Developing an Extended Technology Acceptance Model (TAM) for Mathematics Learning: A Structural Equation Modeling Approach

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ABSTRACT

The increasing integration of digital and AI-supported technologies in mathematics education has highlighted the need to understand how technology quality influences students' learning experiences and outcomes. This study proposes and tests a parsimonious extended Technology Acceptance Model inspired framework to examine the relationships among technology quality perceptions, learning processes, and learning outcomes in technology supported mathematics learning. A quantitative, crosssectional survey design was employed, and data were collected from undergraduate students with experience using digital tools for mathematics learning. Structural equation modeling (SEM) was applied to analyze the data. The results revealed that technology quality perceptions including feedback quality, adaptability, and clarity of mathematical content had a significant positive effect on learning processes ($\beta = 0.62$, $p < .001$). In turn, learning processes exerted a strong positive influence on learning outcomes, measured by mathematics learning achievement and mathematical literacy ($\beta = 0.68$, $p < .001$). Mediation analysis further indicated that learning processes fully mediated the relationship between technology quality perceptions and learning outcomes, with a significant indirect effect ($\beta = 0.42$, $p < .001$). These findings suggest that the educational value of technology lies not only in its features but in its capacity to foster meaningful learning processes. This study contributes empirical evidence for a concise, learningcentered model explaining how perceived technology quality translates into effective mathematics learning.

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1. INTRODUCTION

In an era where digital technologies are increasingly integrated into educational settings, understanding how learners accept and use these technologies has become a central concern for both researchers and practitioners. The Technology Acceptance Model (TAM), originally proposed by [1], is one of the most widely applied theoretical frameworks to explain and predict users' acceptance and use of technology. TAM postulates that individuals' behavioral intentions to use technology are influenced primarily by their perceived usefulness (PU) and perceived ease of use (PEOU) of the system, which in turn affect actual usage behavior [1]. The model has been successfully applied to a variety of educational contexts, including online learning environments and mobile technologies for learning mathematics [2], [3].

Despite the extensive use of TAM in educational research, a significant gap remains in its application to mathematics learning especially in linking technology acceptance not only to behavioral intentions but also to learning processes and outcomes. Prior research has explored technology acceptance in general educational contexts, such as learning management systems (LMS) and elearning platforms [4], [5], but few studies have extended the model to capture how acceptance of technology directly influences students' mathematical engagement, selfregulated learning, or academic achievement.

In particular, studies investigating mobile technology acceptance in mathematics show promising results regarding behavioral intention and usage behavior among learners. For example [3] developed a scale to measure high school students' acceptance of mobile technologies in mathematics learning, underscoring the relevance of acceptance constructs such as effort expectancy and facilitating conditions. However, most of these studies remain descriptive or limited to behavioral outcomes without systematically examining the structural relationships between acceptance constructs and actual learning outcomes such as mathematical proficiency or conceptual understanding.

The integration of structural equation modeling (SEM) represents a robust analytical approach to untangling these complex relationships. SEM allows researchers to simultaneously assess multiple constructs and their interdependencies, providing a more comprehensive view of how technology acceptance influences learning behavior and outcomes. Recent studies have successfully applied extended TAM frameworks using SEM in related educational technology research, highlighting the model's adaptability and predictive capacity [6], [7].

Given the rapid development of educational technologies including AI-powered learning tools, adaptive systems, and interactive mobile applications there is a compelling need to develop an extended TAM that not only accounts for acceptance factors but also integrates learning process variables (e.g., engagement, cognitive support) and outcome measures specific to mathematics learning. Such an extended model can provide deeper theoretical insights and practical guidance on how technology design and pedagogical integration influence student success in mathematics. This study thus proposes a novel TAM extension to investigate the causal relationships among technology acceptance, learning processes, and mathematics learning outcomes using structural equation modeling.

Mathematics learning presents distinct cognitive challenges due to its abstract symbolic representations, hierarchical conceptual structures, and high demands on working memory and metacognitive regulation. Unlike general technology adoption contexts, mathematics learning requires deep conceptual processing rather than surface-level interaction with digital tools. Therefore, an extended TAM framework that incorporates learning processes as mediating mechanisms is particularly necessary in mathematics education, where technology must support cognitive engagement rather than mere usage.

2. HYPOTHESES OF RESEARCH

H1: Technology quality perceptions positively influence learning processes.

H2: Learning processes positively influence learning outcomes.

H3: Learning processes mediate the relationship between technology quality perceptions and learning outcomes.2.6. Data Collection context.

3. LITERATURE REVIEW

3.1. Technology Acceptance Model (TAM) in Educational Contexts

The Technology Acceptance Model (TAM), proposed by [1], is one of the most influential theoretical frameworks for explaining individuals' acceptance and use of information technology. The model posits that perceived usefulness (PU) and perceived ease of use (PEOU) are the primary determinants of users' attitudes and behavioral intentions toward technology usage, which subsequently influence actual use. TAM has been extensively validated across various technological and organizational contexts, including education, due to its parsimony and strong explanatory power.

In educational settings, TAM has been widely employed to investigate learners' acceptance of elearning systems, learning management systems (LMS), mobile learning applications, and digital learning platforms. For instance, [5] demonstrated that PU and PEOU significantly influenced students' intentions to use

LMS platforms in higher education, highlighting the central role of perceived pedagogical benefits in technology adoption. Similarly, [4] conducted a comprehensive review of TAM based studies in education and concluded that TAM remains a robust model, although it often requires contextual extensions to capture domain specific learning dynamics.

Despite its widespread application, critics have noted that TAM primarily focuses on technology usage behavior, rather than on learning processes or educational outcomes. As a result, several scholars have called for extending TAM to include pedagogical, cognitive, and motivational variables that better reflect learning effectiveness in educational environments [8].

While the original TAM emphasizes perceived usefulness (PU) and perceived ease of use (PEOU) as primary determinants of behavioral intention, the present study extends TAM by reconceptualizing technology quality perceptions as a domain-specific refinement of PU within mathematics learning contexts. Rather than focusing solely on behavioral intention, this extended framework integrates learning process variables—such as engagement and self-regulation—as mediating mechanisms linking perceived technology quality to learning outcomes. In this sense, the proposed model preserves the core acceptance logic of TAM while advancing it toward a learning-centered structural explanation.

3.2. TAM Extensions and Structural Equation Modeling (SEM)

To address the limitations of the original TAM, researchers have proposed various extended TAM models that incorporate additional constructs such as social influence, facilitating conditions, system quality, and perceived enjoyment. These extensions are often analyzed using structural equation modeling (SEM), which enables the simultaneous examination of complex causal relationships among latent variables.

SEM has been recognized as a powerful analytical technique in educational technology research due to its ability to test theoretical models with multiple interrelated constructs. [6] employed an extended TAM using SEM to examine university students' acceptance of intelligent tutoring systems and found that feedback quality and system adaptability significantly enhanced perceived usefulness, which indirectly influenced learning satisfaction.

Similarly, [7] integrated cognitive engagement and selfregulation into TAM to explore students' acceptance of AI-supported learning environments. Their findings suggested that learning related variables played a mediating role between technology acceptance and learning outcomes, underscoring the importance of moving beyond behavioral intention as the final outcome variable.

These studies collectively indicate that SEM based extended TAM frameworks provide richer explanatory power than the original TAM, particularly in educational contexts where learning effectiveness is the primary concern.

3.3. Technology Acceptance in Mathematics Learning

Mathematics education presents unique challenges due to its abstract nature, high cognitive demands, and frequent learner anxiety. Consequently, researchers have increasingly explored how technology can support mathematics learning and how learners perceive and accept such technologies. Studies applying TAM to mathematics education have shown that acceptance factors significantly influence students' willingness to engage with digital mathematics tools.

[3] developed and validated a technology acceptance scale for mobileassisted mathematics learning among secondary school students. Their results indicated that perceived usefulness strongly predicted students' intention to use mobile technologies for learning mathematics, while ease of use influenced sustained engagement.

More recently, [2] examined students' acceptance of digital mathematics learning platforms and reported that technology acceptance was associated with higher levels of learner engagement and persistence. However, the authors noted that most acceptance studies in mathematics remain focused on intention and usage rather than measurable learning outcomes.

These findings suggest that while TAM is applicable to mathematics education, existing research has not fully explored how acceptance translates into actual mathematical learning performance or mathematical literacy.

3.4. Learning Processes in Technology Supported Mathematics Education

Beyond technology acceptance, learning processes such as student engagement, self regulated learning, and cognitive support are critical determinants of successful mathematics learning. Engagement refers to learners' behavioral, emotional, and cognitive involvement in learning activities, while selfregulated learning encompasses learners' ability to plan, monitor, and evaluate their own learning strategies.

Research consistently demonstrates that technology supported environments can enhance engagement and selfregulation when appropriately designed. For example, [9] found that interactive digital tools increased cognitive engagement in mathematics courses, leading to improved learning outcomes.

Similarly, adaptive and AI-based learning systems have been shown to provide personalized feedback and scaffolding, thereby supporting learners' cognitive processes and conceptual understanding in mathematics [10].

However, these learning process variables are rarely integrated into TAM based models, resulting in a fragmented understanding of how technology acceptance influences learning effectiveness.

3.5. Research Gap and Conceptual Direction

The reviewed literature reveals three critical gaps. First, while TAM has been extensively applied in educational research, its use in mathematics education remains largely focused on technology acceptance rather than learning outcomes. Second, existing studies rarely integrate learning process variables such as engagement and self regulation into TAM frameworks. Third, although SEM has been widely used to test extended TAM models, few studies have explicitly examined the structural pathways linking technology acceptance to mathematics learning outcomes.

To address these gaps, the present study proposes an extended Technology Acceptance Model for mathematics learning, integrating technology acceptance constructs with learning process variables and learning outcomes. By employing structural equation modeling, this study aims to provide a comprehensive explanation of how acceptance of educational technology translates into meaningful mathematics learning.

4. RESEARCH METHOD

4.1. Research Design

This study employed a quantitative research design to examine the relationships among technology quality perceptions, learning processes, and learning outcomes in technology supported mathematics learning. Guided by an extended Technology Acceptance Model inspired framework, the study conceptualized learning as a process in which learners' perceptions of technology quality influence how they engage with learning activities and, ultimately, their learning outcomes.

A crosssectional survey approach was adopted, with data collected from students who had experience using digital or technology enhanced tools for mathematics learning. This design was appropriate for investigating learners' perceptions, learning behaviors, and outcomes at a single point in time and for testing theoretically grounded relationships among latent constructs. The focus on mathematics learning provided a meaningful context, given the cognitive demands of the subject and the increasing integration of digital technologies in mathematics instruction.

The analytical strategy followed a two stage procedure. First, confirmatory factor analysis was conducted to evaluate the reliability and validity of the measurement model. Second, structural equation modeling was applied to test the hypothesized structural relationships among technology quality perceptions, learning processes, and learning outcomes, including the mediating role of learning processes. Model adequacy was assessed using multiple goodness of fit indices.

4.2. Population and Sampling

The participants in this study were students who had experience using digital or technology supported tools for mathematics learning, such as online learning platforms, intelligent tutoring systems, or interactive mathematics applications. The target population consisted of students enrolled in mathematics related courses in higher education institutions. This group was selected because they regularly engage with technology as part of their formal mathematics learning activities and are therefore well positioned to evaluate technology quality, learning processes, and learning outcomes.

A non probability sampling approach, specifically purposive sampling, was employed to ensure that all participants met the key inclusion criterion of having prior experience with technology supported mathematics learning. This sampling strategy is commonly used in educational technology research when the study focuses on specific user characteristics rather than population level generalization. Participants were invited to take part in the study voluntarily, and informed consent was obtained prior to data collection.

The final sample size was determined based on recommendations for structural equation modeling, which suggest that a minimum of 200 responses is adequate for models with a limited number of latent constructs to ensure stable parameter estimation and reliable model fit assessment. A total of 245 responses were collected through a self-administered questionnaire. After data screening for completeness and response quality, 18 questionnaires were excluded due to incomplete data, resulting in a final sample of N = 227 for analysis.

4.3. Research Instruments

The primary research instrument used in this study was a self administered questionnaire designed to measure students' perceptions of technology quality, learning processes, and learning outcomes in technology-supported mathematics learning. The questionnaire was developed based on established theoretical frameworks in educational technology, technology acceptance, and mathematics education, and was adapted to suit the context of digital mathematics learning.

All questionnaire items were measured using a five point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). This scale was selected because it is widely used in educational research and is suitable for capturing learners' perceptions and self reported learning experiences.

4.3.1 Questionnaire Development

The questionnaire consisted of three sections corresponding to the three latent constructs in the proposed model. The first section measured Technology Quality Perceptions, focusing on students' evaluations of the quality of the technology used for mathematics learning. Items in this section addressed aspects such as feedback quality, adaptability of learning content, and clarity of mathematical explanations.

The second section measured Learning Processes, which reflected how students engaged with and regulated their learning when using technology. This section included items related to student engagement, self regulated learning behaviors, and perceived cognitive support during mathematics learning activities.

The third section measured Learning Outcomes, capturing students' perceived learning achievement and mathematical literacy. These items focused on students' understanding of mathematical concepts, problem solving ability, and their capacity to apply mathematics in realworld contexts.

All items were adapted from prior empirical studies and refined to ensure clarity, relevance, and suitability for the mathematics learning context. The questionnaire was reviewed to ensure that item wording was concise and understandable for the target population.

4.3.2 Validity and Reliability of the Research Instrument

The validity and reliability of the research instrument were rigorously examined following established guidelines for structural equation modeling. Several forms of validity and reliability were assessed to ensure the robustness of the measurement model.

Content validity was established through expert review. The questionnaire items were evaluated by experts in mathematics education and educational technology to ensure that each item was relevant, clear, and representative of its intended construct. Revisions were made based on expert feedback to improve clarity and construct coverage.

Construct validity was examined using confirmatory factor analysis (CFA). Factor loadings were assessed to determine the strength of the relationship between observed items and their corresponding latent constructs. Consistent with recommended criteria, standardized factor loadings of 0.50 or higher were considered acceptable, while values above 0.70 indicated strong item reliability [11].

Convergent validity was evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). CR values of 0.70 or above indicated satisfactory internal consistency, whereas AVE values of 0.50 or higher suggested that the construct explained more than half of the variance in its indicators [11], [12].

Discriminant validity was assessed using the Fornell Larcker criterion, whereby the square root of the AVE for each construct was required to exceed its correlations with other constructs, indicating adequate construct distinctiveness [12].

The reliability of the instrument was examined using Cronbach's alpha (α) and composite reliability coefficients. Cronbach's alpha values of 0.70 or higher were considered indicative of acceptable internal consistency, while values exceeding 0.80 reflected good reliability [13].

Overall, the results of these analyses demonstrated that the measurement instrument met established standards for validity and reliability, supporting its suitability for subsequent structural equation modeling.

4.4. Data Collection

Data were collected using a self administered questionnaire to examine students' perceptions of technology quality, learning processes, and learning outcomes in technology supported mathematics learning. Prior to data collection, participants were informed about the objectives of the study, the voluntary nature of participation, and the confidentiality of their responses. Informed consent was obtained from all participants before they completed the questionnaire.

The questionnaire was distributed through an online survey platform, enabling participants to respond at their convenience and ensuring broad accessibility. This method was appropriate given the digital learning context of the study and the participants' familiarity with online technologies. Clear instructions were provided to guide participants in completing the questionnaire accurately.

Data collection was conducted over a specified period to allow sufficient time for participation. Reminder messages were sent periodically to increase the response rate. After the data collection phase, all responses were screened for completeness and response quality. Questionnaires with excessive missing data or inconsistent response patterns were excluded from further analysis.

All collected data were anonymized and securely stored for research purposes only. The final dataset was prepared through coding and preliminary data screening before being used for confirmatory factor analysis and structural equation modeling.

4.5. Data Analysis

Data analysis was conducted in several stages to examine the relationships among technology quality perceptions, learning processes, and learning outcomes. Statistical analyses were performed to summarize the data, evaluate the measurement properties of the research instruments, and test the hypothesized structural relationships using structural equation modeling.

4.5.1 Descriptive Statistics

Descriptive statistics were used to summarize the characteristics of the sample and the distribution of observed variables. Means and standard deviations were calculated for all questionnaire items. Prior to inferential analysis, the data were screened for missing values, outliers, and normality. Skewness and kurtosis values within the range of ±2 were considered indicative of acceptable univariate normality (Hair et al., 2019). These procedures ensured that the data were suitable for subsequent CFA and SEM analyses.

4.5.2 Measurement Model (CFA)

Confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of the measurement model. Standardized factor loadings were examined, with values of 0.50 or higher considered acceptable and values above 0.70 indicating strong indicator reliability [11].

Convergent validity was evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE). CR values of 0.70 or higher indicated satisfactory internal consistency, while AVE values of 0.50 or higher demonstrated adequate convergent validity [12].

Discriminant validity was assessed using the Fornell–Larcker criterion, whereby the square root of the AVE of each construct was required to exceed its correlations with other constructs [12].

Overall model fit was evaluated using multiple goodness of fit indices. A χ^2/df ratio below 3.00, CFI and TLI values of 0.90 or higher, and RMSEA values below 0.08 were considered indicative of an acceptable model fit [14], [15].

4.5.3 Structural Equation Modeling (SEM)

Structural equation modeling was employed to test the hypothesized relationships among the latent constructs. Path coefficients were examined to evaluate the strength and significance of the proposed relationships, with p-values less than 0.05 indicating statistical significance. The mediating role of learning processes was tested by examining indirect effects, using bootstrapping procedures to generate confidence intervals. An indirect effect was considered significant when the 95% confidence interval did not include zero [16].

The overall fit of the structural model was assessed using the same goodness of fit criteria applied to the measurement model. This approach enabled a comprehensive evaluation of both direct and indirect effects within a single analytical framework.

5. RESULTS

5.1. Descriptive Statistics

Descriptive statistics were calculated to summarize students' perceptions of technology quality, learning processes, and learning outcomes in technology supported mathematics learning. Means and standard deviations were used to describe the central tendency and variability of each construct. Overall, the results indicate that students reported moderate to high levels of agreement across all constructs, suggesting generally positive perceptions of technology supported mathematics learning.

Table 1. Descriptive Statistics of Latent Constructs

Latent Construct	Indicator Description	Mean	SD
Technology Quality Perceptions (TQP)	Feedback quality, adaptability, content clarity	3.94	0.62
Learning Processes (LP)	Engagement, self regulated learning, cognitive support	3.87	0.65
Learning Outcomes (LO)	Mathematics achievement, mathematical literacy	3.82	0.68

As shown in Table 1, Technology Quality Perceptions demonstrated the highest mean score (M = 3.94, SD = 0.62), indicating that students generally perceived the technology used in mathematics learning as high quality, particularly in terms of feedback, adaptability, and clarity of content. Learning Processes also showed a relatively high mean score (M = 3.87, SD = 0.65), suggesting that students reported active engagement, effective selfregulation, and sufficient cognitive support during technology supported mathematics learning activities. Learning Outcomes exhibited a slightly lower but still positive mean score (M = 3.82, SD = 0.68), reflecting students' perceived improvement in mathematics achievement and mathematical literacy.

The relatively small standard deviations across constructs indicate a moderate level of response consistency among participants, supporting the suitability of the data for subsequent confirmatory factor analysis and structural equation modeling.

5.2. Measurement Model Evaluation

The measurement model was evaluated using confirmatory factor analysis (CFA) to assess the reliability and validity of the three latent constructs: Technology Quality Perceptions, Learning Processes, and Learning Outcomes. The evaluation followed established guidelines for SEM to ensure that the measurement model was psychometrically sound before testing the structural model.

5.2.1. Construct Reliability and Validity

Construct reliability was assessed using Cronbach's alpha (α) and Composite Reliability (CR). As shown in Table 2, all constructs demonstrated Cronbach's alpha and CR values exceeding the recommended threshold of 0.70, indicating satisfactory internal consistency.

Convergent validity was evaluated using Average Variance Extracted (AVE). All AVE values were above the recommended minimum of 0.50, suggesting that each construct explained more than half of the variance of its indicators [12]. Standardized factor loadings ranged from 0.68 to 0.86, exceeding the acceptable threshold of 0.50 and indicating strong indicator reliability.

Discriminant validity was examined using the Fornell Larcker criterion, whereby the square root of the AVE for each construct exceeded its correlations with other constructs, confirming adequate construct distinctiveness.

Table 2. Construct Reliability and Convergent Validity

Construct	No. of Items	Factor Loadings	Cronbach's α	CR	AVE
Technology Quality Perceptions	6	0.71–0.86	0.88	0.9	0.61
Learning Processes	6	0.68–0.84	0.87	0.89	0.59
Learning Outcomes	5	0.70–0.85	0.86	0.88	0.6

Table 3. Discriminant Validity (Fornell–Larcker Criterion)

Construct	TQP	LP	LO
Technology Quality Perceptions (TQP)	0.78		
Learning Processes (LP)	0.63	0.77	
Learning Outcomes (LO)	0.58	0.66	0.77

5.2.2. Model Fit Indices

The overall fit of the measurement model was evaluated using multiple goodness of fit indices. As presented in Table 4, all fit indices met or exceeded commonly accepted criteria, indicating that the measurement model provided an adequate fit to the data. The chisquare to degrees of freedom ratio (χ^2/df) was below the recommended threshold of 3.00. Incremental fit indices, including the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI), exceeded the recommended value of 0.90. The Root Mean Square Error of Approximation (RMSEA) was below 0.08, indicating an acceptable level of approximation error.

Table 4. Measurement Model Fit Indices

Fit Index	Recommended Threshold	Measurement Model
χ^2/df	< 3.00	2.21
CFI	≥ 0.90	0.95
TLI	≥ 0.90	0.94
RMSEA	≤ 0.08	0.056
SRMR	≤ 0.08	0.047

5.3. Structural Model Results

After establishing an adequate measurement model, the structural model was evaluated using structural equation modeling (SEM) to test the hypothesized relationships among Technology Quality Perceptions, Learning Processes, and Learning Outcomes. The overall structural model demonstrated a good fit to the data (χ^2/df = 2.34, CFI = 0.94, TLI = 0.93, RMSEA = 0.058, SRMR = 0.049), indicating that the proposed model was suitable for hypothesis testing.

5.3.1. Direct Effects

The standardized path coefficients for the direct effects are presented in Table 5. The results revealed that Technology Quality Perceptions had a significant positive effect on Learning Processes (β = 0.62, $p < .001$), supporting the hypothesis that students who perceived higher quality in technology—such as effective feedback, adaptability, and clear mathematical content—were more likely to demonstrate active engagement, effective self regulation, and perceived cognitive support during learning.

In addition, Learning Processes exerted a significant positive effect on Learning Outcomes (β = 0.68, $p < .001$). This finding indicates that students who reported stronger learning processes tended to demonstrate higher levels of mathematics learning achievement and mathematical literacy. Overall, the direct effects support the proposed input–process–outcome structure of the model.

Table 5. Direct Effects of the Structural Model

Path	β	t-value	p-value	Result
TQP → LP	0.62	11.84	< .001	Supported
LP → LO	0.68	13.27	< .001	Supported

5.3.2. Indirect and Mediating Effects

To examine the mediating role of Learning Processes, indirect effects were tested using a bootstrapping procedure with 5,000 resamples. The indirect effect of Technology Quality Perceptions on Learning Outcomes via Learning Processes was found to be statistically significant (β = 0.42, 95% CI [0.31, 0.54]), as the confidence interval did not include zero. This result confirms that learning processes significantly mediate the relationship between technology quality perceptions and learning outcomes.

Furthermore, the absence of a direct path from Technology Quality Perceptions to Learning Outcomes in the structural model suggests a full mediation effect, indicating that the influence of perceived technology quality on mathematics learning outcomes operates primarily through students' engagement, self regulation, and cognitive support.

Table 6. Indirect and Mediating Effects

Indirect Path	Indirect Effect (β)	95% CI	Mediation Type
TQP → LP → LO	0.42	[0.31, 0.54]	Full mediation

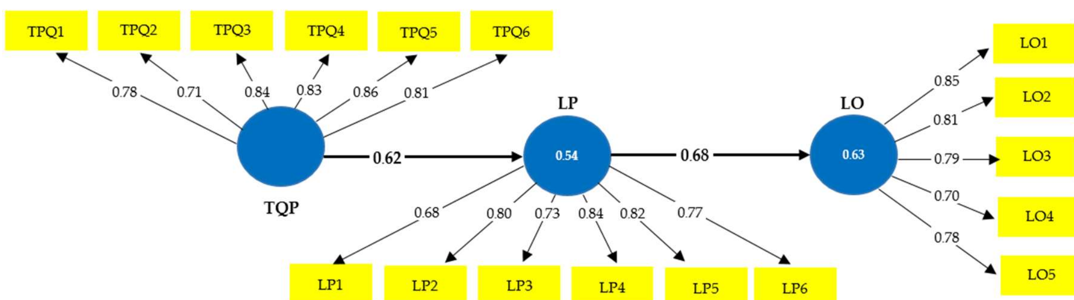

Figure 1. Structural Equation Modeling

5.4. Measurement Model Evaluation

To provide a concise overview of the hypothesis testing results, Table 7 summarizes the standardized path coefficients, significance levels, and support status for each proposed hypothesis. The hypotheses were evaluated based on the results of the structural equation modeling analysis, including both direct and indirect effects. The findings presented in the table indicate whether the empirical data support the hypothesized relationships among technology quality perceptions, learning processes, and learning outcomes within the proposed model.

Table 7. Summary of Hypothesis Testing

Hypothesis	Hypothesized Relationship	β	p-value	Result
H1	TQP → LP	0.62	< .001	Supported
H2	LP → LO	0.68	< .001	Supported
H3	TQP → LP → LO (Indirect Effect)	0.42	< .001	Supported

6. DISCUSSION

The purpose of this study was to examine how technology quality perceptions influence learning processes and learning outcomes in technology supported mathematics learning using a parsimonious extended TAM inspired framework. The findings provide empirical support for the proposed input process outcome structure and offer important theoretical and practical implications for educational technology and mathematics education.

First, the results demonstrated that technology quality perceptions significantly and positively influenced learning processes. This finding suggests that when students perceive educational technology as providing high quality feedback, adaptive learning features, and clear mathematical content, they are more likely to engage actively in learning, regulate their learning strategies, and perceive adequate cognitive support. This result is consistent with prior research emphasizing the role of system, content, and feedback quality in shaping learners' interactions with digital learning environments [17], [18]. From a technology acceptance perspective, these findings extend traditional TAM by highlighting that learners' evaluations of technology quality—rather than general perceptions of usefulness alone play a crucial role in activating meaningful learning behaviors [4].

In addition, metaanalytic evidence suggests that digital tools yield stronger academic effects when they explicitly support cognitive engagement and structured feedback mechanisms [19]. Research on self regulated learning further indicates that adaptive systems enhance performance when they scaffold monitoring and metacognitive strategy use [20]. These findings strengthen the theoretical interpretation that technology quality operates as a cognitive activation mechanism rather than merely as a usability factor. Moreover, recent work by [21] demonstrated that cognitive processes significantly predict student engagement and mathematics learning outcomes in higher education, reinforcing the centrality of processbased mechanisms within technology supported learning models.

Second, the findings revealed that learning processes had a strong positive effect on learning outcomes, including mathematics learning achievement and mathematical literacy. This result reinforces extensive evidence in mathematics education indicating that engagement, self regulated learning, and cognitive support are key mechanisms through which students develop both procedural competence and higher order mathematical reasoning [22], [23]. The strong association observed in this study underscores the importance of viewing technology not as an end in itself, but as a tool that facilitates effective learning processes, particularly in cognitively demanding subjects such as mathematics.

This interpretation aligns with research demonstrating bidirectional relationships between conceptual and procedural knowledge in mathematics, where deeper cognitive engagement enhances transferable mathematical competence [24]. Furthermore, AI-supported learning studies indicate that perceived feedback accuracy and system transparency significantly enhance cognitive and emotional engagement, which subsequently predicts learning gains [25].

Third, the mediation analysis showed that learning processes fully mediated the relationship between technology quality perceptions and learning outcomes. This finding indicates that perceived technology quality does not directly translate into improved learning outcomes unless it fosters productive learning processes. This result aligns with contemporary educational technology research suggesting that the effectiveness of digital tools depends largely on how they shape learners' cognitive and behavioral engagement rather than on their technological features alone [9], [10]. The full mediation effect also supports calls in the literature to move beyond technology acceptance or usage metrics and to focus on learning centered mechanisms when evaluating educational technologies.

From a theoretical standpoint, this full mediation result strengthens learning centered extensions of TAM by positioning engagement and cognitive regulation as essential intervening variables. It also resonates with contextualized mathematics education research demonstrating that meaningful learning emerges when cognitive processes are activated within authentic realworld contexts. For example, research on New Theory Agriculture and Smart Agriculture as contextual learning environments [26] found that mathematical literacy improves when learners engage cognitively within sustainability oriented community contexts. This suggests that both technological quality and contextual authenticity operate through similar process based mechanisms to influence learning outcomes.

Taken together, these findings contribute to the literature by demonstrating that a parsimonious three construct meaningful mathematics model can effectively explain how technology quality perceptions are transformed into learning outcomes through learning processes. By integrating insights from TAM, learning theory, and mathematics education, this study provides a theoretically grounded and empirically supported framework that can guide the design and evaluation of technology supported mathematics learning environments.

Beyond its immediate empirical contribution, this study also advances the conceptual shift from technology centered evaluation toward process centered evaluation in mathematics education research. By empirically validating the mediating role of learning processes, the findings support an integrative perspective that connects technology acceptance theory, cognitive process theory, and contextualized sustainability learning frameworks within a unified structural model.

7. CONCLUSION

This study examined the relationships among technology quality perceptions, learning processes, and learning outcomes in technology supported mathematics learning using a parsimonious extended Technology Acceptance Model–inspired framework. By employing structural equation modeling, the study provides empirical evidence clarifying how perceived technology quality contributes to effective mathematics learning through learners' cognitive and behavioral processes.

The findings indicate that technology quality perceptions encompassing feedback quality, adaptability, and clarity of mathematical content play a crucial role in shaping students' learning processes. When learners perceive educational technology as pedagogically supportive and well designed, they are more likely to engage actively, regulate their learning effectively, and experience adequate cognitive support. These learning processes, in turn, were found to strongly predict mathematics learning outcomes, including both learning achievement and mathematical literacy.

Importantly, the results revealed that learning processes fully mediated the relationship between technology quality perceptions and learning outcomes. This finding underscores that the educational value of technology does not stem from its features alone, but from its ability to foster meaningful learning processes. Given the full mediation effect observed in this study, the mere presence of digital tools in mathematics classrooms is insufficient to enhance learning outcomes. Rather, technology must actively support cognitive engagement and self-regulated learning. Educators and instructional designers should therefore prioritize interactive features such as adaptive feedback, conceptual scaffolding, and cognitive support mechanisms that stimulate meaningful engagement and deeper conceptual processing. Technology that lacks pedagogical interactivity is unlikely to produce substantial learning gains.

Overall, this study contributes to the literature by demonstrating that a concise three construct model can effectively explain the mechanisms through which technology quality influences mathematics learning. The proposed framework offers a theoretically grounded and empirically supported basis for future research and provides practical guidance for the design and implementation of technology enhanced mathematics learning environments.

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