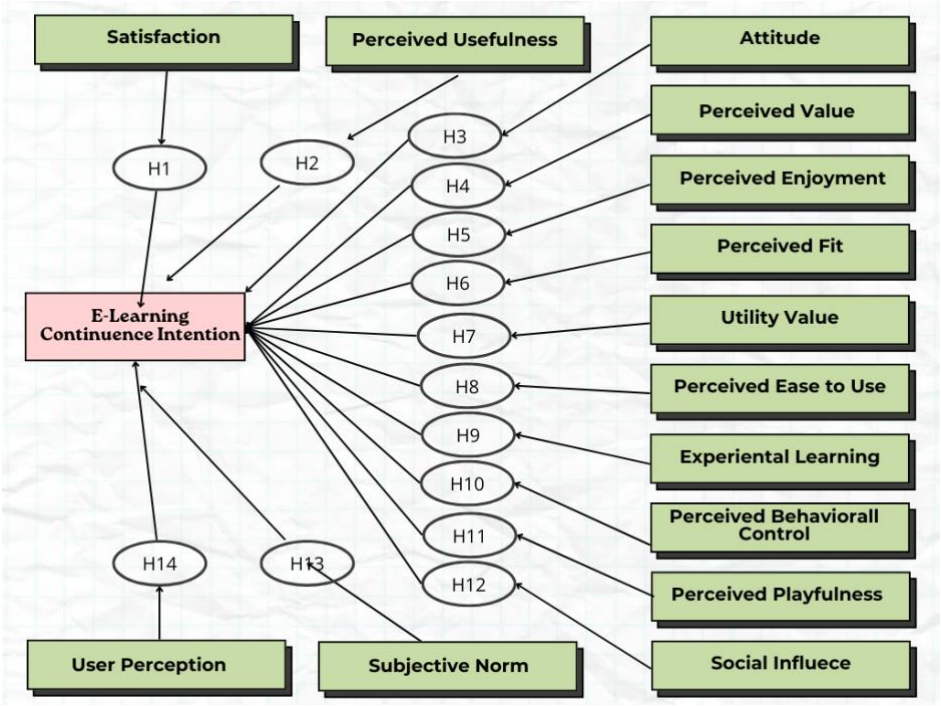

Figure. 1 presents the proposed research model.

2. METHODS

This study analyzes and synthesizes current findings on E-Learning Continuance Intention research. Its primary goal is to provide an in-depth summary of relevant literature, aiming to better understand the factors that influence users' continued engagement with e-learning platforms. The study utilizes PoP Software as a tool for searching publications or literature related to E-Learning Continuance Intention. The literature selection process follows a systematic approach to ensure that the review focuses on high-quality and relevant studies.

The first step in the selection process involves identifying appropriate keywords for the study. These keywords are then applied to the selected research database—Google Scholar—using logical operators such as AND and OR (Hamari & Keronen, 2017). Google Scholar is chosen as the primary database due to its wide accessibility, ease of use, and extensive coverage of both peer-reviewed and gray literature. This broad scope allows for the identification of relevant studies from a variety of sources. However, it is crucial to acknowledge the limitations of Google Scholar. While it provides comprehensive access to a wide range of indexed publications, it may not offer the same level of accuracy or filtering as specialized databases such as Scopus or Web of Science. Furthermore, Google Scholar includes non-peer-reviewed sources, which could impact the rigor and credibility of certain studies. Despite these limitations, Google Scholar remains a valuable resource for gathering a diverse set of publications pertinent to the topic of E-Learning Continuance Intention.

The selection criteria for studies are as follows: (1) Studies published between 2005 and 2022 to capture the most recent developments in the field; (2) Only peer-reviewed studies are included to ensure methodological rigor; (3) The focus is on studies presenting findings at the individual level to provide more granular insights into user behavior; (4) Only quantitative research is considered to

guarantee statistical robustness and objective measurement of variables; (5) Studies must report correlation coefficients between the variables used to support the theoretical model; (6) The study must demonstrate the intensity of the construct or continuance behavior as a result of the theoretical model; (7) The research dataset must be independent to avoid biases from repeated measures or non-independence of observations.

It is also important to elaborate on the rationale for focusing solely on quantitative studies. Quantitative research, with its statistical methods, offers precise measurement of variables and ensures greater objectivity in evaluating the relationships between constructs. This focus on quantitative studies eliminates the potential biases inherent in qualitative research, where subjective interpretations could vary across studies. Additionally, quantitative research allows for more generalized conclusions, which are essential when drawing broader insights into patterns of user behavior in e-learning contexts. Although qualitative studies may offer rich insights into the experiences and perceptions of users, this study aims to provide a more robust, statistically-supported synthesis of E-Learning Continuance Intention by exclusively considering quantitative studies.

Some variables in the selected studies have different names, which were identified through a careful examination of the measurement scales. Table 1 outlines these variables, providing their definitions, alternative names used across studies, and examples of research where these constructs have been utilized.

Meta-analysis is a useful technique for combining results from several studies, as prior research has shown (Dwivedi et al., 2019; Floyd et al., 2014). Weighted analysis can be used to assess the efficacy of the relationships under study and the predictive potential of the independent variables (Jeyaraj et al., 2006; Rana et al., 2015).

Weighted analysis is performed by dividing the number of significant relationships between two constructs by the total number of all relationships between these constructs. Meta-analysis for this study was conducted using the trial version of the Comprehensive Meta-Analysis Software. This software not only generates cumulative correlation coefficients but also provides relevant statistics such as the effect size (p-value) and Z-value. The analysis focuses on the correlation coefficient between each pair of constructs and the sample size.

Constructs were chosen for this study only when the relationship between the independent and dependent variables had been examined three or more times in earlier research, in accordance with earlier studies on meta-analysis and weighted analysis (Dwivedi et al., 2019; Jeyaraj et al., 2006; Rana et al., 2015). This guarantees an adequate number of correlation coefficients, rendering the study robust and statistically significant.

3. FINDINGS AND DISCUSSION

3.1. Results of Weight Analysis and Meta-Analysis

3.1.1 Weight Analysis

The number of significant relationships between the independent and dependent variables is divided by the total number of relationships examined in order to perform a weight analysis (Jeyaraj et al., 2006). For instance, dividing 2 (the number of significant results) by 3 (the total number of times the relationship was evaluated) yields the weight of the association between Attitude and E-Learning Continuance Intention, which is 0.66. The most commonly utilised determinants of E-Learning Continuance Intention in the study are described in Table 2. The number of significant and non-significant results, the total number of correlations examined between the independent and dependent variables, and the weight assigned to each association are all included in the table. The predictor variable's strength is indicated by the weight coefficient.

The findings of this study show how well the independent variable predicts a specific relationship between two variables (Jeyaraj et al., 2006), facilitating communication about the effectiveness of that relationship. Predictors are classified as follows:

a. Best Predictor: If the relationship has been tested five times or more, and the variable must have a weight equal to or greater than 0.8 and is used well (Jeyaraj et al., 2006).
b. Promising Predictor: If the relationship is classified as *experimental* and has a weight of 1.
c. Bad Predictor: If the relationship does not have a significant impact on E-Learning Continuance Intention.

Based on the weight analysis in Table 2, several key patterns emerge. Perceived Playfulness tested five times, Perceived Usefulness (tested 11 times), and Satisfaction (tested 10 times) were the most frequently used predictors in E-Learning studies. These three predictors, with weights greater than 0.8, are classified as best predictors.

On the other hand, predictors that were tested fewer than five times, such as Attitude, Enjoyment, Perceived Behavioural Control, Ease of Use, Perceived Value, Social Influence, Subjective Norms, Perceived Suitability, User Perception, and Utility Value, are categorised as promising predictors. This indicates that, while their relationships have not been extensively tested, there is potential for them to become stronger indicators as research in this area progresses.

However, an unexpected finding emerged with Experiential Learning, which, despite being frequently tested, did not show a significant influence on E-Learning Continuance Intention and was classified as a bad predictor.

Table 1. Results of Weight Analysis

No	Independent variable	Dependent Variable	Number of Significant Results	Number of Non-Significant Results	Total Number of Tests	Analysis Weight
1	Attitude	E-Learning Continuance Intention	2	1	3	0.67
2	Perceived Enjoyment		3	0	3	1.00
3	Experiental Learning		0	3	3	0.00
4	Perceived Behavioral Control		3	0	3	1.00
5	Perceived ease to use		3	0	3	1.00
6	Perceived Playfulness		4	1	5	0.80
7	Perceived usefulness		10	1	11	0.91
8	Perceived Value		3	1	4	0.75
9	Satisfaction		9	1	10	0.90
10	Social Influence		2	1	3	0.67
11	Subjective Norm		3	0	3	1.00
12	Perceived Fit		2	1	3	0.67
13	User Perception		3	0	3	1.00
14	Utility Value		3	0	3	1.00

3.1.2 Meta-Analysis

According to Rosenthal and DiMatteo (2001), meta-analysis is regarded as a good substitute for qualitative and descriptive literature analysis. Meta-analysis is a technique that combines and examines quantitative findings from several empirical investigations in order to statistically synthesize existing literature to represent the backdrop of study (Glass, 1976). The meta-analysis of 14 associations is displayed in Table 3. The Independent and Dependent variables, as well as the frequency with which a certain connection was examined, are displayed in the table. correlation (Mean (r)), effect size (p

(ES)), normal standard deviation (Z value), and 95% upper and lower confidence interval levels. The meta-analysis showed that 14 relationships were significant (Figure 2). Where there is a very strong correlation between E-Learning Continuance Intention and (1) Attitude (r = 0.482), (2) Enjoyment (r = 0.623), (3) Perceived Behavioral Control (r = 0.521), (4) Perceived ease of use (r = 0.342), (5) Perceived Pleasure (r = 0.241), (6) Perceived Usefulness (r = 0.388), (7) Perceived Usefulness (r = 0.521), (8) Perceived Value (r = 0.282), (9) Satisfaction (r = 0.512), (10) Social Influence (r = 0.383), (11) Subjective Norm (r = 0.378), (12) Perceived Suitability (r = 0.580), (13) User Perception (R = 0.631), (14) Utility Value (r = 0.651).

Table 2. Results of Meta-Analysis

Independent Variabel	Dependent Variabel	Rata-rata (r)	p (ES)	Nilai Z-	95% L (r)	95% H (r)
Attitude	E-Learning Continuance Intention	0.482	0.001	3.352	0.215	0.682
Perceived Enjoyment		0.623	0.000	8.346	0.507	0.717
Experiental Learning		0.063	0.076	1.775	-0.007	0.132
Perceived Behavioral Control		0.521	0.000	4.156	0.296	0.691
Perceived ease to use		0.342	0.001	3.413	0.15	0.508
Perceived Playfulness		0.241	0.000	5.449	0.156	0.323
Perceived usefulness		0.341	0.000	8.564	0.267	0.411
Perceived Value		0.282	0.021	2.308	0.044	0.491
Satisfaction		0.512	0.000	23.094	0.476	0.547
Social Influence		0.383	0.000	5.038	0.242	0.509
Subjective Norm		0.378	0.000	5.045	0.239	0.503
Perceived Fit		0.580	0.000	11.255	0.498	0.651
User Perception		0.631	0.000	15.744	0.573	0.684
Utility Value		0.651	0.000	13.269	0.58	0.713

The meta-analysis results revealed that the correlation coefficients of 14 relationships were statistically significant. The largest Z-values were Satisfaction on E-Learning Continuance Intention (23.094), User Perception on E-Learning Continuance Intention (15.744), Utility Value (13.269) and Perceived Fit (11.255).

3.2 Discussion

It is evident from a number of studies in the E-Learning Continuance Intention research that the two types of analysis employed in this study—weight analysis and meta-analysis to ascertain the relationship between predictors and the relevant dependent variables—are closely related.When performing a meta-analysis, the chance that the association between the two variables under study would be significant increases with the weight of a predictor (Rana et al., 2015).

Based on the results of the weight analysis and meta-analysis, it was found that the best predictors and experiments had different results. Perceived usefulness and Satisfaction were categorized as the best predictors because they were tested five times or more and had a weight value of 0.8 or higher, namely Perceived Playfulness (0.8), Perceived usefulness (0.91) and Satisfaction (0.9). Although in meta-analysis, these two variables have a cumulative correlation value below 0.63. Thus, based on the results of the weight analysis H1, H2 and H11 were accepted. This finding is in line with several previous studies (Ashrafi et al., 2020; Chang, Liang, et al., 2013; Gupta et al., 2020; T. Wang et al., 2021). The predictors User Perception and Utility Value are categorized as experimental predictors or promising predictors because they have been tested less than five times. Although included in the promising predictors based on the results of the meta analysis, these two predictors have a cumulative correlation value above 0.63, namely User Perception (0.631) and Utility Value (0.651). Thus, based on the results of the meta analysis, H7 and H14 are accepted. The results of this study are in line with

(Hong et al., 2017b; Zhuang et al., 2016). Furthermore, based on the meta analysis, there are four experimental predictors (Perceived Enjoyment, Perceived Behavioral Control, Perceived ease of use and Subjective Norm) that have a cumulative correlation value below 0.63 but have a weight value above 0.8. Thus, based on the results of the weight analysis, H3, H4, H6 and H12 are accepted. These results are in line with (P. Cheng et al., 2019; Daghan & Akkoyunlu, 2016; W.-S. Lin, 2012). Based on the weight and meta analysis, there are four experimental predictors that have a weight value below 0.8 and a cumulative correlation below 0.63. The four predictors are (1) Attitude, (2) Perceived value (3) Social Influence and (4) Perceived Fit. However, based on the significance test in the weight analysis, the four predictors have higher significant results than the insignificant results. Thus, based on the results of the weight analysis, H5, H8, H10, and H13 are accepted. These results are in line with (Ashrafi et al., 2020; Lew et al., 2019) (Roca & Gagné, 2008) (M.-C. Lee, 2010; Ndubisi, 2004) (Y.-M. Cheng, 2014; R. T. Huang et al., 2014). It is recommended that research discover a compelling cause to keep looking into this kind of predictor as these four predictors can be classified as unsuccessful predictors (Jeyaraj et al., 2006). Furthermore, the Experiential Learning Predictor showed unsatisfactory results for weight analysis and meta-analysis with an insignificant correlation of 0.063, thus the H9 hypothesis is rejected. These results conflict with (Ashrafi et al., 2020; Lew et al., 2019) (Roca & Gagné, 2008) (M.-C. Lee, 2010; Ndubisi, 2004) (Y.-M. Cheng, 2014; R. T. Huang et al., 2014).

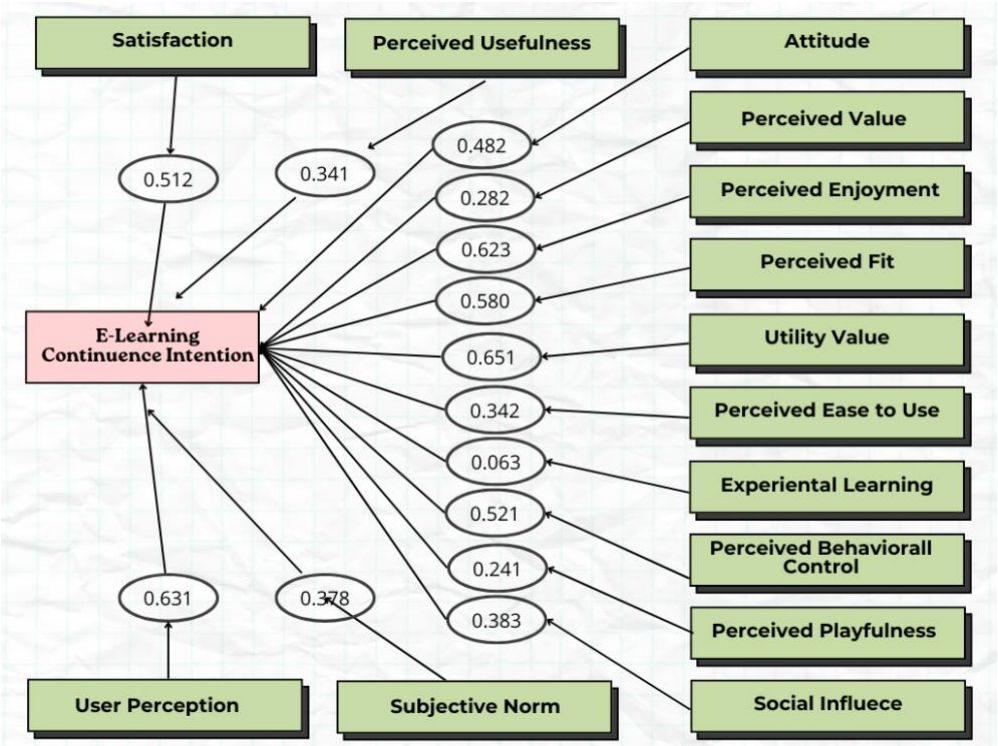

Figure 2. Correlation relationship

4. CONCLUSION

This study provides valuable insights into the factors influencing e-learning continuance intention, further enhancing the understanding of key predictors in this field. The findings challenge and extend existing models, such as the Expectation Confirmation Model (ECM), by highlighting the differential impact of predictors like Perceived Usefulness and Satisfaction. These results indicate that while ECM has been a significant model for understanding users' intention to continue using technology, the

weight of certain predictors may vary depending on the context. By integrating these findings, future models can be refined to more accurately reflect the complexities of e-learning environments.

The theoretical implications of this study offer room for further development, particularly in terms of how these findings can inform the refinement or challenge of existing models like ECM. A deeper understanding of the varying impact between stronger and weaker predictors allows for the development of more flexible, context-specific models. Therefore, future research should consider these differences in the influence of predictors, taking into account contextual factors that shape the experiences of e-learning users in diverse settings.

This study also opens the door for the use of mixed-methods approaches in future studies to address the current limitations. While quantitative methods, such as meta-analysis, provide a broad, data-driven understanding of predictors, qualitative methods, such as in-depth interviews or case studies, could offer richer insights into how and why certain predictors are more influential in specific contexts. For example, future research could explore how different educational settings or learner demographics influence the perceived importance of factors like Perceived Usefulness and Satisfaction. A mixed-methods approach could help address the limitations of relying solely on quantitative data, offering a more comprehensive perspective on e-learning continuance intention.

By combining both approaches, future research can provide a more holistic view of the dynamics at play, enriching both theoretical frameworks and practical applications in the field of e-learning. As this study shows, expanding the methodological scope could address existing gaps and yield more nuanced findings that contribute to the continued development of e-learning research.

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