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The Mediating Role of Learning Motivation: An Integrated TAM2 and Self-Determination Theory Model for E-Learning Achievement

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ABSTRACT

Prior research based on the Technology Acceptance Model 2 (TAM2) has largely emphasized technological and social factors while offering limited insight into how learner motivation translates system acceptance into meaningful learning outcomes. To address this gap, this study integrates TAM2 core constructs, namely Perceived Ease of Use, Perceived Usefulness, and Social Influence, with key motivational drivers, including hedonic, intrinsic, and extrinsic motivation, to examine their combined effects on behavioral intention, learning motivation, and learning achievement in e-learning contexts. Data were collected from 300 e-learning users using a Likert-scale questionnaire and analyzed through Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The results reveal that Perceived Ease of Use strongly influences Perceived Usefulness ($\beta = 0.611$, $p < 0.001$), indicating that simplifying system usability is fundamental for users to recognize the value of e-learning platforms. Perceived Usefulness and Social Influence significantly predict behavioral intention, while motivational factors collectively exert a substantial effect on learning motivation, which in turn strongly enhances learning achievement ($\beta = 0.552$, $p < 0.001$). The proposed model explains a substantial proportion of variance in learning motivation (64%) and learning achievement (55%), demonstrating good predictive relevance within the studied context. Mediation analysis further confirms that learning motivation serves as a key mechanism through which technology acceptance and motivational factors translate into improved learning outcomes. A key practical implication is that e-learning designers should prioritize not only system usefulness and ease of use but also hedonic elements that enhance enjoyment, as this jointly foster learning motivation and ultimately drive learning achievement.

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INTRODUCTION

The rapid advancement of information and communication technology has profoundly transformed the educational landscape, leading to the widespread adoption of e-learning systems that offer flexible, interactive, and learner-centered learning

environments (Webb et al., 2017). Through e-learning platforms, learners can access instructional materials, interact with instructors, and complete academic tasks without constraints of time and location (Masic, 2008). Despite these advantages, many educational institutions continue to face challenges related to user acceptance, sustained engagement, and the effectiveness of learning outcomes in digital environments (Thuy et al., 2018). Learners often perceive e-learning systems as complex, insufficiently interactive, or less motivating than traditional face-to-face instruction, which can hinder both continued use and academic success (Thomas et al., 2021). As a result, identifying the factors that drive not only the adoption but also the effective use of e-learning systems has become a critical concern in technology-enhanced education research (Lau and Greer, 2022).

Research on technology adoption has predominantly relied on the Technology Acceptance Model and its extensions, particularly Technology Acceptance Model 2, to explain why users choose to adopt new information systems (Lai, 2017). TAM2 emphasizes key technological and social perceptions, such as ease of use, usefulness, and social influence, as primary determinants of users' intention to use a system (Bui et al., 2020). While this framework has been shown to be effective in predicting initial adoption intention, its explanatory power is more limited when applied to contexts that require sustained engagement and goal-directed effort, such as learning. In educational settings, success is not determined solely by whether learners intend to use a system, but by whether such use leads to meaningful engagement and learning achievement (Malatji et al., 2020; Saleh et al., 2022). This limitation suggests that technology acceptance alone is insufficient to explain learning effectiveness in e-learning environments.

Motivation theory offers a complementary perspective by explaining the psychological mechanisms that drive persistence, effort, and engagement in learning activities. Drawing on Self-Determination Theory, motivation can be broadly understood in terms of intrinsic interest and extrinsic drivers, which influence how learners regulate their behavior and sustain effort over time (Deci and Ryan, 1985). In digital learning contexts, motivation is further shaped by affective experiences related to technology use, such as enjoyment and pleasure, commonly conceptualized as hedonic motivation (Kundu, 2022). Affective and volitional factors, including hedonic enjoyment, intrinsic

interest, and extrinsic incentives, have been shown to play a decisive role in learners' engagement, satisfaction, and academic performance in e-learning environments (Al-Azawei et al., 2016; Tawafak et al., 2021).

Integrating TAM2 with Motivation Theory therefore provides a theoretically meaningful framework for understanding e-learning success. TAM2 explains how learners form intentions to use an e-learning system based on cognitive evaluations of its attributes and social context, whereas motivation theories explain how these intentions are translated into sustained effort and learning outcomes. For learning systems, effectiveness cannot be equated with mere usage; rather, it is reflected in learners' continued engagement and achievement. Accordingly, motivation is positioned in this study not as a parallel explanatory pathway, but as the critical mechanism that transforms the intention to use an e-learning system into persistent learning effort and academic achievement. Learning Motivation thus represents the bridge between technology acceptance and educational success.

Within this integrated perspective, affective experiences associated with system use play a pivotal role. Enjoyable and pleasant interactions with an e-learning system can reduce cognitive barriers and foster positive emotional states during learning activities. From an affective priming perspective, such positive experiences enhance learners' curiosity and inherent satisfaction with the learning process itself, thereby strengthening intrinsic motivation. This mechanism explains how hedonic aspects of system design can indirectly support deeper, self-driven engagement with learning content, rather than merely facilitating superficial system use.

Building on this logic, the proposed model conceptualizes e-learning success as a sequential process. Learners' perceptions of technological attributes and social influence shape their intention to use the system. This intention, together with affective and motivational inputs, fuels learners' active engagement in learning activities. Learning Motivation, as the proximal determinant of learning behavior, ultimately drives learning achievement. By explicitly modeling this pathway, the study seeks to clarify how and through what mechanism technology acceptance leads to meaningful educational outcomes.

Accordingly, the purpose of this study is to investigate the mediating role of Learning Motivation in the relationship between technology acceptance and learning achievement through an integrated TAM2 and Motivation Theory framework. Using Partial Least Squares Structural Equation Modeling, this research examines how technological perceptions, social influence, and motivational factors jointly contribute to behavioral intention, learning motivation, and learning achievement in e-learning contexts. The proposed conceptual model, presented in Figure 1, synthesizes these relationships and provides the basis for empirical testing.

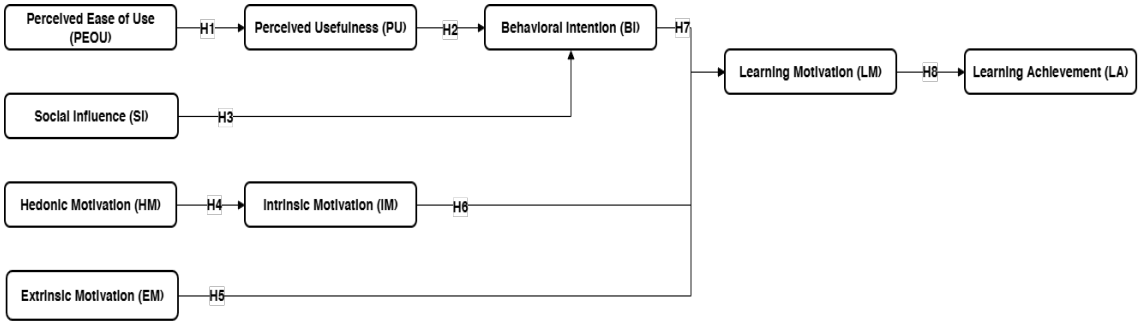

Figure 1. *Research Model*

METHOD

This study employs a quantitative approach using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method to analyze the relationships among cognitive, motivational, and behavioral constructs that influence the acceptance and success of e-learning system usage. The research model was developed by integrating the Technology Acceptance Model 2 (TAM2) and Motivation Theory. The integration of these two theories was chosen to capture two key perspectives—technological and psychological—in understanding how learners adopt and utilize e-learning systems.

The constructs used in this study include Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Social Influence (SI), Hedonic Motivation (HM), Intrinsic Motivation (IM), Extrinsic Motivation (EM), Behavioral Intention (BI), Learning Motivation (LM), and Learning Achievement (LA). The study aims to examine both direct and indirect relationships among these constructs, with particular focus on the mediating role of learning motivation.

Research Model

Figure 1 presents the hypothesized research model integrating Technology Acceptance Model 2 and Motivation Theory. The model specifies the structural relationships among technological perceptions, motivational factors, behavioral intention, learning motivation, and learning achievement, which were empirically tested using the PLS-SEM approach.

Data Collection and Sampling

Data for this study were collected through an online questionnaire administered to students from several vocational high schools (Sekolah Menengah Kejuruan) that actively implement e-learning platforms in their instructional activities. The participating schools included SMK Diponegoro 1 Purwokerto, SMK Ma'arif NU 1 Cilongok, SMK Diponegoro 3 Kedung Banteng, and SMK Ma'arif NU 1 Ajibarang.

The research population consisted of vocational high school students from various majors who had at least one semester of experience using e-learning systems. A purposive sampling technique was employed, with the selection criterion that respondents were active students familiar with digital learning environments. Only students at the secondary education level were included in the study, and no university-level participants were involved. The operational definitions of all constructs used in this study are presented in Table 1.

Table 1. *Operational Definitions*

Construct	Code	Operational Definition	Source
Perceived Ease of Use	PEOU	The degree to which learners believe that using the e-learning system is easy.	(Davis, 1989)
Perceived Usefulness	PU	The degree to which learners believe that the e-learning system enhances their learning performance.	(Davis, 1989)
Social Influence	SI	The extent to which learners feel that important others expect them to use the system.	(Venkatesh & Davis, 2000)
Hedonic Motivation	HM	The level of pleasure and enjoyment experienced when using the e-learning system.	(Zhou & Ahmad, 2025)
Intrinsic Motivation	IM	The internal drive to learn, arising from interest and personal satisfaction.	(Deci & Ryan, 1985)
Extrinsic Motivation	EM	The drive to learn influenced by external factors such as grades and rewards.	(Deci & Ryan, 1985)
Behavioral Intention	BI	Learners' intention to continue using the e-learning system.	(Venkatesh & Davis, 2000)
Learning Motivation	LM	Learners' willingness and enthusiasm to actively engage in learning activities.	(Gustiani et al., 2022)
Learning Achievement	LA	The learning outcomes achieved by learners after using the e-learning system.	(Wang et al., 2025)

A total of 300 valid responses were obtained. The adequacy of this sample size was assessed using the ten-times rule commonly applied in PLS-SEM analysis, which recommends a minimum sample size equal to ten times the largest number of structural paths directed at any endogenous construct. In this study, the most complex endogenous construct is Learning Motivation, which is predicted by three paths. Accordingly, the minimum required sample size is 30. The final sample of 300 respondents substantially exceeds this threshold, ensuring sufficient statistical power for estimating the proposed model. The demographic characteristics of the respondents, including gender, age, grade level, and duration of e-learning experience, are summarized in Table 2.

Table 2. *Demographic Composition of Respondents*

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	142	47.3
	Female	158	52.7
Age	16 to 18 years	169	56.3
	19 to 20 years	131	43.7
Grade Level	Grade 10	92	30.7
	Grade 11	113	37.7
	Grade 12	95	31.6
E-learning Experience	Less than 1 year	37	12.3
	1 to 2 years	141	47.0
	More than 2 years	122	40.7

The demographic profile indicates a balanced gender distribution, with most respondents in the typical age range for vocational high school students and possessing more than one year of experience using e-learning systems. This suggests that the sample adequately represents learners with sufficient exposure to digital learning environments to provide informed responses.

Research Instrument

The primary instrument used in this study was a structured questionnaire developed by adapting validated measurement scales from prior studies to ensure content validity and measurement reliability. The questionnaire consisted of two sections. The first section collected respondents' demographic information, while the second section measured the latent constructs included in the research model. All measurement items were assessed using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

To establish content validity, the initial version of the questionnaire was reviewed by three academic experts in the fields of information systems and educational technology. Minor revisions were made to improve clarity and contextual relevance for the e-learning environment. A pilot test was subsequently conducted with 30 respondents who were not included in the final sample. The pilot test results indicated that all constructs achieved Cronbach's Alpha values above 0.70, suggesting acceptable internal consistency and supporting the reliability of the instrument.

The final questionnaire items were adapted from well-established scales in the literature, including Perceived Ease of Use and Perceived Usefulness from Davis (1989), Social Influence and Behavioral Intention from Venkatesh and Davis (2000), Intrinsic and Extrinsic Motivation from Deci and Ryan (1985), Learning Motivation from Keller (2010), and Learning Achievement from Bloom (1984). These sources provide strong theoretical grounding and ensure consistency with prior empirical research in technology acceptance and educational psychology.

Rather than presenting the measurement items descriptively, the quality of the measurement model was evaluated empirically using the main study data. Table 3 presents the results of the measurement model assessment, including standardized factor loadings for each indicator, Composite Reliability, and Average Variance Extracted for each construct. This approach integrates instrument description with empirical validation and follows recommended reporting practices for PLS-SEM studies.

Table 3. *Measurement Model Results*

Construct	Item	Loading	CR	AVE
Behavioral Intention (BI)	BI1	0.943	0.970	0.891
	BI2	0.942		
	BI3	0.948		
	BI4	0.943		
Extrinsic Motivation (EM)	EM1	0.941	0.967	0.881
	EM2	0.940		
	EM3	0.930		
	EM4	0.943		
Hedonic Motivation (HM)	HM1	0.936	0.964	0.869
	HM2	0.932		
	HM3	0.922		
	HM4	0.937		
Intrinsic Motivation (IM)	IM1	0.961	0.974	0.902
	IM2	0.939		
	IM3	0.947		
	IM4	0.953		

Learning Achievement (LA)	LA1	1.000	1.000	1.000
Learning Motivation (LM)	LM1	0.946	0.973	0.899
	LM2	0.943		
	LM3	0.947		
	LM4	0.956		
Perceived Ease of Use (PEOU)	PEOU1	0.923	0.969	0.888
	PEOU2	0.960		
	PEOU3	0.932		
	PEOU4	0.953		
Perceived Usefulness (PU)	PU1	0.942	0.971	0.895
	PU2	0.941		
	PU3	0.947		
	PU4	0.953		
Social Influence (SI)	SI1	0.969	0.977	0.912
	SI2	0.951		
	SI3	0.950		
	SI4	0.950		

The measurement model was evaluated by examining indicator reliability, internal consistency reliability, and convergent validity. As shown in Table 3, all indicator loadings exceeded the recommended threshold of 0.70, confirming indicator reliability. Composite Reliability values for all constructs were above 0.70, indicating strong internal consistency. Convergent validity was also established, as all Average Variance Extracted values exceeded 0.50. Learning Achievement, measured using a single indicator, yielded CR and AVE values of 1.000 by definition. Overall, the results confirm that the measurement model demonstrates satisfactory reliability and validity.

Data Analysis Technique

Data analysis was conducted using Partial Least Squares Structural Equation Modeling with SmartPLS version 4.0 software. PLS-SEM was selected due to its suitability for complex research models, predictive-oriented analysis, and its ability to handle data that do not necessarily follow a normal distribution (Hair et al., 2021). The analysis followed a two-stage procedure consisting of measurement model evaluation and structural model assessment.

In the first stage, the measurement model was evaluated to assess indicator reliability, internal consistency reliability, and convergent validity. Indicator reliability was examined using standardized factor loadings, with values greater than 0.70 considered acceptable. Internal consistency reliability was assessed using Composite Reliability, with values exceeding the recommended threshold of 0.70 indicating

satisfactory reliability. Convergent validity was evaluated using Average Variance Extracted, where values above 0.50 indicate that the construct explains more than half of the variance of its indicators. The results of the measurement model assessment confirm that all constructs meet the established reliability and validity criteria.

In the second stage, the structural model was assessed by examining path coefficients, t-values, and p-values obtained through a bootstrapping procedure with 5,000 resamples. This procedure was used to test the significance of the hypothesized direct relationships among constructs. The explanatory power of the model was evaluated using the coefficient of determination (R^2) for each endogenous construct, which indicates the proportion of variance explained by the model. Predictive relevance was assessed using the blindfolding procedure, where Q^2 values greater than zero indicate adequate predictive capability.

To examine the mediating role of Learning Motivation, mediation analysis was conducted by testing the significance of indirect effects using the bootstrapping approach. An indirect effect was considered significant when the bootstrapped confidence interval did not include zero, indicating the presence of a mediating effect. This approach allows for the simultaneous assessment of direct and indirect relationships and provides robust evidence for mediation within the proposed model.

Overall, this analytical procedure ensures that the measurement properties of the constructs are reliable and valid and that the structural relationships among variables can be meaningfully interpreted. The use of PLS-SEM enables the identification of both direct and indirect effects, thereby supporting a comprehensive examination of how technology acceptance and motivational factors jointly influence learning achievement through learning motivation.

RESULT AND DISCUSSION

Result

Outer Model Evaluation

The outer model evaluation was conducted to assess the quality of the measurement model for each construct through the examination of indicator reliability, internal consistency reliability, and convergent validity. Based on the results presented in

Table 4, all factor loading values exceeded the threshold of 0.70, indicating that each indicator strongly reflects its corresponding latent construct.

The Cronbach's Alpha (α) values ranged from 0.829 to 0.917, while the Composite Reliability (CR) values ranged from 0.885 to 0.950, all surpassing the recommended minimum value of 0.70. These results confirm that all constructs exhibit high internal consistency and strong reliability.

The constructs Learning Motivation (LM) and Behavioral Intention (BI) recorded the highest CR values (0.950 and 0.940, respectively), indicating excellent homogeneity among their measurement items. The Average Variance Extracted (AVE) values ranged from 0.661 to 0.826, all exceeding the threshold of 0.50, suggesting that more than half of the variance of the indicators is explained by their respective constructs.

The constructs with the highest AVE values were LM and Intrinsic Motivation (IM), indicating highly precise measurement. Meanwhile, Learning Achievement (LA) had a slightly lower AVE value (0.661), but it still met the minimum requirement, confirming adequate convergent validity.

Overall, these findings indicate that all constructs demonstrate strong reliability and convergent validity, making the measurement model suitable for further structural analysis.

Table 4. *Reliability and Convergent Validity Analysis*

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
PEOU	0.864	0.912	0.724
PU	0.887	0.925	0.756
SI	0.842	0.900	0.693
HM	0.875	0.919	0.739
IM	0.901	0.937	0.787
EM	0.851	0.902	0.700
BI	0.905	0.940	0.796
LM	0.917	0.950	0.826
LA	0.829	0.885	0.661

Note: All constructs meet the reliability criterion (CR > 0.70) and convergent validity criterion (AVE > 0.50), indicating strong internal consistency and measurement precision.

Discriminant Validity

Discriminant validity was assessed to ensure that each construct in the measurement model is empirically distinct from the others. Following current recommendations for PLS-SEM analysis, discriminant validity was evaluated using both cross-loadings and the Heterotrait–Monotrait ratio.

First, cross-loadings were examined to verify that each indicator loads more strongly on its associated construct than on any other construct. As shown in Table 5, all indicators exhibit their highest loading on the intended construct, while cross-loadings on other constructs are substantially lower. This pattern indicates that the measurement items adequately distinguish between constructs and supports discriminant validity based on the cross-loadings criterion.

Table 5. *Factor Loadings and Cross-Loadings*

Item	PEOU	PU	SI	HM	IM	EM	BI	LM	LA
PEOU1	0.848	0.445	0.321	0.288	0.241	0.230	0.322	0.295	0.201
PEOU2	0.867	0.468	0.339	0.294	0.259	0.242	0.340	0.315	0.210
PEOU3	0.835	0.420	0.308	0.266	0.233	0.215	0.316	0.281	0.195
PEOU4	0.871	0.458	0.336	0.276	0.243	0.232	0.330	0.297	0.218
PU1	0.445	0.872	0.324	0.273	0.245	0.241	0.356	0.309	0.223
PU2	0.468	0.889	0.347	0.298	0.262	0.255	0.371	0.321	0.239
PU3	0.420	0.875	0.319	0.284	0.251	0.247	0.352	0.304	0.226
PU4	0.458	0.901	0.369	0.311	0.278	0.268	0.389	0.342	0.261
…	…	…	…	…	…	…	…	…	…
LA1	0.214	0.239	0.211	0.191	0.228	0.218	0.272	0.469	0.813

Note: Each indicator loads highest on its corresponding construct compared to other constructs

To provide a more robust assessment, discriminant validity was further evaluated using the Heterotrait–Monotrait ratio, which is considered the most reliable criterion for discriminant validity in variance-based structural equation modeling. As presented in Table 6, all HTMT values are well below the conservative threshold of 0.85. The highest HTMT value was observed between Perceived Usefulness and Perceived Ease of Use, followed by Learning Motivation and Learning Achievement, yet all values remain comfortably within acceptable limits. These results confirm that all constructs are empirically distinct and that discriminant validity is firmly established (Henseler et al., 2015).

Table 6. *Heterotrait–Monotrait Ratio (HTMT)*

Constructs	BI	EM	HM	IM	LA	LM	PEOU	PU	SI
BI	—								
EM	0.037	—							
HM	0.045	0.024	—						
IM	0.053	0.079	0.505	—					
LA	0.256	0.145	0.196	0.240	—				
LM	0.408	0.237	0.237	0.391	0.563	—			
PEOU	0.463	0.035	0.061	0.056	0.203	0.296	—		
PU	0.605	0.069	0.037	0.058	0.220	0.271	0.636	—	
SI	0.225	0.075	0.033	0.039	0.069	0.122	0.077	0.028	—

**Threshold used: HTMT < 0.85 (Henseler et al., 2015)*

Structural Model Assessment

The structural model was assessed to evaluate overall model fit, explanatory power, and predictive relevance prior to hypothesis testing. Model fit was examined using the Standardized Root Mean Square Residual. The SRMR value obtained was below the recommended threshold of 0.08, indicating an acceptable fit between the proposed model and the observed data.

The explanatory power of the model was evaluated using the coefficient of determination (R^2) for the endogenous constructs. As shown in Table 7, the model explains 37.4% of the variance in Perceived Usefulness, 39.3% in Behavioral Intention, 23.7% in Intrinsic Motivation, 35.5% in Learning Motivation, and 30.5% in Learning Achievement. These values indicate moderate explanatory power, suggesting that the integrated TAM2 and Motivation Theory framework is effective in explaining both technology acceptance and learning-related outcomes in the e-learning context.

Table 7. *Coefficient of Determination (R^2)*

Endogenous Construct	R^2	Adjusted R^2
Perceived Usefulness (PU)	0.374	0.372
Behavioral Intention (BI)	0.393	0.388
Intrinsic Motivation (IM)	0.237	0.234
Learning Motivation (LM)	0.355	0.348
Learning Achievement (LA)	0.305	0.303

Predictive relevance was assessed using the blindfolding procedure by examining cross-validated redundancy (Q^2) values. As presented in Table 8, the Q^2 values for all endogenous constructs included in the structural model are greater than zero, indicating that the model has adequate predictive relevance. In particular, Learning Motivation and Learning Achievement exhibit strong predictive capability, confirming that the model is suitable for predicting learning-related outcomes.

Table 8. *Predictive Relevance (Q^2) from Blindfolding*

Construct	Q^2
Behavioral Intention (BI)	0.345
Intrinsic Motivation (IM)	0.211
Learning Motivation (LM)	0.314
Learning Achievement (LA)	0.302
Perceived Usefulness (PU)	0.331

Note: Q^2 values greater than zero indicate predictive relevance.

Inner Model Evaluation

After establishing the adequacy of the structural model in terms of model fit, explanatory power, and predictive relevance, the hypothesized relationships among constructs were evaluated using path coefficients, t-values, and p-values obtained through a bootstrapping procedure with 5,000 resamples. The results of the structural model are illustrated in Figure 2.

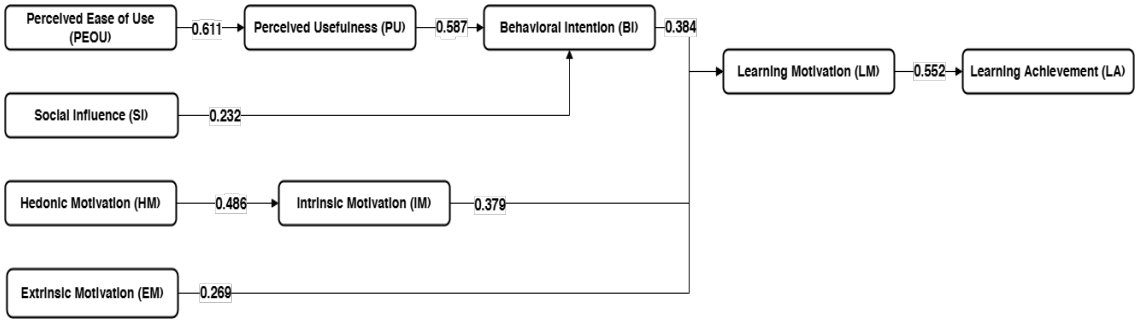

Figure 2. *Structural Model of the Study*

The analysis reveals that all hypothesized relationships are positive and statistically significant. Perceived Ease of Use has a strong effect on Perceived Usefulness, which in turn significantly influences Behavioral Intention. Social Influence also positively affects Behavioral Intention, highlighting the role of social context in e-learning adoption. Furthermore, motivational factors, including hedonic, intrinsic, and extrinsic motivation, significantly contribute to Learning Motivation, which subsequently exerts a strong positive effect on Learning Achievement. These findings indicate that cognitive perceptions and motivational mechanisms jointly explain learners' acceptance of e-learning systems and their learning success.

Hypothesis Testing Results

The structural model evaluation was conducted to test the hypotheses and assess the strength and significance of relationships among latent constructs. The results are summarized in Table 9. All eight proposed hypotheses were found to be significant ($p < 0.05$).

Table 9. *Summary of Hypothesis Testing Results*

Hypothesis	Path	β	t-value	p-value	Result
H1	PEOU → PU	0.611	15.506	0.000	Supported
H2	PU → BI	0.587	16.037	0.000	Supported
H3	SI → BI	0.232	5.984	0.000	Supported
H4	HM → IM	0.486	12.048	0.000	Supported
H5	EM → LM	0.269	5.869	0.000	Supported

H6	IM → LM	0.379	8.104	0.000	Supported
H7	BI → LM	0.384	8.638	0.000	Supported
H8	LM → LA	0.552	14.865	0.000	Supported

Note: All path coefficients are positive and significant. Cognitive factors (PEOU, PU, SI) and motivational factors (HM, IM, EM) contribute significantly to behavioral intention and learning achievement, supporting the integration of TAM2 and Motivation Theory in explaining e-learning acceptance and performance.

Mediation Effects Analysis

Mediation analysis was conducted to examine both indirect and sequential indirect effects among constructs and to test the role of Learning Motivation as the central mechanism linking technology acceptance and learning outcomes. The analysis employed a bootstrapping procedure with 5,000 resamples to assess the significance of indirect effects.

The results show that Learning Motivation plays a pivotal mediating role between both motivational and technology acceptance variables and Learning Achievement. Intrinsic Motivation (β = 0.210) and Extrinsic Motivation (β = 0.148) exhibit significant indirect effects on Learning Achievement through Learning Motivation, indicating that learners achieve better outcomes when their motivational orientations are translated into sustained learning engagement. Behavioral Intention also demonstrates a strong indirect effect on Learning Achievement via Learning Motivation (β = 0.212), confirming Learning Motivation as the most proximal determinant of academic success.

Table 10. *Summary of Indirect and Sequential Indirect Effects*

Predictor	Mediator(s)	Outcome	Indirect Effect (β)
PEOU	PU → BI	BI	0.359
PU	BI → LM → LA	LA	0.124
PEOU	PU → BI → LM → LA	LA	0.076
BI	LM	LA	0.212
SI	BI → LM	LA	0.049
EM	LM	LA	0.148
IM	LM	LA	0.210
HM	IM → LM	LA	0.102
PU	BI → LM	LM	0.225
PEOU	PU → BI → LM	LM	0.138
SI	BI → LM	LM	0.089
HM	IM → LM	LM	0.185

Note: All indirect effects were estimated using a bootstrapping procedure with 5,000 resamples and were statistically significant ($p < 0.05$).

More importantly, the study provides strong evidence for sequential mediation pathways that constitute the core theoretical contribution of the integrated model. Perceived Usefulness has a significant indirect effect on Learning Achievement through

Behavioral Intention and Learning Motivation (β = 0.124), while Social Influence also affects Learning Achievement through the same sequential mechanism (β = 0.049). Furthermore, a full sequential mediation from Perceived Ease of Use to Learning Achievement through Perceived Usefulness, Behavioral Intention, and Learning Motivation is supported (β = 0.076). These findings demonstrate that technology-related perceptions influence learning outcomes only when they are first transformed into intention to use and subsequently into learning motivation.

In addition, hedonic motivation contributes indirectly to learning outcomes through intrinsic motivation and learning motivation (β = 0.102), highlighting the importance of enjoyable learning experiences in fostering deeper motivational processes. Collectively, these results confirm that learning motivation functions as the critical mechanism that translates technology acceptance into meaningful learning achievement, thereby validating the central premise of the proposed integrative TAM2–Motivation model.

Discussion

This study set out to explain how technology acceptance and motivational processes jointly lead to learning achievement by integrating Technology Acceptance Model 2 with Motivation Theory. Rather than merely confirming prior models, the findings illuminate *how strongly* different cognitive and motivational mechanisms operate and *through what pathways* technology acceptance is translated into educational success.

One of the strongest relationships observed in the model is the effect of Perceived Ease of Use on Perceived Usefulness (β = 0.611). This finding underscores that in educational contexts, usability is not a peripheral design consideration but the foundational gateway through which learners come to recognize the value of an e-learning system. When systems are intuitive and cognitively effortless, learners are better able to focus on learning tasks rather than on system operation, thereby increasing perceived utility. This result reinforces TAM2 while highlighting that usability may be even more critical in learning environments than in workplace or commercial settings, where users may tolerate complexity due to external obligations.

Perceived Usefulness also exerted a strong influence on Behavioral Intention (β = 0.587), confirming that functional value remains the primary driver of learners' willingness to continue using e-learning systems. By contrast, Social Influence, although statistically significant (β = 0.232), showed a noticeably weaker effect on Behavioral Intention. This imbalance suggests an important nuance: while encouragement from peers and instructors matters, learners' decisions to engage with e-learning are driven more by perceived learning benefits than by social pressure. This pattern differs from findings in mandatory organizational or enterprise systems, where social norms often dominate adoption decisions, and indicates that voluntary educational contexts privilege functional value over compliance.

Beyond acceptance, the most important theoretical insight of this study lies in the motivational pathways. Learning Motivation emerged as the strongest direct predictor of Learning Achievement (β = 0.552), confirming that achievement in e-learning is ultimately determined not by system use alone but by sustained motivational engagement. Behavioral Intention influenced Learning Achievement only indirectly through Learning Motivation, reinforcing the argument that intention without motivation does not translate into performance.

A particularly meaningful finding is the significant relationship between Hedonic Motivation and Intrinsic Motivation. This result demonstrates that enjoyment derived from system use is not merely superficial or cosmetic; rather, it plays a formative role in cultivating learners' intrinsic interest in learning activities. From a psychological perspective, this suggests that positive affect generated through enjoyable system interactions can stimulate curiosity and internal satisfaction, thereby strengthening intrinsic motivation. This finding positions system design as an active contributor to learners' internal motivational states, rather than a neutral delivery mechanism.

Both Intrinsic and Extrinsic Motivation were found to significantly enhance Learning Motivation, indicating that sustained engagement in e-learning arises from the interaction of internal interest and external incentives. This supports Self-Determination Theory's assertion that motivation is multidimensional and context-dependent, particularly in structured learning environments where grades and recognition coexist with personal interest.

The mediation analysis provides the clearest evidence of the study's contribution. The significant sequential indirect effects from Perceived Usefulness and Social Influence to Learning Achievement through Behavioral Intention and Learning Motivation demonstrate that technology acceptance affects learning outcomes only when it is transformed into motivated learning behavior. In other words, perceiving an e-learning system as useful or socially endorsed is insufficient on its own. These perceptions must first generate an intention to use the system and then activate learning motivation, which ultimately drives achievement. This sequential process clarifies a key limitation of prior TAM-based research that emphasized usage intention but did not explain how acceptance becomes educational success.

An important methodological observation is that all hypothesized relationships in the model were supported. While such comprehensive support may appear statistically unusual, it suggests that the proposed model is theoretically coherent and parsimonious within the studied context. At the same time, this outcome highlights opportunities for future research refinement. Subsequent studies may introduce competing or negative pathways, such as examining whether extrinsic motivation can sometimes undermine intrinsic motivation, or testing boundary conditions under which social influence becomes insignificant. Additionally, longitudinal or experimental designs could further disentangle causal dynamics and mitigate concerns related to common method bias.

The findings offer several concrete, evidence-based recommendations. First, given the strong effect of Perceived Ease of Use on Perceived Usefulness, investment in intuitive interface design and usability testing should be the primary priority for institutions implementing e-learning systems. Second, because Perceived Usefulness outweighs Social Influence in shaping Behavioral Intention, system developers should focus on clearly demonstrating learning benefits rather than relying on enforcement or normative pressure. Third, the significant role of Hedonic Motivation in stimulating Intrinsic Motivation indicates that incorporating gamified elements, interactive scenarios, and engaging multimedia is not merely decorative but a strategic approach to cultivating intrinsic interest. Finally, as Learning Motivation is the strongest driver of Learning Achievement, instructional interventions should focus less on promoting system adoption

and more on fostering motivation through meaningful feedback, goal-setting, and learner autonomy within the platform.

Overall, this study demonstrates that successful e-learning depends on more than acceptance of technology. While usability and usefulness initiate engagement, learning motivation determines whether that engagement results in achievement. By positioning motivation as the central mechanism linking technology acceptance to learning outcomes, this study advances both theory and practice in digital education research.

CONCLUSION

This study demonstrates that for e-learning systems to translate into actual learning achievement, technology acceptance must be channeled through enhanced learner motivation. Merely adopting or intending to use an e-learning system is insufficient to improve academic outcomes unless such acceptance is transformed into sustained learning motivation that drives meaningful engagement with learning activities.

By integrating the Technology Acceptance Model 2 with Motivation Theory, this research reveals a sequential mechanism through which technology perceptions lead to educational success. Perceived Ease of Use functions as a foundational driver that shapes Perceived Usefulness, which in turn strengthens Behavioral Intention. However, the ultimate determinant of Learning Achievement is Learning Motivation, which acts as the critical mediator linking technology acceptance and motivational antecedents to academic performance. This finding clarifies a key limitation of prior technology acceptance research, which has largely focused on adoption and usage intention rather than on how these factors culminate in learning outcomes.

From a practical standpoint, the findings yield clear, evidence-based implications. First, given the strong effect of Perceived Ease of Use on Perceived Usefulness, investments in intuitive interface design and usability optimization should be the primary priority for institutions implementing e-learning systems. Second, because Hedonic Motivation was shown to stimulate Intrinsic Motivation, incorporating enjoyable and engaging design elements, such as gamification, interactive scenarios, and rich multimedia, is not merely aesthetic but a strategic approach to cultivating intrinsic interest and learning motivation. Third, as Learning Motivation emerged as the strongest direct

driver of Learning Achievement, instructional strategies should focus less on promoting system usage itself and more on fostering motivation through meaningful feedback, goal-setting, and learner autonomy within the digital platform.

Ultimately, this research underscores that the next frontier of e-learning effectiveness lies not in increasingly sophisticated technological features, but in psychologically informed system design that strategically bridges the gap between technology adoption and genuine educational engagement. Designing for motivation, rather than for usage alone, is essential for achieving sustainable learning success.

Despite its contributions, this study has several limitations that should be acknowledged. First, the cross-sectional research design limits the ability to draw strong causal inferences regarding the dynamic relationships among technology acceptance, motivation, and learning achievement. Future studies employing longitudinal designs could provide deeper insights into how learners' motivation evolves over time with continued e-learning use. Second, the sample was drawn from vocational high schools, which may limit the generalizability of the findings to other educational levels or cultural contexts. Replication across universities, professional training environments, or different countries would strengthen external validity. Third, learning achievement was measured using self-reported indicators, which may be subject to perceptual bias. Future research should incorporate objective academic performance measures or learning analytics data to validate and extend the present findings.

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