frontiers | Frontiers in Education

TYPE Original Research
PUBLISHED 09 February 2026
DOI 10.3389/feduc.2026.1737107

Check for updates

OPEN ACCESS

EDITED BY
Sergio Ruiz-Viruel,
University of Malaga, Spain

REVIEWED BY
Uzma Noor,
Soochow University, China
Faisol Faisol,
Nusantara PGRI University of Kediri, Indonesia

*CORRESPONDENCE
Rabab Alsaffar
✉ rd.alsaffar@paaet.edu.kw

RECEIVED 01 November 2025
REVISED 14 January 2026
ACCEPTED 16 January 2026
PUBLISHED 09 February 2026

CITATION
Alsaffar R (2026) Impact of AI-enhanced multimedia quality, usage frequency, and ease of integration on learning effectiveness: case of basic education colleges in Kuwait.
*Front. Educ.* 11:1737107.
doi: 10.3389/feduc.2026.1737107



# Impact of AI-enhanced multimedia quality, usage frequency, and ease of integration on learning effectiveness: case of basic education colleges in Kuwait

Rabab Alsaffar *

Public Authority for Applied Education and Training, College of Basic Education, Kuwait City, Kuwait

This study investigates the impact of AI-enhanced multimedia on learning effectiveness (LEF), focusing on the roles of multimedia quality (AMQ), ease of integration (EOI), and usage frequency (UFAM). Building on TAM, UTAUT, Self-Determination Theory, and Self-Efficacy Theory, the research develops a structural equation model incorporating student engagement (STE) and technology self-efficacy (TSE) as mediators. Data were collected from 232 students across six departments in Kuwait's Colleges of Basic Education using validated measurement scales. Reliability and validity were confirmed through confirmatory factor analysis, with all constructs meeting established thresholds. Structural model results indicated that EOI was the strongest predictor of STE, TSE, and LEF, while AMQ significantly influenced TSE and LEF. In contrast, UFAM showed no significant direct or indirect effects. Mediation analysis revealed that both STE and TSE mediated the effects of EOI on LEF, while TSE mediated the AMQ–LEF relationship. The findings underscore the importance of integration quality and self-efficacy in AI-mediated learning. Theoretical and practical implications have been provided based on the findings of this research that could be useful for academicians and practitioners.

KEYWORDS

**multimedia quality, multimedia usage, student engagement, technology integration, technology self-efficacy**

## 1 Introduction

The rapid advancement of artificial intelligence (AI) has significantly transformed educational practices by introducing intelligent systems that enhance the design, delivery, and effectiveness of multimedia learning environments. In higher and basic education, AI-driven multimedia tools are increasingly recognized for their ability to foster interactive learning, provide adaptive content, and support diverse learner needs (Sun and Chen, 2016; Binti Mohd et al., 2024). Unlike traditional instructional methods, AI-enhanced multimedia integrates adaptive feedback, personalized pathways, and interactive visuals, making learning more engaging and efficient. The application of such technologies has become particularly relevant in Kuwait, where efforts to modernize the educational system emphasize digital transformation in classroom teaching and learning processes.

Despite these advancements, the successful integration of AI-enhanced multimedia into education is not without challenges. Research suggests that adoption depends on multiple factors, including perceived quality, ease of integration into teaching practices, and frequency of use (Davis, 1989; Venkatesh et al., 2003). While high-quality multimedia resources can improve student comprehension, their impact may be limited if they are not easily embedded within curricular frameworks or if students lack the confidence to use them effectively (Teo, 2011). Moreover, although frequency of use has often been associated with improved learning outcomes, emerging evidence indicates that usage alone may not guarantee effectiveness unless supported by meaningful engagement and strong self-efficacy (Fredricks et al., 2004; Compeau and Higgins, 1995). These complexities highlight the need for a systematic investigation into how different attributes of AI-enhanced multimedia interact to influence learning effectiveness.

In Kuwait's Colleges of Basic Education, multimedia adoption is gaining momentum, yet empirical evidence on its effectiveness remains scarce. While prior studies in global contexts have explored multimedia adoption, few have considered the unique challenges faced in Kuwait, such as infrastructural limitations, varying levels of faculty digital competence, and diverse student readiness for AI-driven learning. Furthermore, there is limited understanding of how student engagement (STE) and technology self-efficacy (TSE) act as mediating mechanisms linking multimedia features to learning effectiveness (LEF).

Nostalgia, cultural revival, and aesthetic trend are theorized to influence behavioral intentions through affective attachment and identity reinforcement, as explained by Self-Efficacy Theory. However, empirical research has not adequately examined how nostalgia-driven emotions translate into intention to engage with ancient-style games. This study addresses this gap by explicating nostalgia as a psychological mechanism shaping behavioral intention beyond aesthetic appreciation.

Addressing this research gap is critical, as insights from end-users the studentscan provide valuable guidance for educators, administrators, and policymakers aiming to optimize AI-driven educational strategies. This study examines the impact of AI-Enhanced Multimedia Quality (AMQ), Ease of Integration (EOI), and Usage Frequency of AI-Enhanced Multimedia (UFAM) on Learning Effectiveness (LEF), with a particular focus on the mediating roles of Student Engagement (STE) and Technology Self-Efficacy (TSE). By developing and testing a structural equation model, this research not only contributes to the theoretical understanding of technology adoption in educational settings but also provides empirical evidence from Kuwait's Basic Education context, where digital transformation in teaching and learning remains a priority.

# 2 Theoretical background

There are four theories that have been instrumental in the construction of the conceptual model of this research and heir relevance has been discussed in the following sections.

## 2.1 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) posits that users' behavioral intention to use a technology is primarily driven by perceived usefulness (PU) and perceived ease of use (PEOU), which shape attitudes toward use and subsequent adoption (Davis, 1989). In education, TAM has been widely applied to explain learners' and instructors' uptake of digital tools, including multimedia platforms, by linking usability and functional benefits to actual usage. Meta-analyses show robust effects of PU and PEOU across contexts and measurement variations, supporting TAM's parsimony and predictive validity for e-learning environments (King and He, 2006). Extensions of TAM (e.g., external variables such as system quality and self-efficacy) further refine its explanatory power for classroom technologies and AI-enhanced multimedia (Legris et al., 2003; Teo, 2011).

## 2.2 Unified Theory of Acceptance and Use of Technology

The Unified Theory of Acceptance and Use of Technology (UTAUT) synthesizes eight prior models to explain technology adoption through four core determinants—performance expectancy, effort expectancy, social influence, and facilitating conditions—moderated by age, gender, experience, and voluntariness (Venkatesh et al., 2003). In educational settings, UTAUT predicts students' and teachers' acceptance of learning management systems, mobile learning, and intelligent tutoring, emphasizing institutional support and perceived utility (Al-Mamary et al., 2024). Subsequent refinements (UTAUT2) add hedonic motivation and habit, improving prediction of usage in learning ecosystems blending productivity and engagement (Venkatesh et al., 2012). Recent reviews affirm UTAUT's strong explanatory scope for digital and AI-mediated education when combined with context-specific variables (Dwivedi et al., 2020).

## 2.3 Self-Determination Theory

Self-Determination Theory (SDT) explains engagement and persistence as functions of autonomy, competence, and relatedness needs; when learning environments satisfy these needs, intrinsic motivation and deep learning improve (Deci and Ryan, 1985). AI-enhanced multimedia can support autonomy (choice paths), competence (immediate feedback), and relatedness (collaborative features), thereby elevating student engagement (STE) as a mediator of outcomes. Empirical syntheses in education show that need-supportive instruction enhances interest, effort, and achievement across age groups and modalities (Ryan and Deci, 2000). Reviews of classroom applications further demonstrate that autonomy-supportive practices foster deeper processing and better performance, aligning with multimedia designs that personalize pacing and difficulty (Niemiec and Ryan, 2009; Deci et al., 1991).

## 2.4 Self-Efficacy Theory

Self-Efficacy Theory (SET) posits that individuals' beliefs in their capabilities to organize and execute actions required for performance (TSE in this study) regulate choice, effort, and resilience—key precursors to learning effectiveness (Bandura, 1997). In technology-rich classrooms, higher computer/IT self-efficacy predicts adoption, problem-solving, and persistence with digital tools, including AI-enhanced multimedia (Rahman et al., 2019). Educational research consistently links self-efficacy to strategy use, self-regulated learning, and academic achievement, positioning it as a pivotal cognitive mediator between system attributes (quality, integration) and outcomes (Paz-Baruch, 2025). Thus, interventions that build mastery experiences and timely feedback can elevate TSE, which in turn enhances engagement and performance within AI-mediated learning environments.

# 3 Literature review

The integration of technology into education has long been analyzed through models such as the Technology Acceptance Model (TAM) (Davis, 1989; King and He, 2006; Legris et al., 2003) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003, 2012). These frameworks emphasize perceived usefulness, ease of use, effort expectancy, and facilitating conditions as determinants of adoption, forming a foundation for understanding engagement with AI-enhanced multimedia tools. Extensions further highlight self-efficacy and motivational factors as critical predictors in educational contexts (Rahman et al., 2019). In addition, Self-Determination Theory (SDT) (Deci and Ryan, 1985; Ryan and Deci, 2000) underscores intrinsic motivation, autonomy, competence, and relatedness in sustaining engagement, suggesting AI-driven multimedia is effective when supporting these psychological needs, fostering academic persistence and deeper learning outcomes across educational environments.

Complementing adoption models, self-determination perspectives highlight intrinsic motivation, autonomy, competence, and relatedness in sustaining learner engagement (Deci and Ryan, 1985; Ryan and Deci, 2000; Niemiec and Ryan, 2009). These constructs align with AI-driven multimedia, which personalizes instruction, provides adaptive feedback, and fosters collaboration (Wu et al., 2024; Yang et al., 2025). By addressing these psychological needs, AI-enhanced learning environments improve academic outcomes and promote long-term motivation and satisfaction. Similarly, self-efficacy theory emphasizes learners' belief in technological competence as a predictor of persistence and performance (Compeau and Higgins, 1995; Paz-Baruch, 2025). Recent interventions show scaffolding and training enhance self-efficacy, amplifying learning outcomes in digital environments (Allagui, 2024; Chang et al., 2025). This suggests motivational and cognitive perspectives work in tandem, offering a holistic understanding of AI-driven multimedia's impact on learning experiences.

The growing literature on technology-enhanced learning confirms the significance of multimedia quality and design. Well-structured digital content enhances engagement, satisfaction, and perceived learning effectiveness (Gray and DiLoreto, 2016; Sun and Chen, 2016; Wang et al., 2023). Empirical evidence suggests that AI-mediated tools positively affect behavioral and cognitive engagement, improving motivation and academic resilience (Fredricks et al., 2004; Bhatt and Muduli, 2024). These findings highlight that the effectiveness of AI-driven systems depends not only on the presence of digital tools but also on the quality of their design and the way they connect with learners' needs. Systematic reviews further highlight that integration ease and contextual fit are crucial for sustainable ICT adoption in classrooms (e.g., Binti Mohd et al., 2024; Mouza and Lavigne, 2013). Together, these insights emphasize that high-quality multimedia, when effectively integrated, can transform learning environments by fostering deeper engagement and long-term educational impact.

At the methodological level, the reliability and validity of constructs in technology adoption studies have been consistently tested through advanced statistical approaches, particularly structural equation modeling (Hair et al., 2013; Ahmad et al., 2016; Mustafa et al., 2020). Researchers also emphasize adequate sample sizes and confirmatory factor analysis for robust validation (Wolf et al., 2013; Shrestha, 2021; Taber, 2018; Julious, 2005). These approaches have enabled rigorous testing of theoretical models linking multimedia quality, engagement, and learning outcomes.

Despite this progress, significant gaps remain in the literature. Most prior studies have focused on adoption and motivation in general digital learning contexts, with limited exploration of how AI-enhanced multimedia quality (AMQ), ease of integration (EOI), and usage frequency (UFAM) collectively shape learning effectiveness (LEF). While prior work has confirmed the importance of engagement and self-efficacy as mediators (Gray and DiLoreto, 2016; Allagui, 2024; Bhatt and Muduli, 2024), there is little empirical evidence from the Middle East, particularly Kuwait, where digital transformation in education is an emerging priority. Moreover, the relative insignificance of usage frequency observed in some studies suggests the need to revisit assumptions about quantity of use vs. quality and integration.

Therefore, this study addresses the research gap by examining the combined effects of AMQ, EOI, and UFAM on LEF, with STE and TSE as mediating variables, using empirical evidence from Kuwait's Colleges of Basic Education.

# 4 Research methodology

To guide the empirical analysis, this study adopted a quantitative, cross-sectional research design using survey methodology. Structural Equation Modeling (SEM) was employed as the primary analytical technique, given its ability to simultaneously test complex relationships among multiple independent, mediating, and dependent variables. SEM is particularly suited for validating measurement models while also examining direct and indirect effects within the proposed conceptual framework (Hair et al., 2013). The adoption of this approach ensured methodological rigor and provided a robust basis for testing the study hypotheses.

### 4.1 The hypothetical model

The hypothetical model developed for this study is grounded in established theories of technology acceptance and learning effectiveness, particularly the Technology Acceptance Model (TAM) (Davis, 1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), Self-efficacy theory (SET), and the Self-Determination Theory (SDT) (Deci and Ryan, 1985). Drawing on these frameworks, the model integrates cognitive, motivational, and behavioral dimensions to explain how AI-enhanced multimedia impacts student learning outcomes. The predictors—AMQ, EOI, and UFAM represent key attributes influencing technology adoption and utilization. The mediators -STE, supported by SDT, and TSE grounded in self-efficacy theory, capture the psychological, motivational, and participatory mechanisms through which these predictors translate into improved LEF. By integrating these perspectives, the model provides a comprehensive theoretical foundation for understanding how AI-driven educational technologies shape learning experiences in Kuwait's Basic Education context.

In the hypothetical model, nostalgia is conceptualized as a cognitive–affective memory-based construct reflecting symbolic attachment to the past, while technical immersion denotes system-driven sensory and interactive depth, and affective immersion captures emotional absorption during gameplay in the multimedia usage for educational purposes (Alsaffar, 2025). These constructs are theoretically distinct yet sequentially linked, where nostalgia initiates meaning, technical immersion enables experience, and affective immersion mediates emotional student engagement, jointly justifying their roles within the mediation framework.

#### 4.1.1 Linkage between AMO and STE

High-quality multimedia resources are expected to foster greater STE by providing clarity, interactivity, and relevance to the learning process. When AI-enhanced multimedia is perceived as effective and well-designed, students are more likely to demonstrate higher levels of cognitive and behavioral engagement. Prior research emphasizes that engaging instructional tools significantly influence participation and attentiveness in classroom environments (Fredricks et al., 2004). Empirical studies further show that multimedia quality enhances learner involvement, satisfaction, and perceived usefulness (Alsaffar et al., 2022; Gray and DiLoreto, 2016). Recent evidence on AI-mediated learning also highlights quality as a determinant of student motivation and engagement (Bhatt and Muduli, 2024). Hence, the following hypothesis is developed.

H1: There is a significant and positive relationship between AMO and STE.

#### 4.1.2 Linkage between AMO and TSE

AMQ plays a crucial role in shaping TSE of the student, as well-structured and interactive resources foster confidence in navigating digital learning environments. When multimedia tools are perceived as reliable and user-friendly, learners are more likely to believe in their ability to use such technologies effectively. Prior studies highlight that high-quality digital content enhances learners' competence and reduces apprehension toward technology (Compeau and Higgins, 1995). Similarly, self-efficacy is strongly linked to improved technology adoption and learning outcomes (Paz-Baruch, 2025). Recent evidence also confirms that scaffolding through quality multimedia enhances students' perceived capabilities in AI-driven education (Allagui, 2024). Hence, the following hypothesis is developed.

H2: There is a significant and positive relationship between AMO and TSE.

#### 4.1.3 Linkage between UFAM and STE

The frequency of multimedia usage is often associated with higher levels of STE, as consistent exposure reinforces active participation and sustained interest in learning activities. Regular use of AI-enhanced tools provides opportunities for learners to interact with content, collaborate, and develop meaningful connections with course material. Prior studies indicate that repeated use of digital platforms significantly influences behavioral and cognitive engagement (Fredricks et al., 2004). Empirical evidence in mobile and e-learning contexts also confirms that higher frequency of use leads to stronger intention and engagement (Park et al., 2012). Similarly, AI-based studies show usage as a predictor of enhanced engagement outcomes (Bhatt and Muduli, 2024). Hence, the following hypothesis is developed.

H3: There is a significant and positive relationship between UFAM and STE.

#### 4.1.4 Linkage between UFAM and TSE

Frequent usage of AI-enhanced multimedia is expected to strengthen TSE, as consistent interaction with digital tools provides learners with mastery experiences that build confidence in their technological abilities. Repeated practice helps reduce uncertainty, enhances familiarity, and supports competence development in using multimedia systems. Prior research highlights that usage intensity positively influences perceptions of technological capability (Compeau and Higgins, 1995). Similarly, empirical studies show that higher exposure to digital tools promotes stronger self-efficacy beliefs and better performance outcomes (Paz-Baruch, 2025). More recent findings also confirm that guided and repeated AI-mediated learning experiences significantly enhance learners' self-efficacy (Allagui, 2024). Hence, the following hypothesis is developed.

H4: There is a significant and positive relationship between UFAM and TSE.

#### 4.1.5 Linkage between EOI and STE

EOI of AI-enhanced multimedia into teaching and learning contexts is a key driver of STE. When digital tools can be seamlessly embedded into classroom practices without excessive effort, students are more likely to interact with them actively and meaningfully. Prior studies confirm that well-integrated educational technologies foster higher levels of attentiveness and participation (Fredricks et al., 2004). Research on ICT adoption further indicates that integration ease positively influences engagement and satisfaction in learning environments

(Sun and Chen, 2016). More recent evidence highlights that smooth incorporation of AI-enhanced systems promotes student involvement and collaborative engagement (Wu et al., 2024). Hence, the following hypothesis is developed.

H5: There is a significant and positive relationship between EOI and STE.

### 4.1.6 Linkage between EOI and TSE

EOI of AI-enhanced multimedia is closely linked to the development of TSE, as systems that are simple to adopt and align with instructional practices foster learners' confidence in their ability to use them effectively. When technologies require minimal effort to embed into coursework, students are more likely to perceive themselves as capable of managing and benefiting from them. Prior research emphasizes that seamless integration enhances both self-efficacy and learning efficiency (Compeau and Higgins, 1995). Similarly, Sun and Chen (2016) reported that integration ease supports confidence in technology-mediated learning. Recent studies further highlight that simplified AI integration strengthens user self-efficacy and overall adoption (Allagui, 2024). Hence, the following hypothesis is developed.

H6: There is a significant and positive relationship between EOI and TSE.

### 4.1.7 Linkage between STE and LEF

STE is a critical determinant of LEF, as higher levels of cognitive, emotional, and behavioral involvement directly translate into improved comprehension, retention, and academic performance. Engaged students are more attentive, motivated, and willing to invest effort, thereby achieving deeper learning outcomes. Fredricks et al. (2004) emphasized that engagement is strongly predictive of persistence and achievement in educational settings. Similarly, Gray and DiLoreto (2016) demonstrated that student satisfaction and engagement significantly influence perceived learning effectiveness in online environments. More recent findings affirm that active engagement in AI-mediated learning fosters resilience, motivation, and improved academic results (Yang et al., 2025). Hence, the following hypothesis is developed.

H7: There is a significant and positive relationship between STE and LEF.

### 4.1.8 Linkage between TSE and LEF

TSE significantly influences LEF, as students who feel confident in their ability to use AI-enhanced multimedia are more likely to engage actively and achieve better academic outcomes. Self-efficacy fosters persistence, problem-solving, and resilience in technology-mediated tasks, which directly enhance comprehension and performance. Compeau and Higgins (1995) identified self-efficacy as a central predictor of effective technology adoption and use. Similarly, Zimmerman (2000) emphasized the role of self-efficacy in self-regulated learning and achievement. More recent evidence shows that strengthened self-efficacy in AI-supported environments contributes to improved academic motivation and measurable learning gains (Paz-Baruch, 2025). Hence, the following hypothesis is developed.

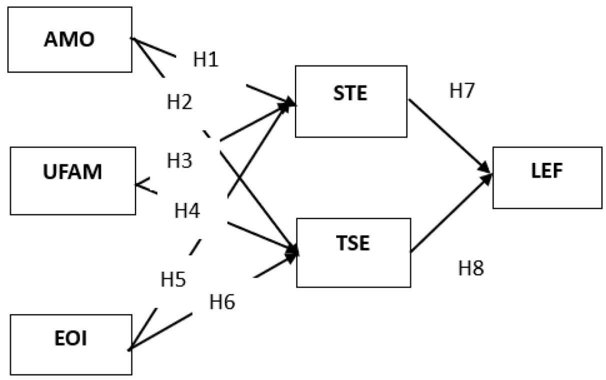


FIGURE 1
The hypothetical model. AMQ, AI-Enhanced Multimedia Quality; UFAM, Usage Frequency of AI-Enhanced Multimedia; EOI, Ease of Integration; STE, Student Engagement; TSE, Technology Self-Efficacy; LEF, Learning Effectiveness.

H8: There is a significant and positive relationship between TSE and LEF.

The hypothetical model is shown in Figure 1.

## 4.2 Metric development

In this study, we utilized validated measurement scales to measure the primary constructs, adapting specific items to suit our research context while maintaining their conceptual clarity. To verify the psychometric properties of these adapted measures, we conducted confirmatory factor analysis (CFA), which supported their reliability and validity. The dimensions, meaning, scales and contributing authors, and items chosen are provided in Table 1. Initially five items were chosen for each dimension from the standard scales and through factor reduction they were reduced to three items each through the pilot study using confirmatory factor analysis (CFA) with a sample size of 30 (about 10–20% of the primary sample size) (Julious, 2005).

Measurement items adapted from established, peer-reviewed scales to fit the research context while preserving their original conceptual meanings. Content validity was ensured through expert review and minor wording refinements. Factor structure was validated using confirmatory factor analysis, assessing item loadings, cross-loadings, and model fit indices using a pilot study conducted with a sample size of 35. Items with low loadings or conceptual overlap were removed, resulting in a parsimonious and theoretically coherent measurement model with robust construct validity.

## 4.3 Research design

This study adopted a quantitative, cross-sectional research design to investigate the relationships among the research constructs. The cross-sectional approach allowed data collection at a single point in time providing a snapshot of students' perceptions

TABLE 1 The dimensions, meaning, scales and contributing authors, and items chosen.

| Dimension | Meaning | Scales and authors | Items chosen |
|---|---|---|---|
| AI-Enhanced Multimedia Quality (AMQ) | The perceived effectiveness, clarity, and interactivity of AI-driven multimedia in supporting learning. | Adapted from Binti Mohd et al. (2024); Sun and Chen (2016). | 1. The multimedia content is clear and easy to understand. |
| | | | 2. The design of the AI-enhanced multimedia is visually appealing. |
| | | | 3. The multimedia provides interactive features that aid learning. |
| | | | 4. The content quality matches the course objectives. |
| | | | 5. The multimedia supports critical thinking and deeper understanding. |
| Ease of Integration (EOI) | The degree to which AI-enhanced multimedia can be seamlessly incorporated into teaching and learning. | Adapted from Davis (1989); Teo (2011). | 1. AI-enhanced multimedia can be easily integrated into classroom activities. |
| | | | 2. It is simple to align multimedia tools with curriculum content. |
| | | | 3. Using multimedia does not require much additional effort. |
| | | | 4. Multimedia fits naturally into my teaching/learning style. |
| | | | 5. Multimedia tools save time during lessons. |
| Usage Frequency of AI-Enhanced Multimedia (UFAM) | How often faculty/students make use of multimedia tools enhanced by AI. | Adapted from Venkatesh et al. (2003); Park et al. (2012). | 1. I frequently use AI-driven multimedia for class activities. |
| | | | 2. I regularly engage with multimedia tools during coursework. |
| | | | 3. AI-enhanced multimedia is part of my daily study/teaching routine. |
| | | | 4. I rely on multimedia to complete assignments. |
| | | | 5. Multimedia tools are consistently used across different subjects. |
| Student Engagement (STE) | The level of active participation, attention, and interest students show when using AI-enhanced multimedia. | Adapted from Fredricks et al. (2004); Wang (2020). | 1. I feel more engaged in class when AI-driven multimedia is used. |
| | | | 2. Multimedia motivates me to participate actively. |
| | | | 3. I concentrate more during multimedia-supported lessons. |
| | | | 4. Multimedia helps me stay interested throughout the class. |
| | | | 5. I am more involved in discussions when multimedia is used. |
| Technology Self-Efficacy (TSE) | The confidence in one's ability to effectively use AI-enhanced multimedia for learning. | Adapted from Compeau and Higgins (1995); Teo (2011). | 1. I am confident in my ability to use AI-driven multimedia tools. |
| | | | 2. I can troubleshoot minor issues when using multimedia. |
| | | | 3. I feel capable of learning through AI-based multimedia systems. |
| | | | 4. I believe I can integrate multimedia tools effectively into my studies. |
| | | | 5. I can use multimedia tools without assistance from others. |
| Learning Effectiveness (LEF) | The extent to which AI-enhanced multimedia improves comprehension, retention, and academic performance. | Adapted from Sun and Chen (2016); Binti Mohd et al. (2024). | 1. AI-driven multimedia improves my understanding of course material. |

*(Continued)*

TABLE 1 (Continued)

| Dimension | Meaning | Scales and authors | Items chosen |
|---|---|---|---|
| | | | 2. I retain knowledge better when multimedia is used. |
| | | | 3. Multimedia contributes to better academic performance. |
| | | | 4. I apply what I learn more effectively through multimedia. |
| | | | 5. AI-enhanced multimedia improves overall learning outcomes. |

and experiences within the Colleges of Basic Education in Kuwait. Given the objective of testing hypothesized pathways, the design was supported by the use of structural equation modeling (SEM), which is well-suited for examining both direct and indirect effects in complex theoretical frameworks (Hair et al., 2013). This design ensured methodological rigor while aligning with the study's focus on validating relationships between theoretical constructs and empirical evidence.

### 4.4 The sample design

This study employed a convenience sampling technique, selected for its accessibility and practical feasibility in line with the research objectives and available resources. The target population consisted of students from the Colleges of Basic Education in Kuwait, chosen to capture their perspectives on multimedia interactivity, visual design quality, and access frequency in relation to academic motivation. Since students represent the direct end-users of these educational technologies, their insights provide valuable input for decision-makers in the education sector, making this cohort particularly suitable for the present research.

The study employed participants with prior experience of multimedia interactivity. Respondents were recruited through online forums and social media platforms. Inclusion criteria required participants to be at least 18 years old, active multimedia user in basic Educational Colleges within atleast the past one year, and familiar with multimedia interactivity environments.

The study sample comprised 232 students, selected using a convenience sampling approach. As noted by Hair et al. (2013), a minimum of 200 participants is considered adequate for Structural Equation Modeling (SEM), while Wolf et al. (2013) recommend at least 10 observations per estimated parameter, equivalent to 180 in this study. Both criteria were satisfied by the chosen sample size. Additionally, a G*Power analysis was conducted to further validate adequacy. For a linear regression fixed model, for *post-hoc* power analysis with a medium effect size ($f^2 = 0.15$), an alpha error probability of 0.05, five predictors, and the sample size of 232, the power estimation was 0.99, exceeding the recommended threshold of 0.80. This confirms the statistical adequacy of the sample size for robust hypothesis testing (Figure 2).

### 4.5 Ethical clearance

Ethical approval for data collection was secured from the Institutional Ethical Clearance Committee (IECC). Participation in the study was voluntary, with all respondents informed of the research objectives prior to data collection. To protect participant rights, anonymity and confidentiality were strictly upheld, ensuring that no identifying information was recorded or disclosed. Informed consent was obtained from every participant, and they were explicitly assured of their right to withdraw from the study at any stage without penalty. The research process was conducted in full compliance with institutional requirements and international ethical standards governing studies involving human participants.

## 5 Results and analysis

The analysis of results was conducted in two stages: descriptive statistics and inferential statistics. The measurement model in Structural Equation Modeling (SEM) was employed to assess the descriptive statistics, while the structural model was utilized to perform the inferential statistics in the form of hypothesis testing.

### 5.1 The sample distribution

Based on the nature of this research, data were collected from a total of 232 students across six departments in the Colleges of Basic Education, Kuwait. The distribution was as follows: Department of Educational Technology (36 students, 15.5%), Department of Curriculum and Teaching Methods (34 students, 14.7%), Computer Department (36 students, 15.5%), Department of English Language (28 students, 12.1%), Department of Science (48 students, 20.7%), and Department of Mathematics (50 students, 21.6%). The proportional allocation across departments ensured that no single group was overrepresented or underrepresented. By maintaining approximate balance in participant numbers relative to departmental size, the sampling strategy can be considered both fair and unbiased, thereby enhancing the representativeness of the findings across the varied academic disciplines included in the study.

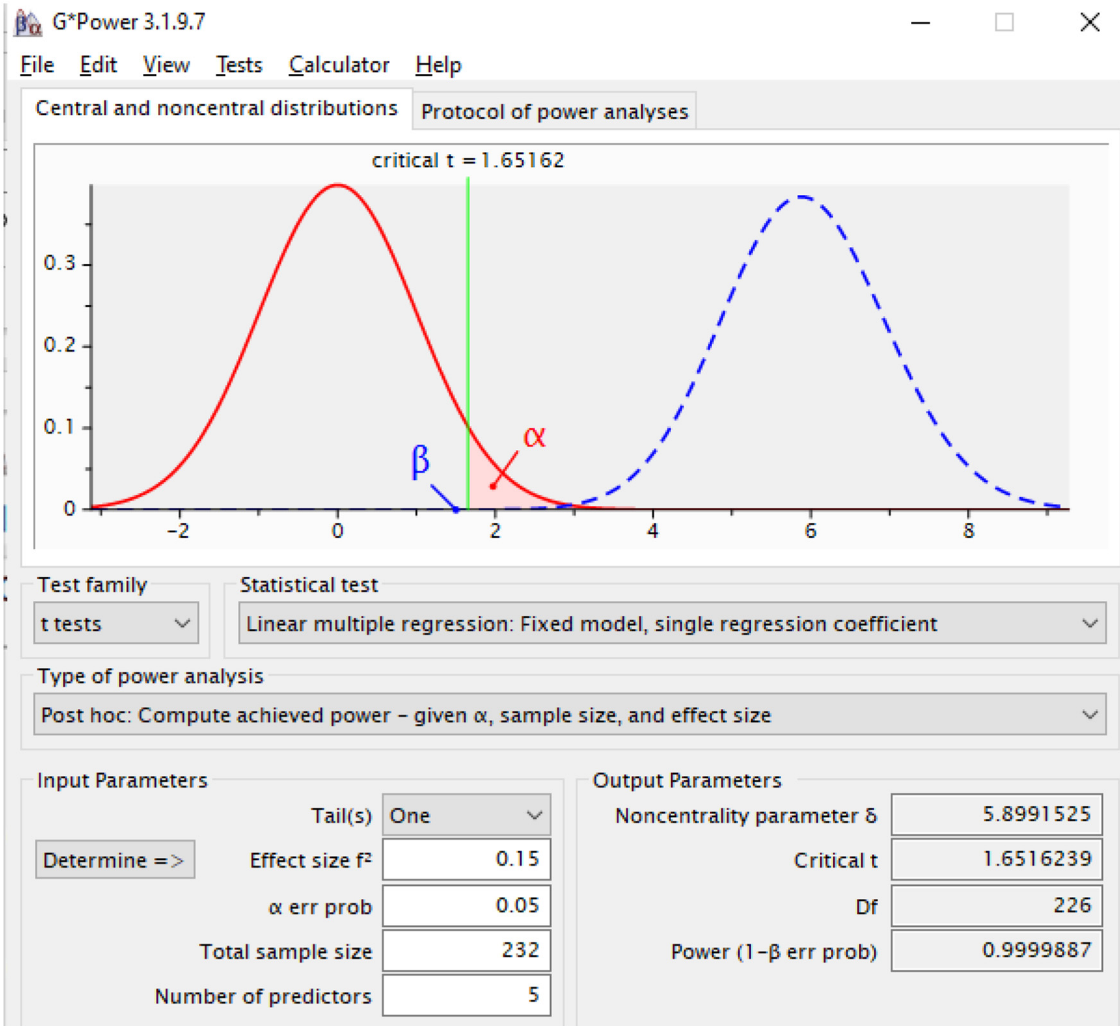


FIGURE 2
Sample size adequacy through G*Power estimation.

## 5.2 The measurement model

The factor loadings for all measurement items were above the threshold value of 0.70, confirming strong indicator reliability (cut off 0.6; Hair et al., 2019). Within AMQ, the loadings ranged from 0.806 to 0.880, while EOI items ranged between 0.770 and 0.852 (Table 2, Figure 3). LEF items showed the highest loadings, ranging from 0.924 to 0.933. STE recorded loadings between 0.876 and 0.911, TSE between 0.878 and 0.925, and UFAM between 0.850 and 0.905. These results establish that all constructs demonstrated adequate indicator reliability.

The internal consistency of the constructs was evaluated using Cronbach's alpha, rho_A, and composite reliability (CR). Cronbach's alpha values exceeded the recommended benchmark of 0.70 (Taber, 2018) across all constructs, ranging from 0.725 (EOI) to 0.920 (LEF). Similarly, rho_A values were all above 0.70, with the lowest recorded for EOI (0.734) and the highest for LEF (0.921) (Table 2; Taber, 2018). Composite reliability values ranged from 0.845 for EOI to 0.949 for LEF, again exceeding the acceptable cutoff, further confirm internal consistency-based reliability (cutoff of 0.6; Mustafa et al., 2020).

Convergent validity was examined through the average variance extracted (AVE). All AVE values exceeded the recommended minimum of 0.50 (Shrestha, 2021), indicating that each construct accounted for more than 50% of the variance in its indicators. Specifically, AMQ (0.708), EOI (0.645), LEF (0.862), STE (0.800), TSE (0.806), and UFAM (0.783) (Table 2) all demonstrated sufficient convergent validity. Among these, LEF displayed the highest AVE, reflecting strong shared variance between its items.

The measurement model demonstrates satisfactory reliability and convergent validity, as all constructs meet the required thresholds for factor loadings, internal consistency measures, and AVE values. This establishes the robustness of the constructs and supports their suitability for further structural equation modeling analysis.

The R-square values indicate the proportion of variance explained by the predictors in the model for each dependent

TABLE 2 Reliability and validity.

| Construct | Items | Factor loadings | Cronbach's alpha | Rho_a | Composite reliability | Average variance extracted (AVE) |
|---|---|---|---|---|---|---|
| AMQ | AMQ1 | 0.806 | 0.794 | 0.800 | 0.879 | 0.708 |
| | AMQ2 | 0.880 | | | | |
| | AMQ3 | 0.836 | | | | |
| EOI | EOI1 | 0.770 | 0.725 | 0.734 | 0.845 | 0.645 |
| | EOI2 | 0.852 | | | | |
| | EOI3 | 0.786 | | | | |
| LEF | LEF1 | 0.928 | 0.920 | 0.921 | 0.949 | 0.862 |
| | LEF2 | 0.924 | | | | |
| | LEF3 | 0.933 | | | | |
| STE | STE1 | 0.896 | 0.875 | 0.881 | 0.923 | 0.800 |
| | STE2 | 0.911 | | | | |
| | STE3 | 0.876 | | | | |
| TSE | TSE1 | 0.878 | 0.880 | 0.883 | 0.926 | 0.806 |
| | TSE2 | 0.925 | | | | |
| | TSE3 | 0.890 | | | | |
| UFAM | UFAM1 | 0.905 | 0.862 | 0.868 | 0.916 | 0.783 |
| | UFAM2 | 0.850 | | | | |
| | UFAM3 | 0.900 | | | | |

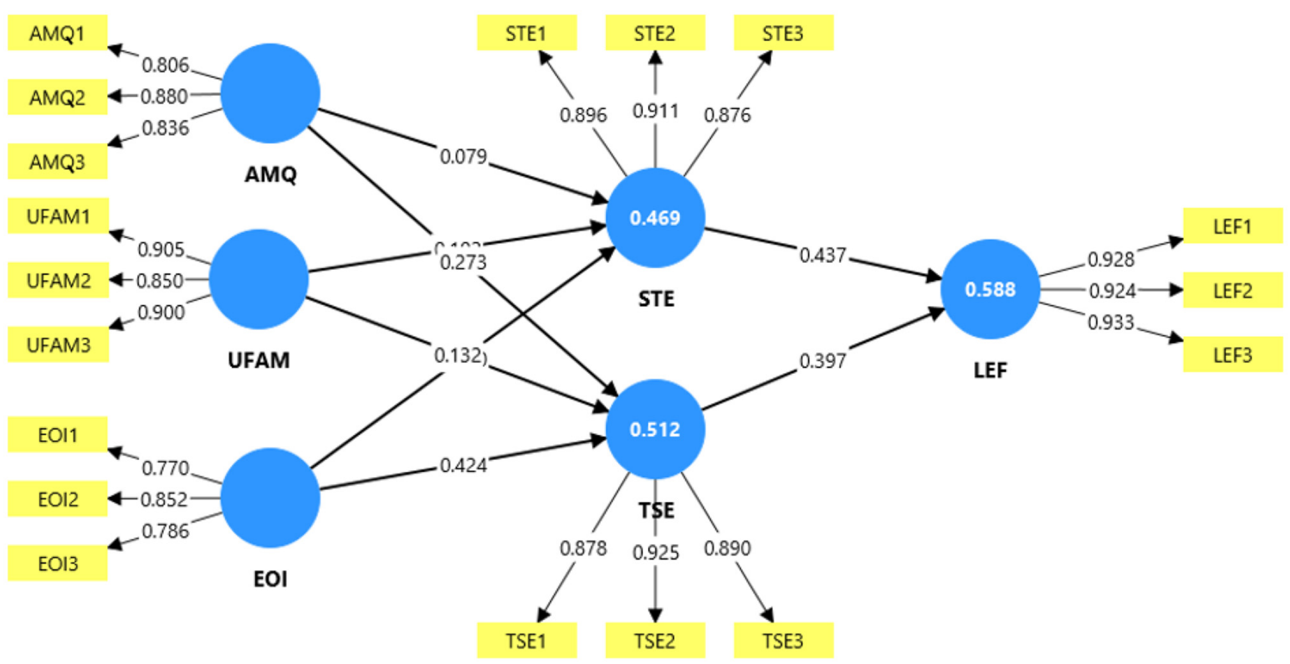


FIGURE 3
The measurement model.

construct. Specifically, 46.9% of the variance in STE, 51.2% in TSE and 58.8% in LEF (Figure 3) are explained by their respective independent variables. These values suggest a moderate to substantial level of explanatory power (Cut off 0.1; Hair et al., 2019), reflecting that the model accounts for a meaningful portion of the variation in these key academic outcomes.

Psychometric validity was established through confirmatory factor analysis, demonstrating satisfactory factor loadings,

TABLE 3 The inter-item correlations.

| | AMO | EOI | LEF | STE | TSE | UFAM |
|---|---|---|---|---|---|---|
| AMO | **0.841** | | | | | |
| EOI | 0.790 | **0.803** | | | | |
| LEF | 0.710 | 0.780 | **0.928** | | | |
| STE | 0.562 | 0.734 | 0.790 | **0.894** | | |
| TSE | 0.712 | 0.730 | 0.775 | 0.786 | **0.898** | |
| UFAM | 0.640 | 0.710 | 0.674 | 0.532 | 0.592 | **0.885** |

composite reliability, and average variance extracted for all constructs. Discriminant validity was confirmed using the Fornell–Larcker criterion, ensuring clear conceptual separation among the latent variables.

Table 3 presents the inter-item correlations among the study constructs. The diagonal values, representing the square root of the Average Variance Extracted (AVE), all exceed 0.70, indicating strong convergent validity and confirming that each construct is well-measured. The correlation analysis shows that EOI has the strongest associations with LEF ($r = 0.780$) and STE ($r = 0.734$), suggesting that ease of integrating AI-enhanced multimedia is a critical factor in shaping both learning outcomes and student engagement. TSE also demonstrates high correlations with LEF ($r = 0.775$) and STE ($r = 0.786$), reinforcing its role as a cognitive mechanism that links technology use with improved academic performance. AMQ is strongly correlated with both EOI ($r = 0.790$) and TSE ($r = 0.712$), highlighting the interconnectedness of multimedia quality, ease of use, and learner confidence. By contrast, UFAM shows only moderate correlations, particularly with STE ($r = 0.532$) and TSE ($r = 0.592$), implying that frequency of use alone may not guarantee deeper engagement or confidence in technology use. Overall, the correlation matrix provides evidence of discriminant validity and supports the structural pathways tested in the model. Importantly, all inter-construct correlations were lower than the corresponding AVE square root values, satisfying the Fornell-Larcker criterion (Ahmad et al., 2016) and establishing discriminant validity, ensuring that each construct remains empirically distinct while demonstrating significant associations.

## 5.3 The structural model

Table 4, Figure 4 report the structural model results, including path coefficients, t-statistics, and significant levels. Among the hypothesized relationships, most paths were supported at conventional significance levels. AMQ significantly influenced LEF ($\beta = 0.143$, $t = 2.142$, $p = 0.032$) and TSE ($\beta = 0.273$, $t = 2.730$, $p = 0.006$), while its effect on STE was not supported ($p = 0.345$). EOI demonstrated strong and significant effects on LEF ($\beta = 0.417$, $t = 7.422$, $p < 0.001$), STE ($\beta = 0.570$, $t = 7.615$, $p < 0.001$), and TSE ($\beta = 0.424$, $t = 5.441$, $p < 0.001$). Both STE ($\beta = 0.437$, $t = 5.292$, $p < 0.001$) and TSE ($\beta = 0.397$, $t = 4.087$, $p < 0.001$) were significant predictors of LEF, highlighting their mediating role. In contrast, UFAM did not significantly influence LEF, STE, or TSE (all $p > 0.05$), indicating limited direct impact in the model.

To strengthen the mediation analysis, indirect effects were tested using bootstrapping with 5,000 resamples, allowing robust estimation of confidence intervals. Both direct and indirect paths were examined simultaneously to distinguish partial and full mediation effects. The significance of mediators was confirmed only when bias-corrected confidence intervals excluded zero, ensuring rigorous and transparent mediation assessment.

Table 5 presents the mediation analysis results, examining the indirect effects of AMQ, EOI, and UFAM on LEF through the mediators TSE and STE. The findings indicate that UFAM did not exert significant indirect effects on LEF via either TSE ($\beta = 0.052$, $t = 1.420$, $p = 0.156$) or STE ($\beta = 0.045$, $t = 1.319$, $p = 0.187$), rendering both hypotheses unsupported. For AMQ, mediation through TSE was significant ($\beta = 0.108$, $t = 2.280$, $p = 0.023$), confirming a partial mediating effect, whereas the path through STE was not supported ($p = 0.355$). In contrast, EOI exhibited strong indirect effects on LEF through both mediators, with TSE ($\beta = 0.168$, $t = 3.137$, $p = 0.002$) and STE ($\beta = 0.249$, $t = 4.012$, $p < 0.001$) fully supported. These results underscore the mediating roles of TSE and STE in linking EOI, and to a lesser extent AMQ with enhanced learning effectiveness.

# 6 Discussions

The findings of this study facilitated through hypothesis testing extend prior research on the role of AI-enhanced multimedia in higher education by highlighting both direct and mediated pathways to LEF. In the direct relationships, AMQ showed a significant effect on LEF and TSE but not on STE. This partially aligns with earlier work suggesting that multimedia quality improves learners' confidence in technology adoption (Al-Emran et al., 2025) but contradicts studies that reported a strong positive effect on engagement (Gray and DiLoreto, 2016). The non-significant effect on STE suggests that quality alone may not be sufficient to stimulate engagement, particularly when AI integration is still at an early adoption stage. This may also imply that students perceive quality more in terms of usability and reliability rather than as a direct motivator for interaction, thereby reinforcing the role of self-efficacy as the key psychological mechanism.

EOI emerged as the most robust predictor, positively influencing LEF, TSE, and STE. These results are consistent with earlier studies emphasizing the centrality of seamless integration in driving both engagement and self-efficacy (Wu et al., 2024). The finding underscores that tools perceived as effortless to incorporate within classroom activities not only enhance students' confidence but also create conditions for deeper participation and improved outcomes. In contrast, UFAM did not significantly influence LEF, TSE, or STE, a finding that diverges from prior studies that linked higher usage frequency with improved academic outcomes (Mouza and Lavigne, 2013). This discrepancy may indicate that frequency alone is less important than the perceived usefulness and integration quality of AI tools. It also suggests that repetitive exposure without meaningful engagement does not necessarily

TABLE 4 The *t*-statistic.

| Relationship | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | *t* statistics | *p* values | Hypothesis |
|---|---|---|---|---|---|---|
| AMQ -> LEF | 0.143 | 0.140 | 0.067 | 2.142 | 0.032 | **Supported** |
| AMQ -> STE | 0.079 | 0.079 | 0.083 | 0.943 | 0.345 | Unsupported |
| AMQ -> TSE | 0.273 | 0.268 | 0.100 | 2.730 | 0.006 | **Supported** |
| EOI -> LEF | 0.417 | 0.422 | 0.056 | 7.422 | 0.000 | **Supported** |
| EOI -> STE | 0.570 | 0.574 | 0.075 | 7.615 | 0.000 | **Supported** |
| EOI -> TSE | 0.424 | 0.427 | 0.078 | 5.441 | 0.000 | **Supported** |
| STE -> LEF | 0.437 | 0.437 | 0.083 | 5.292 | 0.000 | **Supported** |
| TSE -> LEF | 0.397 | 0.397 | 0.097 | 4.087 | 0.000 | **Supported** |
| UFAM -> LEF | 0.097 | 0.102 | 0.055 | 1.760 | 0.078 | Unsupported |
| UFAM -> STE | 0.102 | 0.104 | 0.073 | 1.396 | 0.163 | Unsupported |
| UFAM -> TSE | 0.132 | 0.137 | 0.077 | 1.714 | 0.087 | Unsupported |

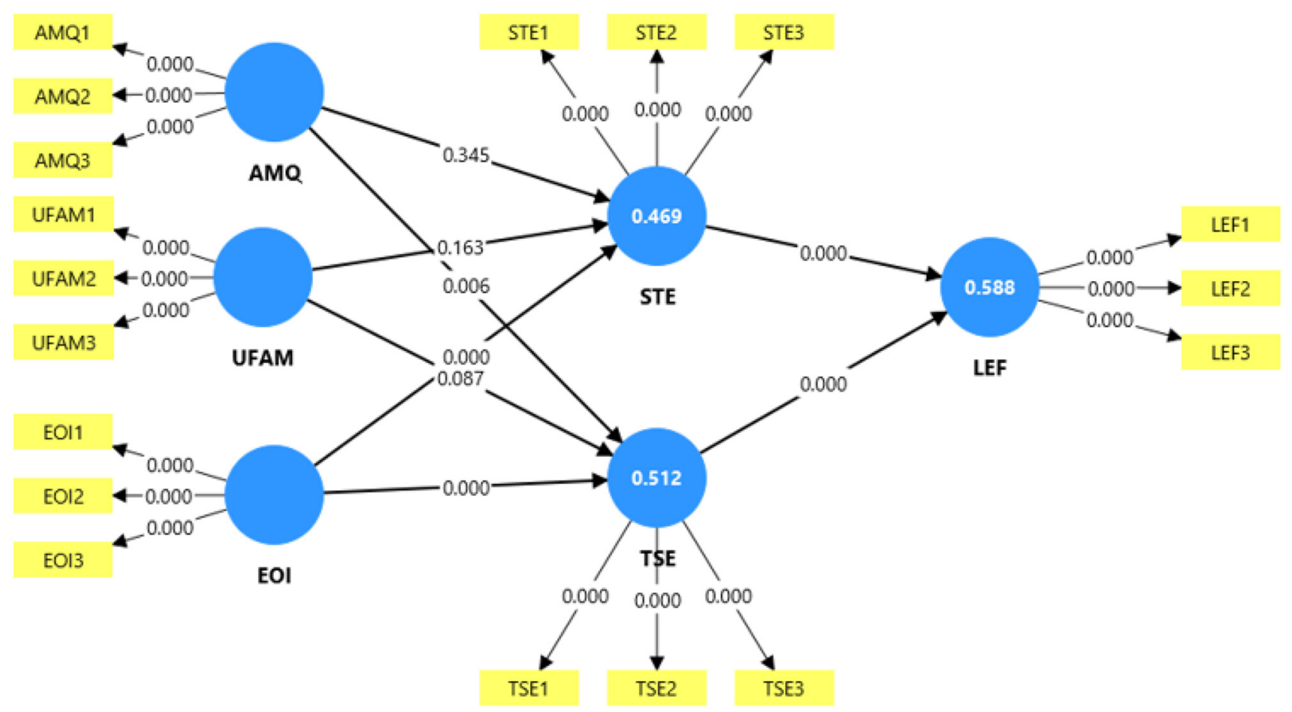


FIGURE 4
The structural model.

yield better results, highlighting the importance of context-driven and purposeful use.

The mediation analysis provided further insights. TSE mediated the relationship between AMQ and LEF, in line with earlier findings that self-efficacy often acts as a bridge between technological features and learning outcomes (Chang et al., 2025). However, STE did not mediate this relationship, contradicting studies where engagement was found to be a critical pathway linking multimedia attributes with performance (Fredricks et al., 2004). This indicates that engagement may require more than quality; factors such as interactivity, collaborative opportunities, and relevance to student goals could be necessary to activate this pathway. For EOI, both STE and TSE significantly mediated its effect on LEF, confirming earlier work that highlighted the dual role of engagement and self-efficacy in explaining the effectiveness of well-integrated multimedia systems (Davis, 1989; Allagui, 2024). Conversely, UFAM showed no significant mediation through either STE or TSE, diverging from prior findings that emphasized usage as a driver of psychological and behavioral engagement (Bhatt and Muduli, 2024; Park et al., 2012).

TABLE 5 Mediation analysis.

| Mediation | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | *t* statistics | *p* values | Hypothesis |
|---|---|---|---|---|---|---|
| UFAM -> TSE -> LEF | 0.052 | 0.056 | 0.037 | 1.420 | 0.156 | Unsupported |
| UFAM -> STE -> LEF | 0.045 | 0.046 | 0.034 | 1.319 | 0.187 | Unsupported |
| AMQ -> TSE -> LEF | 0.108 | 0.106 | 0.047 | 2.280 | 0.023 | **Supported** |
| AMQ -> STE -> LEF | 0.034 | 0.034 | 0.037 | 0.925 | 0.355 | Unsupported |
| EOI -> TSE -> LEF | 0.168 | 0.170 | 0.054 | 3.137 | 0.002 | **Supported** |
| EOI -> STE -> LEF | 0.249 | 0.252 | 0.062 | 4.012 | 0.000 | **Supported** |

The results suggest that while multimedia quality and integration remain central drivers of learning effectiveness, the mediating mechanisms differ depending on whether engagement or self-efficacy is emphasized. These findings both align with and challenge existing evidence, underscoring the complexity of AI-enhanced multimedia adoption in educational contexts. Importantly, they highlight that successful implementation requires more than access and frequency—it depends on building confidence, aligning with pedagogical practices, and fostering active participation to maximize the transformative potential of AI in education.

## 7 Theoretical implications

This study makes several contributions to theory by extending and refining existing models of technology adoption and learning effectiveness in higher education. The findings reinforce the applicability of the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) by demonstrating that EOI serves as a pivotal construct influencing both TSE and STE, which in turn enhance LEF. While TAM emphasizes perceived ease of use and usefulness, the results suggest that seamless integration of AI-enhanced multimedia provides a stronger explanatory mechanism than mere frequency of use, thereby refining the theoretical scope of technology acceptance. By foregrounding integration as a central determinant, this research advances the understanding that adoption is not only a matter of willingness to use but also of how effortlessly tools can be embedded into the learning environment.

The study contributes to the literature on self-efficacy theory (Bandura, 1997) by confirming the mediating role of TSE in linking multimedia quality and integration with learning outcomes. This supports the view that confidence in using AI-enhanced tools is not simply an outcome of adoption but a central theoretical construct mediating educational effectiveness. Importantly, this positions TSE as both a psychological outcome and a mechanism for sustained learning, providing a more nuanced understanding of how cognitive appraisals shape academic performance in AI-mediated contexts.

The findings challenge prior frameworks that place usage frequency as a central driver of learning outcomes. The lack of significant direct and indirect effects of UFAM on LEF suggests that theoretical models should account for qualitative dimensions of technology adoption such as perceived quality and integration rather than treating usage intensity as inherently beneficial. This distinction broadens theoretical discussions by shifting focus from quantitative measures of use to experiential and contextual factors that ultimately determine effectiveness.

The mediation results provide evidence for a dual-path theoretical framework, where both cognitive (TSE) and behavioral (STE) mediators operate simultaneously to explain the impact of AI-enhanced multimedia on learning. This extends existing theoretical models by highlighting the necessity of integrating psychological and behavioral dimensions within a unified explanatory framework for AI-supported learning environments. By acknowledging the complementary nature of engagement and self-efficacy, this study enriches theory with a more holistic model that can guide future investigations into the interplay between technology features, learner psychology, and educational outcomes.

This study advances theory by clarifying how nostalgia operates as an antecedent psychological mechanism that shapes immersion and behavioral intention, extending affect-based consumption and experiential AI-Enhanced Multimedia usage in education.

## 8 Practical implications

The results of this study offer several practical insights for educators, administrators, and policymakers in Basic Education colleges. The strong influence of EOI on both TSE and STE underscores the importance of designing AI-enhanced multimedia tools that are simple to adopt within existing curricula. Institutions in Kuwait should therefore prioritize user-friendly platforms that align with the Ministry of Education's digital transformation agenda while minimizing technical challenges for faculty and students. Ensuring that multimedia systems are compatible with existing infrastructure will reduce barriers to adoption and allow for smoother integration into day-to-day teaching practices.

The mediating role of TSE suggests that training and capacity-building initiatives are essential. Faculty members and students alike need opportunities to build confidence in navigating AI-driven systems. Colleges could implement structured workshops, continuous professional development sessions, and peer-support initiatives to address varying levels of digital readiness across departments. Such efforts would not only build technological competence but also create a culture of innovation that motivates both faculty and students to engage with new tools.

The significant role of STE as a mediator highlights the need to incorporate multimedia features that promote interactivity and collaboration. For the Kuwaiti context, this could involve embedding AI-driven simulations, gamified content, or adaptive assessments into courses, which would foster higher participation levels among students accustomed to traditional lecture-based formats. Such practices can enhance classroom dynamics and improve long-term learning outcomes.

The lack of significant effects for UFAM indicates that institutions should shift their focus away from promoting sheer frequency of tool use toward fostering meaningful and contextually relevant integration. For the Colleges of Basic Education, this means that policy frameworks should emphasize quality, curricular alignment, and instructional relevance rather than simply measuring adoption rates.

Practically, the findings guide game designers and cultural content developers to strategically embed nostalgic cues alongside technically rich environments to enhance affective immersion, thereby improving user engagement and sustained intention toward ancient-style digital games.

At a broader level, these implications directly align with Kuwait Vision 2035, which emphasizes human capital development, innovation, and the integration of digital technologies in education. By promoting effective AI-enhanced multimedia adoption, Basic Education colleges can serve as pioneers in operationalizing this vision, equipping students with future-ready skills while enhancing teaching effectiveness. Embedding AI-driven learning practices within Kuwait's education system also supports the national agenda of transitioning toward a knowledge-based economy, ensuring that digital transformation efforts in higher education are both sustainable and socially impactful.

The non-significant or weaker effects observed for certain direct paths suggest that nostalgia alone may be insufficient to influence behavioral intention without immersive mediation. This unexpected finding highlights the conditional role of experiential depth, indicating that nostalgic meaning must be activated through technical and affective immersion. Such results refine existing assumptions and underscore the importance of mediation mechanisms rather than direct-effect models.

The non-significant impact of usage frequency suggests that institutional strategies should move beyond encouraging repeated exposure to AI-enhanced multimedia. Instead, emphasis must be placed on purposeful instructional design, alignment with learning objectives, and seamless pedagogical integration. This finding implies that learning effectiveness is driven more by how and why multimedia is used rather than how often. Policymakers and educators should therefore invest in faculty training, curriculum alignment, and learner support mechanisms that prioritize meaningful engagement and technology self-efficacy over usage metrics alone.

# 9 Conclusion

This study examined the impact of AMQ, EOI, and UFAM on LEF among students in Kuwait's Colleges of Basic Education, with STE and TSE as mediators. The findings reveal that EOI emerged as the strongest determinant, significantly influencing both TSE and STE, which in turn enhanced LEF. AMQ also played an important role, exerting a direct effect on LEF and an indirect effect through TSE. In contrast, UFAM did not demonstrate significant direct or mediated effects, suggesting that the frequency of use alone is insufficient to drive positive learning outcomes without meaningful integration and learner confidence.

The study advances theoretical perspectives by reinforcing TAM, UTAUT, Self-Determination Theory, and Self-Efficacy Theory in the context of AI-enhanced education, while challenging assumptions that usage frequency is a key predictor of learning outcomes. Practically, the results underscore the importance of designing multimedia systems that integrate seamlessly into curricula, promote learner confidence, and actively foster engagement. For policymakers and educators in Kuwait, these insights highlight the need to prioritize quality and integration over quantity of use, supported by training initiatives that build self-efficacy and interactive features that sustain engagement.

While this study provides valuable insights into the role of AI-enhanced multimedia in shaping learning effectiveness within Kuwait's Colleges of Basic Education, several limitations should be acknowledged. The use of a convenience sampling method and focus on a single institutional context may limit the generalizability of the findings to other higher education settings or countries with different technological and cultural conditions. The cross-sectional research design restricts the ability to capture changes in perceptions and outcomes over time, particularly as AI integration in education is still evolving. The study focused exclusively on student perspectives, overlooking the role of faculty readiness, institutional support structures, and infrastructural constraints that may influence adoption and outcomes. This study is subject to limitations including potential sampling bias due to non-probability recruitment, possible common method variance arising from self-reported measures, and limited generalizability beyond the sampled gamer population and cultural context, which should be addressed in future multi-context and longitudinal research designs.

Contrary to traditional assumptions, this study demonstrates that frequent use of AI-enhanced multimedia does not automatically translate into improved learning effectiveness. The absence of significant effects for usage frequency highlights a critical shift in understanding technology-enhanced learning, where quality of integration and learner confidence outweigh repetitive use. This unexpected result reinforces the conclusion that AI-driven educational effectiveness depends on contextual relevance, seamless integration, and psychological readiness, offering a more nuanced perspective on how digital tools contribute to sustainable learning outcomes.

Future research could address these gaps by employing longitudinal designs to examine dynamic changes in self-efficacy and engagement, expanding the sample to include diverse institutions and cultural contexts, and integrating faculty and administrative perspectives for a more holistic understanding. Moreover, comparative studies across countries or disciplines, as well as experimental interventions that test specific AI-driven multimedia features, could further enrich theoretical and practical knowledge in this domain.

The research demonstrates that the effectiveness of AI-enhanced multimedia lies not in its mere availability or use but in its capacity to integrate smoothly into learning environments, strengthen students' confidence, and foster meaningful engagement, thereby contributing to more effective and sustainable educational transformation.

## 10 Suggestions

Based on the results of this study, which identified ease of integration (EOI) and technology self-efficacy (TSE) as the most crucial determinants of learning effectiveness, future research should shift its focus toward examining how these factors can be strengthened and sustained in educational contexts. A promising new direction would be to investigate the interplay between institutional support, faculty readiness, and curriculum alignment in enhancing integration ease, as well as to explore the long-term development of self-efficacy through structured training and capacity-building initiatives. Accordingly, future objectives may include evaluating the effectiveness of targeted interventions aimed at improving student confidence in using AI-enhanced tools, assessing the contribution of interactive and collaborative multimedia features in sustaining engagement, and identifying contextual barriers and enablers within higher education systems. To address these objectives, a longitudinal mixed-methods design is recommended, integrating quantitative approaches such as structural equation modeling with qualitative methods including focus groups and interviews. This combination would allow for capturing both causal relationships over time and in-depth experiential insights, thereby offering a more comprehensive understanding of how AI-driven multimedia can be effectively implemented to achieve sustainable educational transformation.

## Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

## Ethics statement

The studies involving humans were approved by Department of Educational Technology, College of Basic Education, Public Authority for Applied Education and Training. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

## Author contributions

RA: Writing – original draft, Writing – review & editing.

## Funding

The author(s) declared that financial support was not received for this work and/or its publication.

## Acknowledgments

The author is thankful to the Top Leadership of The Public Authority for Applied Education and Training (PAAET), Kuwait and students of Colleges of Basic Education in Kuwait for providing the data for this research.

## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

## Generative AI statement

The author(s) declared that generative AI was not used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

## Publisher's note



## References

Ahmad, S., Zulkurnain, N., and Khairushalimi, F. (2016). Assessing the validity and reliability of a measurement model in Structural Equation Modeling (SEM). *Br. J. Mathem. Comp. Sci.* 15, 1–8. doi: 10.9734/BJMCS/2016/25183

Al-Emran, M., Al-Sharafi, M. A., Foroughi, B., Al-Qaysi, N., Mansoor, D., Beheshti, A., et al. (2025). Evaluating the influence of generative AI on students' academic performance through the lenses of TPB and TTF using a hybrid SEM-ANN approach. *Educ. Inform. Technol.* 30, 17557–17587. doi: 10.1007/s10639-025-13485-w

Allagui, B. (2024). A scaffolding intervention to improve self-efficacy in source-based argumentative writing. *Front. Psychol.* 15:1454104. doi: 10.3389/fpsyg.2024.1454104

Al-Mamary, Y. H. S., Siddiqui, M. A., Abdalraheem, S. G., Jazim, F., Abdulrab, M., Rashed, R. Q., et al. (2024). Factors impacting Saudi students' intention to adopt learning management systems using the TPB and UTAUT integrated model. *J. Sci. Technol. Policy Managem.* 15, 1110–1141. doi: 10.1108/JSTPM-04-2022-0068

Alsaffar, R. D. (2025). The role of AI-driven adaptive multimedia systems on personalized learning paths. *Asian J. Univer. Educ.* 21, 380–402. doi: 10.24191/ajue.v21i1.26

Alsaffar, R. D., Alfayly, A., and Ali, N. (2022). Extended technology acceptance model for multimedia-based learning in higher education. *Int. J. Inform. Educ. Technol.* 12, 1300–1310. doi: 10.18178/ijiet.2022.12.12.1754

Bandura, A. (1997). *Self-Efficacy: The Exercise of Control*. New York, NY: W. H. Freeman.

Bhatt, P., and Muduli, A. (2024). AI learning intention, learning engagement and behavioral outcomes: an empirical study. *J. Managem. Dev.* 43, 920–938. doi: 10.1108/JMD-05-2024-0173

Binti Mohd, R. F., Zulkifli, H., Hamzah, M. I., and Tamur, A. H. (2024). Systematic literature review of ICT integration in teaching and learning. *TEM J.* 13, 3146. doi: 10.18421/TEM134-49

Chang, S. H., Yao, K. C., Chen, Y. T., Chung, C. Y., Huang, W. L., and Ho, W. S. (2025). Integrating motivation theory into the AIED curriculum for technical education: examining the impact on learning outcomes and the moderating role of computer self-efficacy. *Information* 16:50. doi: 10.3390/info16010050

Compeau, D. R., and Higgins, C. A. (1995). Computer self-efficacy: development of a measure and initial test. *MIS Quart.* 19, 189–211. doi: 10.2307/249688

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quart.* 13, 319–340. doi: 10.2307/249008

Deci, E. L., and Ryan, R. M. (1985). *Intrinsic Motivation and Self-Determination in Human Behavior*. New York: Springer.

Deci, E. L., Vallerand, R. J., Pelletier, L. G., and Ryan, R. M. (1991). Motivation and education: the self-determination perspective. *Educ. Psychol.* 26, 325–346. doi: 10.1080/00461520.1991.9653137

Dwivedi, Y. K., Hughes, D. L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2020). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Inf. Manag.* 57:101994. doi: 10.1016/j.ijinfomgt.2019.08.002

Fredricks, J. A., Blumenfeld, P. C., and Paris, A. H. (2004). School engagement: potential of the concept, state of the evidence. *Rev. Educ. Res.* 74, 59–109. doi: 10.3102/00346543074001059

Gray, J. A., and DiLoreto, M. (2016). The effects of student engagement, student satisfaction, and perceived learning in online learning environments. *Int. J. Educ. Leadership Prepar.* 11, 32–48.

Hair, J., Ringle, C., and Sarstedt, M. (2013). Partial least squares structural equation modeling: rigorous applications, better results and higher acceptance. *Long Range Plann.* 46, 1–12. doi: 10.1016/j.lrp.2013.01.001

Hair, J. F., Black, W. C., Babin, B. J., and Anderson, R. E. (2019). *Multivariate Data Analysis,* 8th Edn. Andover: Cengage.

Julious, S. A. (2005). Sample size of 12 per group rule of thumb for a pilot study. *Pharmaceut. Statist.: J. Appl. Statist. Pharmaceut. Indust.* 4, 287–291. doi: 10.1002/pst.185

King, W. R., and He, J. (2006). A meta-analysis of the technology acceptance model. *Inform. Managem.* 43, 740–755. doi: 10.1016/j.im.2006.05.003

Legris, P., Ingham, J., and Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Inform. Managem.* 40, 191–204. doi: 10.1016/S0378-7206(01)00143-4

Mouza, C., and Lavigne, N. (2013). *Emerging Technologies for the Classroom: A Learning Sciences Perspective*. New York: Springer.

Mustafa, M. B., Nordin, M. B., and Razzaq, A. B. A. (2020). Structural equation modelling using AMOS: confirmatory factor analysis for taskload of special education integration program teachers. *Univ. J. Educ. Res.* 8, 127–133. doi: 10.13189/ujer.2020.080115

Niemiec, C. P., and Ryan, R. M. (2009). Autonomy, competence, and relatedness in the classroom: applying self-determination theory to educational practice. *Theory Res. Educ.* 7, 133–144. doi: 10.1177/1477878509104318

Park, S. Y., Nam, M. W., and Cha, S. B. (2012). University students' behavioral intention to use mobile learning: evaluating the technology acceptance model. *Br. J. Educ. Tech.* 43, 592–605. doi: 10.1111/j.1467-8535.2011.01229.x

Paz-Baruch, N. (2025). The impact of self-efficacy and self-regulated learning strategies on students' achievements in STEM disciplines. *Educ. Res. Eval.* 30, 167–189. doi: 10.1080/13803611.2024.2401409

Rahman, S. F. A., Yunus, M., and Hashim, H. (2019). A technology acceptance model (TAM): Malaysian ESL lecturers' attitude in adapting flipped learning. *Jurnal Pendidikan Malaysia* 44, 43–54. doi: 10.17576/JPEN-2019-44.01SI-04

Ryan, R. M., and Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *Am. Psychol.* 55, 68–78. doi: 10.1037/0003-066X.55.1.68

Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *Am. J. Appl. Mathem. Statist.* 9, 4–11. doi: 10.12691/ajams-9-1-2

Sun, A., and Chen, X. (2016). Online education and its effective practice: a research review. *J. Inform. Technol. Educ.: Res.* 15, 157–190. doi: 10.28945/3502

Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Res. Sci. Educ. 48*(6), 1273–1296. doi: 10.1007/s11165-016-9602-2

Teo, T. (2011). Factors influencing teachers' intention to use technology: model development and test. *Comput. Educ.* 57, 2432–2440. doi: 10.1016/j.compedu.2011.06.008

Venkatesh, V., Morris, M. G., Davis, G. B., and Davis, F. D. (2003). User acceptance of information technology: toward a unified view. *MIS Quart.* 27, 425–478. doi: 10.2307/30036540

Venkatesh, V., Thong, J. Y., and Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quart.* 36, 157–178. doi: 10.2307/41410412

Wang, F. (2020). Artificial intelligence in education: current applications and future directions. *IEEE Intell. Syst.* 35, 1–8. doi: 10.1109/MIS.2020.3009004

Wang, W., Liu, H., Wu, Y. J., and Goh, M. (2023). Disconfirmation effect on online reviews and learner satisfaction determinants in MOOCs. *Educ. Inform. Technol.* 28, 15497–15521. doi: 10.1007/s10639-023-11824-3

Wolf, E. J., Harrington, K. M., Clark, S. L., and Miller, M. W. (2013). Sample size requirements for structural equation models: an evaluation of power, bias, and solution propriety. *Educ. Psychol. Meas.* 73, 913–934. doi: 10.1177/0013164413495237

Wu, D., Zhang, S., Ma, Z., Yue, X. G., and Dong, R. K. (2024). Unlocking potential: Key factors shaping undergraduate self-directed learning in AI-enhanced educational environments. *Systems* 12:332. doi: 10.3390/systems12090332

Yang, C., Wei, M., and Liu, Q. (2025). Intersections between cognitive-emotion regulation, critical thinking and academic resilience with academic motivation and autonomy in EFL learners: Contributions of AI-mediated learning environments. *Br. Educ. Res. J.* doi: 10.1002/berj.4140

Zimmerman, B. J. (2000). "Attaining self-regulation: a social cognitive perspective," in *Handbook of Self-Regulation,* eds. M. Boekaerts, P. R. Pintrich, and M. Zeidner (San Diego, CA: Academic Press), 13–39.