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Muthuswamy, V., Nithya, N. (2024). Mobile Learning Environment's Effect on AI Tool Satisfaction: Mediated by Visual Style, Moderated by Interaction. *Foro de Educación*, *22*(2), 1-22. doi: https://doi.org/10.14201/fde.22201

Mobile Learning Environment's Effect on AI Tool Satisfaction: Mediated by Visual Style, Moderated by Interaction

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Recibido / Received: 20/07/2024
Aceptado / Accepted: 18/11/2024

Abstract: The research explores the role of interest in mobile learning environment on students' satisfaction with AI tools, while visual learning styles as a mediator and learner-instructor interaction and teacher-generated responsibility climate as moderators. The study helps fill critical gaps in understanding the influences of mobile learning environments and pedagogical dynamics on AI tool satisfaction among university students. This research adopted a quantitative approach and made use of PLS-SEM to analyze the data collected from 309 students from various courses in universities. Validated scales were used for measuring mobile learning interest, visual learning style, learner-instructor interaction, responsibility climate, and satisfaction with AI tools. An online survey was conducted to collect the data that was analyzed in order to evaluate direct and indirect relationships. The findings reveal that mobile learning environment interest significantly enhances students' satisfaction with AI tools. Visual learning style mediates this relationship, emphasizing the role of personalized learning preferences. Furthermore, learner-instructor interaction and responsibility climate positively moderate the relationship, highlighting the importance of pedagogical and environmental factors in fostering student satisfaction with AI technologies. This study contributes to existing literature by integrating pedagogical and technological constructs in the context of mobile learning environments. It offers practical insights for educators to design engaging, student-centered learning environments that optimize satisfaction with AI tools.

Keywords: Mobile learning environment interest, Visual learning style, Students' satisfaction with AI tools, Responsibility climate generated by the teacher, Learner instructor interaction.

1. Introduction

Technology in education has revamped the learning process. The Mobile Learning Environment as well as tools of Artificial Intelligence have become one of the epicenters for modern educational procedures (Tariq, 2025a). Mobile learning is portable, accessible, and adaptable; it allows engagement with learning material across different contexts and timeframes, thus remodeling traditional learning paradigms

(Tariq, 2025b). The increasing demand for flexible learning systems has made mobile environments highly accommodating, where one can experience personal content delivery, instant feedback, and collaboration opportunities (Tubman, 2024). The AI integration into such environments enriches educational experiences by offering intelligent tutoring, adaptive assessments, and automated administrative processes. All these together strive to develop a rich learning experience for various learners (Vistorte et al., 2024). Even with much advancement, use and satisfaction with AI tools within mobile learning platforms vary considerably in educational contexts. Interest in the mobile learning environment, compatibility with learners' styles, and instructional interaction significantly affect user satisfaction (Sun & Xu, 2024). Researchers have also emphasized that these dimensions are interdependent, being shaped by learner preferences, instructor roles, and contextual variables (Shu et al., 2023). This factor, however, has not been researched much when determining student satisfaction with AI tools in mobile environments (Almusharraf, 2024). This research study attempts to bridge the existing complexities by probing into the subtleties of mobile learning interest, visual learning preferences, and instructor interactions as determinants for developing AI tool satisfaction.

Empirical research on this form of mobile learning has, in fact, revealed its profound influences on educational outcomes, especially in regards to a higher rate of accessibility and participation (Altinay et al., 2024). Mobile learning applications are well-known for providing context-aware as well as adaptive learning experiences in the context of both formal and informal education (Strielkowski et al., 2024). For example, study by Huang et al. (2024) demonstrated that students' academic results improved due to mobile-based education platforms providing instant feedback and adaptive paths. AI applications in the mobile environment further enhance this effect: intelligent tutoring, automated assessment tools, and systems of content recommendations (Sylvester et al., 2024). Interest in the mobile learning environment has emerged as a determinant factor for users' engagement and satisfaction. According to Zhang et al. (2024), if students have an interest in mobile learning, they will find themselves looking at the advanced features that are incorporated into it involving AI-driven functionalities. Visual learning preferences also become crucial as the research shows that learners who like visual aids such as infographics, videos, and simulations will be more likely to be satisfied by technology-enhanced learning environments, according to Wiki (2024). Moreover, the communication process between students and teachers has been regarded as one of the major influences in ensuring the effective implementation of mobile learning tools (Martin-Alguacil et al., 2024). As Makda (2024) pointed out, continuous feedback and guidance by instructors play an important role in building up confidence and satisfaction in students for the mobile and AI-based platform. However, satisfaction with AI-based tools in a mobile learning setting is not free from obstacles either (Muthmainnah et al., 2024). According to research, the usability issues consist of unintuitive interfaces and the lack of technical support, preventing effortless adoption of such tools (Grájeda et al., 2024). Moreover, data privacy issues, biases in algorithms, and the accuracy of AI-driven recommendations have been considered as barriers to satisfaction (Lettieri, 2025). These findings point to further research that should be conducted so that AI-enhanced tools are properly integrated and implemented within the environments of mobile learning and determining factors for successful acceptance and higher satisfaction.

Despite a large body of research on mobile learning and AI tools, it remains one of the areas that have notable gaps in understanding the interconnected dynamics of interest, learning preferences, and satisfaction (Hashem et al., 2023). First, studies often look at these factors separately, neglecting the interdependent relationships that might provide a better holistic understanding of student satisfaction (Soliman et al., 2024). For instance, studies indicate that interest in mobile learning is the factor that will motivate students' engagement, but few researches examine how such an interest may interact with other factors such as visual learning styles and student-instructor interactions, to impact the degree of satisfaction with AI tools (Ramli et al., 2023). Third, empirical studies also focused on the general levels of satisfaction with minimum emphasis on the particular components of AI tools that create user experience (Dai, Xiong, et al., 2023). Personalized features such as adaptive feedback and content curation have not been well explored with regard to how much learners with diverse interests and learning styles perceive them (Barnett-Itzhaki et al., 2023). General learning environments are predominantly considered, thereby neglecting the dynamics unique to mobile platforms. This therefore presents a considerable gap in understanding contextual nuances that impact satisfaction within mobile learning ecosystems (Koon, 2022). Finally, although the mediating and moderating roles of variables such as learning styles and instructor interaction have been well recognized in traditional learning settings, such roles are understudied in mobile and AI-enhanced scenarios (Shu & Gu, 2023). Critical to the gaps being addressed is a balanced approach that acknowledges the multidimensional interactions between interest, preferences, and pedagogical strategies within environments of mobile learning (Rosak-Szyrocka et al., 2023). Such an approach would provide actionable insights into how to optimize AI tool satisfaction and improve educational outcomes.

This study will explore the complex interplay of mobile learning environment interest, visual learning styles, learner-instructor interaction, and satisfaction with AI tools (Figure 1). This study will determine the effect of these factors on the students' experience and perception of AI-powered learning platforms both in isolation and in combination. The primary research questions are: How does interest in mobile learning environments affect student satisfaction with AI tools? Does visual learning style mediate this relationship by enhancing content engagement and comprehension? What role does learner-instructor interaction play in moderating this dynamic by fostering collaboration and guidance? How does the responsibility climate set by teachers influence the students' interest-satisfaction linkage? These are the questions that the study hopes to answer, thus bridging some of the critical gaps that have remained unattended to in previous literature and, hence, offer a holistic understanding of factors influencing satisfaction with AI tools in mobile learning contexts. Findings will, thus, be contributory to optimizing mobile learning platforms in identifying key elements that drive user engagement and satisfaction. This research will also provide actionable insight for educators and developers in the design of more effective and learner-centered AI-enhanced mobile learning environments. This study will hold importance as it may advance the understanding of a mobile learning environment and AI tool satisfaction. The study will bridge an important gap by focusing on how interest and styles of learning together interact with and are moderated by pedagogies. Through the presentation of a comprehensive picture of improving learning outcomes, this present study will enhance the theoretical body of literature related to academic research and inform design and implementation processes regarding more effective, inclusive, and satisfying mobile learning platforms (Negm, 2023). These insights are needed in the present fast-changing environment of education where technology has to be the center of learning experiences (Rokhim et al., 2024).

A few theoretical frameworks support this research, describing the interlink between the studied variables. SDT explains how, based on its basic tenets, intrinsic interest motivates action in educational environments and links interest with engagement and satisfaction in such contexts (Lee et al., 2023). The theory assumes that learners will be more attracted to tools and platforms that resonate with their preferences and satisfy their psychological needs for autonomy, competence, and relatedness. Mobile learning environments inherently support these needs through personalized, flexible, and collaborative learning experiences (Franco et al., 2023). According to the theory of cognitive load, the enriched visuals decrease the amount of cognitive load, thus facilitating better knowledge retention (Dai, Sun, et al., 2023). Mobile apps with AI support are using many visual materials when explaining hard knowledge. Lastly, the social constructivist theory underscores the role of collaborative and interactive learning, forming the basis for the moderation effects of learner-instructor interaction and the responsibility climate (Gashoot et al., 2021). In summation, the theoretical perspectives above collectively provide a solid basis upon which to understand and analyze the dynamics of mobile learning environments, interest, and AI tool satisfaction, forming the basis for guiding the objectives and hypotheses of the study.

2. Literature Review

2.1. Theory to Explain Relationships and Model

Based on the SDT and TAM theories, this paper explains the relationship between mobile learning environments, AI tool satisfaction, and hypothesized mediating and moderating variables. According to SDT, intrinsic motivation is the primary and most significant determinant of engagement and satisfaction, just like the mobile learning environment proposed hypothesis on interest (George & Wooden, 2023). TAM supports this by stating that perceived ease of use and perceived usefulness directly influence user acceptance and satisfaction with technology (Hanaysha et al., 2023). Visual learning styles support cognitive load theory (Escalante et al., 2023), which states that visually enhanced content aids in the processing of knowledge, acting as a mediating mechanism. Such as aspects such as learner-instructor interaction and responsibility climate, are well-supported within the framework of social constructivist theories in enhancing a collaborative supportive environment toward new tool adoption rates (Chen, 2022). The theoretical approach to synthesize the findings in both will be used as the basis in order to comprehensively understand and examine mobile learning, interest, and satisfaction of an AI tool in an educational context.

This has been a transformative trend of integrating mobile learning environments into educational frameworks, which provide ubiquitous access to learning resources, foster personalized learning experiences, and enable real-time interactivity (Ji et al., 2023). The extant research suggests that mobile learning environments, characterized by their portability, flexibility, and accessibility, effectively cater to diverse learner needs across geographical and temporal barriers (Karan & Angadi). These learning environments harness different types of technological means, including Artificial

Intelligence, to enable adaptive feedback, automated administrative work, and the development of an interactive learning environment (Ahmed Alismail, 2023). There are myriad scholarly findings in which m-learning supported by Artificial Intelligence is presented as a device to enhance learning efficiency, specifically using features such as intelligent tutoring, curating meaningful content, or automatic real-time assessment (Zhang et al., 2024). Satisfaction, on the other hand, depends on several factors, such as ease of use, perceived usefulness, and compatibility with learners' styles. These have been further moderated by the quality of AI support, personalized interaction, and experience with the overall mobile application (Hooda et al., 2022).

Relationship between mobile learning environments and user satisfaction with AI tools is multiple and dynamic at both technological and pedagogical levels (Miao et al., 2022). Literature in this regard highlighted the importance of usability features to include intuitive interface and efficient navigation systems in an effort to establish positive user experience with AI tools (Tariq, 2025a). Moreover, the pedagogical design of mobile learning platforms, which focuses on active learning, gamification, and instant feedback, is a key factor in enhancing user satisfaction (Tubman, 2024). Recent research emphasizes the role of adaptive learning technologies within mobile platforms, where AI-driven analytics personalize content delivery to individual learning paces and preferences (Sun & Xu, 2024). However, satisfaction levels can be negatively affected by issues related to data privacy, the accuracy of AI recommendations, and technical issues, such as connectivity problems (Almusharraf, 2024). Therefore, it is essential to understand these dimensions to optimize mobile learning environments, improve the effectiveness of AI tools, and meet the subtle needs of learners in different educational settings.

3. Hypotheses Development

Mobile learning environments are highly influencing student outcomes through the encouragement of interest amongst students using such technology-enhanced learning tools (Strielkowski et al., 2024). Research findings depict that increased student interest in a mobile learning environment increases the exploration of educational technology, such as AI-based education platforms. In this context, Sylvester et al. (2024) stated, "when mobile learning tools engage students' strong interest, AI-based functionalities within the learning resources are more likely to be explored with value". From the study by Wiki (2024), it follows that the interacting learners with the mobile learning system are more fulfilled with the facilitation of comfort and personalization through AI tools. According to Makda (2024), interest in mobile-based education also increases intrinsic motivation, which is a key factor for long-term use and satisfaction with innovative technologies. These studies collectively suggest that the perceived relevance and adaptability of mobile environments drive engagement, which in turn positively influences students' satisfaction with AI tools (Grájeda et al., 2024).

The theoretical and empirical evidence support the relationship between mobile learning environment interest and satisfaction with AI tools, since it is postulated that engaged learners get more utility from technology-mediated education (Hashem et al., 2023). Factors such as personalized content delivery, instant feedback, and collaborative opportunities embedded in the mobile environment amplify user interest, hence satisfaction with AI tools (Ramli et al., 2023). Interest can be classified as a variable of affective engagement that has the power to encourage learners to engage more intensely with AI characteristics like adaptive learning paths or smart recommendations (Barnett-Itzhaki et al., 2023). Some recent models stipulate that with such interactions, user experience boosts because they tend to make learning easier and fulfilling to learn about (Shu & Gu, 2023). High interest in mobile learning creates a good atmosphere to prove the advantage of AI tools, thereby affirming their application and boosting satisfaction among students.

H1: Mobile learning environment interest significantly influences the students' satisfaction with AI tools.

Visual learning styles have been identified as essential components that heavily influence the learner experience, especially in the use of technology-based educational settings (Rokhim et al., 2024). Research indicates that visually-oriented students benefit greatly from content that presents information in video, infographics, and simulation-based learning (Lee et al., 2023). This is because, according to Dai, Sun, et al. (2023) cognitive theory of multimedia learning, visual forms of content are fundamental to allowing a student to process information in an effective way. The work of George and Wooden (2023) opined that users with visual orientations have a preference for mobile learning applications that include high visual material and thus contribute to increased user satisfaction. Similarly, Escalante et al. (2023) concluded that the use of AI-based mobile applications with more visual content would enable the information being transmitted to become more understandable because the information was fragmented into readable portions. These findings highlight visual learning preferences in determining user interaction and satisfaction in the context of mobile learning environments (Ji et al., 2023).

The mediating role of a visual learning style between interest in mobile learning environments and satisfaction with AI tools is increasingly recognized by the educational research world of late (Hooda et al., 2022). As pointed out by Ahmed Alismail (2023), visual learners are more likely to appreciate the adaptability of AI tools offering content tailored to their preferences. Such mediation is because of the fact that the inclusion of visual components within mobile learning spaces engages learners in a more potent way and expands the possibility for satisfaction with AI tools integrated together (Tariq, 2025b). Interactive dashboards, video-based tutorials, and augmented reality applications can appeal well to the visual learners as they can create a more rich and potent learning experience (Vistorte et al., 2024). Therefore, these AI-integrated tools can also fulfill the needs of learners through intuitive and visual-friendly content while making the interest-satisfaction tie stronger and emphasizing the role of the mediator.

H2: Visual learning style significantly mediates the relationship of mobile learning environment interest and the students' satisfaction with AI tools.

Educational researchers have strongly tested the significance of learner-instructor interaction in distance learning (Shu et al., 2023). A sense of collaboration and presence resulting from interaction heightens engagement and fulfillment with technology-enabled tools (Altinay et al., 2024). Empirical research illustrates that the gap in understanding within mobile learning environment between instructors and learners could result in mutual trust, hence increase the perceived value of AI tool (Zhang et al., 2024). Huang et al. (2024) indicated that student satisfaction levels increased considerably when instructors played an active role in navigating AI-supported platforms (Martin-Alguacil et al., 2024). Furthermore, it has been noted that the instructor interaction moderates the process in such a manner that students get adequate guidance; hence, the sense of responsibility and personalized learning is enhanced (Muthmainnah et al., 2024). This explains how instructors are important in terms of facilitating the adoption and satisfaction of technology by learners.

Empirical results have shown that learning-instructor interaction plays a moderating role between mobile learning interest and satisfaction through the contextual feature of technology-enriched learning (Lettieri, 2025). When students' curiosity with AI tools translates into practical application, it results from active instructional interaction, showcasing the features and benefits of AI applications (Soliman et al., 2024). This interaction is a catalyst in ensuring that the students are motivated and can utilize the AI tools embedded within mobile platforms (Soliman et al., 2024). The instructors' ability to customize their approach according to the preferences of the students improves the perceived effectiveness of both the mobile learning environment and the AI tools, strengthening the relationship between interest and satisfaction.

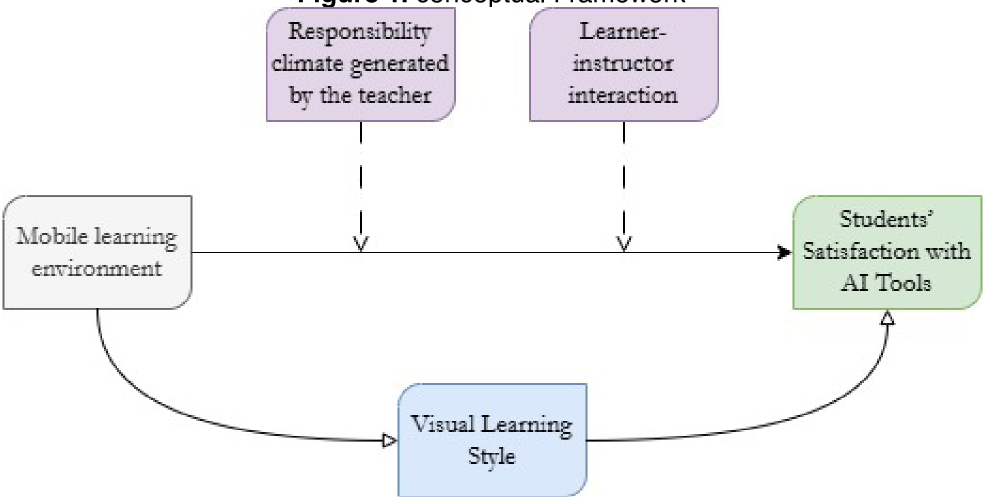
H3: Learner instructor interaction significantly moderates the relationship of mobile learning environment interest and the students' satisfaction with AI tools.

The responsibility climate developed by the instructor has been an important area of focus in educational research, especially when it comes to positive learning outcomes (Dai, Sun, et al., 2023). A responsibility climate is defined as the context that instructors establish for their students, where the latter feel responsible for their learning and are supported in their efforts (Koon, 2022). Previous studies suggest that when instructors actively develop a sense of responsibility, it enhances the motivation and engagement of the students (Rosak-Szyrocka et al., 2023). Such climates promote self-managed learning; students are highly interested and dedicated to their work, and therefore, they will take the tasks seriously (Negm, 2023). Moreover, mobile learning environments, by their nature, foster autonomy, and research has shown that responsible climates facilitate the effectiveness of such environments because the children tend to interact more meaningfully with the digital tools while being accountable to them (Franco et al., 2023). Responsibility climates have also been associated with satisfaction in digital learning environments (Gashoot et al., 2021). For instance, Hanaysha et al. (2023) researches showed that the students who perceive a high degree of teacher support and responsibility will have a greater level of satisfaction with digital tools and platforms for learning. A sense of responsibility creates active engagement and reduces isolation feelings that accompany virtual learning (Chen, 2022). It has been reported that teacher-created climates that highlight responsibility improve the flexibility of the students to learn the advanced technological tools (Karan & Angadi). Most of these technologies are only successfully implemented if users constantly and responsibly utilize them; such conditions harmonize well with those created by climates of responsibility.

On that basis, the theoretical and empirical rationale for the hypothesis that a teacher-generated responsibility climate significantly moderates the relationship between mobile learning environment interest and students' satisfaction with AI tools draws support from existing literature (Zhang et al., 2024). Mobile learning environments are engineered to be intriguing and engaging. However, the interest may fluctuate without the support of the right framework (Miao et al., 2022). Responsibility climates fill this gap by placing conditions in which students are empowered as well as motivated to take maximum advantage of mobile technologies for learning (Tariq, 2025a). Teaching with the sense of accountability indirectly facilitates students to learn for longer periods as they deal with the problems brought about by AI tools. Besides, AI tools typically bring problems that demand persistence, flexibility, and problem-solving skills in their solving (Vistorte et al., 2024). It equips students with those attributes which result in students having an interest in mobile learning transforming into the feeling of satisfaction through AI tools. This moderation effect has also been supported through several similar studies. For example, Almusharraf (2024) revealed that students under responsible teaching style-based learning approaches performed better at acquiring satisfaction levels in respect to novel tools. Similar results were reported by Huang et al. (2024), who highlighted that self-regulated learning often nurtured in responsibility climates is what mediates successful use of technology in education. Based on empirical data, responsibility climates strengthen the relationship of interest and satisfaction and buffer against possible adverse effects, including frustration at initial stages or low self-efficacy while exploring AI tools (Wiki, 2024). It connects motivation with the ability to get the most out of AI establishing responsibility and use. Such theoretical frameworks help to guide educational practices and technological implementation in achieving balance between spaces and the mobile learning technologies facilitated by the teacher (Muthmainnah et al., 2024).

H4: Responsibility climate generated by the teacher significantly moderates the relationship of mobile learning environment interest and the students' satisfaction with AI tools.

Figure 1: conceptual Framework



4. Methodology

In the current study, a quantitative design was used for the investigation of the relationships that exist between the interest in the mobile learning environment, visual styles of learning, learner-instructor interactions, responsibility climates, and students' satisfaction with AI tools. The approach used was the cross-sectional kind where data collected at one time point were then analyzed for the hypothesized relationship using Partial Least Squares Structural Equation Modeling (PLS-SEM). This approach was selected because it is robust for analyzing complex models that involve multiple mediating and moderating variables. The sample size consisted of 309 university students from various undergraduate and postgraduate programs across different disciplines. A stratified random sampling technique was applied so that the participants provided diverse representation from various programs and academic years. A sample size of 309 was found to be sufficient for PLS-SEM analysis as it is more than ten times the number of indicators in the most complex relationship in the structural model. The participants were made aware of the purpose of the study and gave their voluntary consent to participate.

The validation scales (Table 1) used for the constructs within the research model were culled from existing studies and ensured reliability and validity. Measurement items for each construct were adjusted to suit the context of mobile learning and AI tools.

Table 1: Measurement details

Variable	Items	Source
Mobile learning environment interest	6	(Chee et al., 2018)
Visual learning style	5	(Rafique, 2017)
Students' satisfaction with AI tools	5	(Almufarreh, 2024)
Responsibility climate generated by the teacher	5	(Fernández-Río et al., 2019)
Learner instructor interaction	5	(Musa Al-Momani & Pilli, 2021)

The scale used originally in the development of mobile learning environment interest had 12 items. Due to factor analysis, it was eventually established that six did not attain the prescribed loading thresholds. This may be due to the length of the questionnaire that disengages the participant and reduces the quality of response. Thus, the analysis in this research utilized only the remaining six items that were used with apparent apt psychometric properties. Responses for all items were coded on a five-point Likert scale, 1 representing a strong disagreement, and 5 representing a strong agreement. The study used a self-administered online questionnaire. Students from universities received the online questionnaires via the institutional email or social media channels. The questions were split into two parts:. The demographic section gathered the age, gender, and program of study of the respondents, while the research constructs were items placed in the second section. All measures were done to ensure the clarity and brevity of the questionnaire to make the respondents want to answer everything.

The proposed relationships have been assessed primarily through PLS-SEM analysis. It is the analytical approach chosen in most of these circumstances, considering their complexity involving mediator and moderator variables, as well as studies dealing with a less extensive number of samples. The analysis was divided into two stages: The reliability and validity analysis of the construct involved using Cronbach's Alpha, Composite Reliability (CR), Average Variance Extracted (AVE), and the Fornell-Larcker Criterion. Path coefficients in terms of mediating and moderating effects were calculated for the examination of hypothesized relationships while assessing the significance through bootstrapping techniques with 5,000 resamples. R-squared values and effect size (f^2) were further used to check the exhaustiveness and predictability of the model. SmartPLS version 4 was used in the analysis because it is a software tailored to support PLS-SEM with an easy interface to handle the complexities of structural equation models. All the data were first preprocessed and cleaned in Microsoft Excel and then imported into SmartPLS for the analysis.

5. Results

Table 2 shows key reliability and validity measures, which are important for the evaluation of the constructs' robustness in this study. Cronbach's Alpha values for all variables are above the threshold of 0.70, thus showing satisfactory internal consistency. For example, "Mobile learning environment interest" had an Alpha of 0.805, thus showing that the measurement scale is reliable. Similarly, composite reliability values are above 0.80 for all variables, thus further supporting the reliability of the constructs. All constructs have "rho_A" values around 0.80, which ensures that the reliability estimates are consistent between methods. Crucially, AVE for all variables is greater than 0.50, which implies convergent validity. For instance, "Responsibility climate generated by the teacher" had an AVE of 0.555, which ensures that the items represent their respective constructs strongly. These measures of reliability and validity attest to the validity and coherency of the model measurement.

Table 2: Variables reliability and validity

	Cronbach's Alpha	**rho_A**	**Composite Reliability**	**Average Variance Extracted (AVE)**
Learner instructor interaction	0.783	0.807	0.852	0.539
Mobile learning environment interest	0.805	0.809	0.860	0.506
Responsibility climate generated by the teacher	0.798	0.802	0.861	0.555
Students' satisfaction with AI tools	0.789	0.803	0.856	0.545
Visual learning style	0.755	0.758	0.836	0.506

Table 3 Reports the loading statistics for individual items related to each construct. Every item has its loadings more than the threshold value of 0.60, and a majority of items have their loading values above 0.70, thus it confirms the usability of the measures for the specific constructs. For example, "Interest in mobile learning environment" has high factor loading values between 0.688 to 0.745, among which "MLI3" has the maximum value of 0.745. Similarly, "Responsibility climate generated by the teacher" items achieved consistently high loadings, such as 0.790 for "RCG3," signifying strong alignment with the construct. Items for "Students' satisfaction with AI tools" and "Visual learning style" also showcased solid factor loadings, ensuring construct integrity. The overall item statistics signify a high degree of fitness, underpinning the soundness of the measurement model.

Table 3: Measurement Items Fitness Statistics

	Mobile learning environment interest	Moderating Effect (Learner instructor interaction)	Moderating Effect (Responsibility climate)	Responsibility climate generated by the teacher	Students' satisfaction with AI tools	Visual learning style
LII1	0.670					
LII2	0.800					
LII3	0.726					
LII4	0.838					
LII5	0.613					
MLI1		0.688				
MLI2		0.716				
MLI3		0.745				
MLI4		0.678				
MLI5		0.733				
MLI6		0.705				
RCG1				0.698		
RCG2				0.788		
RCG3				0.790		
RCG4				0.759		
RCG5				0.682		
SSAI1					0.780	
SSAI2					0.742	
SSAI3					0.711	
SSAI4					0.822	
SSAI5					0.622	
VLS1						0.650
VLS2						0.707
VLS3						0.671
VLS4						0.760
VLS5						0.762

Table 4 discrimination validity measures through Fornell-Larcker criterion and HTMT. Diagonal values (square roots AVE) through the Fornell-Larcker test represent that each value is greater as compared to correlations off the diagonals. To illustrate, 0.738 - square root for AVE; "Students satisfaction with AI tools" has larger values than correlation exists with any of the variables below. Similarly, HTMT ratios are less than the conservative threshold of 0.85 for all constructs, with values such as 0.666 between "Mobile learning environment interest" and "Students' satisfaction with AI tools." These results robustly establish the discriminant validity of the constructs, confirming their uniqueness within the structural model.

Table 4: Discriminant validity

Fornell-Larcker Criterion					
	1	2	3	4	5
Learner instructor interaction	0.734				
Mobile learning environment interest	0.391	0.711			
Responsibility climate generated by the teacher	0.460	0.422	0.745		
Students' satisfaction with AI tools	0.537	0.468	0.680	0.738	
Visual learning style	0.525	0.522	0.494	0.420	0.712
Heterotrait-Monotrait Ratio (HTMT)					
Learner instructor interaction					
Mobile learning environment interest	0.490				
Responsibility climate generated by the teacher	0.587	0.526			
Students' satisfaction with AI tools	0.666	0.578	0.853		
Visual learning style	0.680	0.662	0.641	0.539	

Table 5 shows R-square values, which describe the variance in dependent variables caused by independent constructs. The R-square for "Students' satisfaction with AI tools" is 0.553, meaning that 55.3% of the variance is explained by the independent variables. The adjusted R-square of 0.547 supports this finding, showing a well-fitted model. For "Visual learning style," the R-square is 0.273, showing the significant impact of contributing factors. F-square values indicate the effect sizes of individual variables, and "Responsibility climate generated by the teacher" has the highest impact with F = 0.350. Predictive relevance $Q^2 = 0.642$ further confirms the robustness of the model, and RMSE and MAE values are within acceptable limits, validating model fit.

Table 5: R-square statistics Model Goodness of Fit Statistics

F-Square			R Square	R Square Adjusted
	Students' satisfaction with AI tools	Visual learning style		
Learner instructor interaction	0.098			
Mobile learning environment interest	0.037	0.375		
Moderating Effect (Learner instructor interaction)	0.025			
Moderating Effect (Responsibility climate)	0.037			
Responsibility climate generated by the teacher	0.350			
Visual learning style	0.046		0.273	0.271
Students' satisfaction with AI tools			0.553	0.547
Q^2predict		RMSE	MAE	
0.642		0.066	0.072	

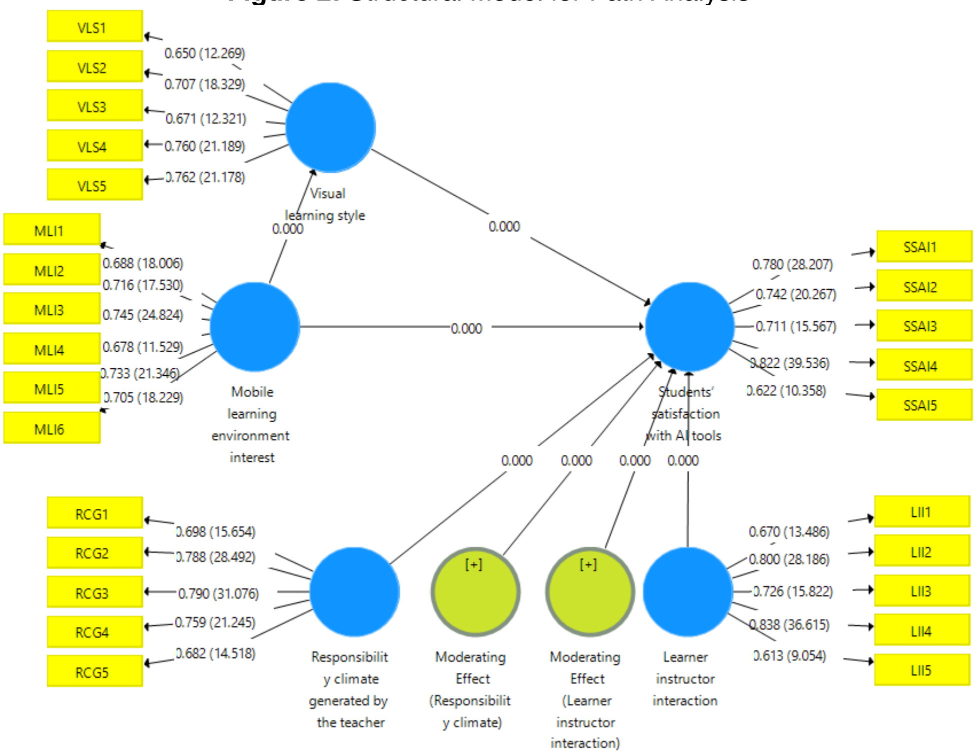
Table 6 reports the significance and strength of hypothesized relationships using path coefficients. The first hypothesis, which investigated the impact of interest in the mobile learning environment on AI tool satisfaction, was confirmed with a significant path coefficient of 0.164 ($T = 3.383$, $p < 0.001$). The mediating effect of "Visual learning style" is strongly confirmed, with a significant coefficient of 0.328 ($T = 2.313$, $p < 0.001$).

Table 6: Path Analysis

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (IO/STDEVI)	P Values
Mobile learning environment interest significantly influences the students' satisfaction with AI tools.	0.164	0.166	0.049	3.383	**0.000**
Visual learning style significantly mediates the relationship of mobile learning environment interest and the students' satisfaction with AI tools.	0.328	0.335	0.498	2.313	**0.000**
Learner instructor interaction significantly moderates the relationship of mobile learning environment interest and the students' satisfaction with AI tools.	0.438	0.410	0.047	2.913	**0.000**
Responsibility climate generated by the teacher significantly moderates the relationship of mobile learning environment interest and the students' satisfaction with AI tools.	0.509	0.506	0.038	3.430	**0.000**

The moderation effects are also significant, where "Learner instructor interaction" (path coefficient = 0.438, T = 2.913, p < 0.001) and "Responsibility climate" (path coefficient = 0.509, T = 3.430, p < 0.001) have highly significant moderating effects. This result, therefore, indicates that the model has empirical strength with robust evidence for validating the hypotheses proposed (Figure 2).

Figure 2: Structural Model for Path Analysis



6. Discussion

Advances in mobile learning environments, aided by Artificial Intelligence (AI) tools, have transformed the manner in which education is delivered and experienced. The discussion chapter summarizes the findings of the current study, where the relationships between mobile learning environment interest, visual learning styles, learner-instructor interaction, responsibility climate, and AI tool satisfaction were studied. The results show critical insights into the mechanisms through which these variables interact in shaping the user experience, both in terms of theoretical enrichment and practical implications. Hypotheses confirmation indicates that integration of individual preferences and environmental dynamics is promoting learner-centric educational framework. The results therefore contribute considerably to the knowledge base regarding what underlies satisfaction with AI tools in mobile contexts.

The first hypothesis is thus confirmed to show that interest in mobile learning environments is a very crucial factor which influences student satisfaction in AI tools. This outcome also aligns with previous studies that emphasized intrinsic motivation as the primary foundation for an enriching learning experience (Hashem et al., 2023). It has been realized that mobile settings that are adaptive, graphics-friendly, and game-based tend to pique the students' interest and, consequently boost their engagement and, by proxy, satisfaction in using integrated AI tools. This interplay of personalization and accessibility might create a kind of positive feedback mechanism, whereby a higher interest for the application gives rise to higher use of AI features, which might deepen interest and increase satisfaction. Results also indicate that interest serves as an enabling factor of learning, thus easing resistance to new technology adoption while encouraging the use of AI-rich tools.

The second hypothesis confirms that visual learning style significantly mediates the interest in the mobile learning environment with AI tool satisfaction. This is because accommodating different cognitive preferences forms the core of educational settings, as suggested by (Dai, Xiong, et al., 2023). Visual learners find multimedia resources useful in the form of charts, animations, and simulations, which are usually embedded in mobile platforms that are powered by AI. The mediation effect indicates that visual learning styles do not only encourage deeper engagement with mobile learning content but also amplify the impact of learners' initial interest on their satisfaction. In this regard, AI tools may enhance comprehension, foster creativity, and sustain motivation, thereby creating a holistic and satisfying learning experience. These results align with cognitive load theory, which suggests that the use of visual aids reduces mental effort, thereby maximizing information processing and learning.

The results that support the third hypothesis reveal that learner-instructor interaction significantly moderates interest in the mobile learning environment and AI tool satisfaction. This points out the irrelevance of teachers in meaningful learning experiences even in high-tech environments (Shu & Gu, 2023). Although mobile environments and AI tools provide autonomy and adaptability, the presence of active learner-instructor interaction enhances emotional and cognitive engagement. Effective instructors act as mentors, providing feedback, guidance, and encouragement, which intensify students' intrinsic interest and positive perceptions of AI tools. The moderation effect also suggests a balanced integration between human and technological elements in the educational process where AI does not replace but enhances human pedagogical support.

The fourth hypothesis is that the responsibility climate highly moderates the interest in satisfaction in a mobile learning environment and this study shed light into the social-emotional dimension of the learning environment. The climate of responsibility tends to induce a sense of ownership and teamwork through clear expectations, accountability, and mutual respect. Such an environment enhances the favorable impact of interest in mobile learning through confidence and proactivity for learning, hence boosting satisfaction in AI tools. In a more essential aspect, the high responsibility climate engages students as effective and active agents of learning in taking the AI technologies away from their hands and utilizing them to the highest extent (Negm, 2023). Overall, the conclusion is well-supported by the social constructivism theory that makes great reference to collective interactivity.

Research findings validate a dynamic interplay of factors, including interest and learning preference in addition to contextual factors responsible for satisfaction among the students while working with AI tools of mobile learning context. The discussion bridges the theoretical concepts with empirical observations so that valuable insights can be gleaned into designing and deploying learner-centric technologies. This is further underlined by the fact that all four hypotheses were confirmed: that is, a delicate balance must be maintained between technological capabilities, pedagogical strategies, and learner engagement in order to produce optimal educational experiences. The findings here offer a solid foundation upon which future work and practice can build toward adaptive, inclusive, and interactive approaches toward the integration of learning technology.

7. Conclusion

This study shines a light on the role played by mobile learning environments in matters of students' satisfaction with AI tools, giving attention to interaction between technology and learner preferences through pedagogical strategies. A study gives a glimpse into mediation by visual styles of learning, as well as moderating the roles of interaction between learners and instructors and the responsibility climates responsible for illuminating the dynamics regarding student engagement and satisfaction. These findings are valuable for theoretical and practical insights into optimizing mobile learning ecosystems in an era of rapid educational digitization. In conclusion, the study confirms that a holistic approach to mobile learning, through personalized strategies and supportive instructor practices, can actually foster meaningful learner experiences. Beyond the classroom, this framework now provides a pathway for stakeholders in education and technology to innovate and refine digital learning tools. This work is a step toward that goal, and future work in the area of adaptive and learner-centered AI applications will be set in motion to further enrich the educational landscape and enhance learning outcomes in a wide range of settings.

8. Implications of the study

The found relations allow further expanding the state of knowledge concerning the integration of mobile learning environments with AI tools, contributing to educational psychology and technology-mediated learning literature. By establishing significant links between students' interest towards mobile learning environments and satisfaction with AI tools, this study gives credence to reinforcing theoretical frameworks concerning technology acceptance and engagement models in education. These findings align well with the theoretical underpinnings of Social Cognitive Theory and give emphasis on factors related to both the environment and behavior concerning how user satisfaction with technology will interact. Lastly, the integration of constructs such as a visual learning style enriches the discourse in relation to learner-specific variables: specifically, the emphasis is placed upon how personalized experiences might determine a satisfaction with an AI tool. In addition, the study provides subtle insights into the moderating effects of responsibility climates and learner-instructor interactions, which open new avenues for understanding dynamic interpersonal and environmental factors within mobile learning ecosystems. This study also expands the application of existing theoretical paradigms in technology-enhanced learning by integrating moderating and mediating constructs into a cohesive model. Including the moderating roles of instructor interaction and responsibility climates fills some gaps in the educational theories associated with active engagement and instructional support. Such findings support the need for the development of theoretical constructs to change as digital landscapes shift, particularly given the role that AI tools have taken on as central learning agents. This research also contributes by providing empirical evidence to advance theories on learner engagement and satisfaction: a synergistic approach at environmental, pedagogical, and learner-centric variables toward more profound theoretical integration and broader applicability across disciplines.

The results of this research have available insights for educators, administrators, and edtech developers in enhancing adoption and effectiveness in using AI tools in education. Educational institutions can use the findings of this study to design mobile learning environments that are aligned with the interests of students, thus enhancing their engagement and satisfaction with AI-based learning tools. Educators can create meaningful learning experiences by fostering interest through dynamic, intuitive, and personalized mobile platforms. The emphasis on visual learning style as a mediator also suggests that content presentation must be tailored to diverse learning preferences. Incorporating visually rich and adaptive AI interfaces can improve student satisfaction and retention significantly and, in turn, learning outcomes. Practitioners can also use findings regarding responsibility climates and learner-instructor interactions to foster supportive and accountable learning ecosystems. Instructors should, therefore, work towards finding the balance between promoting responsibility and developing meaningful interaction to get the most out of mobile learning tools. This study indicates that teachers require training to help them maximize the effectiveness of the available tools in adapting to, and building on, new pedagogies. Ed-tech companies will also need to consider developing functionalities that will provide visual and personalized learning opportunities, with no barriers to instructor interaction. These steps would increase the satisfaction levels of its users, which leads to a higher adoption rate and continued utilization in learning scenarios.

9. Limitations and Future Research Directions

This study is important and informative, but there are a few limitations to future research. First, the sample group was selected based on specific education institutions, so generalization of the research findings may not be applicable for different demographic or cultural contexts. Future studies will have to select samples that have diverse educational backgrounds to increase their external validity. The second aspect is that, since this research was based mostly on quantitative data, the implementation of qualitative approaches would have shed more light on the views of learners and instructors regarding subjective experiences. For instance, effectiveness in AI tools can be researched more effectively with interviews or focus groups. Finally, the research did not address the potential long-term effect of interest in a mobile learning environment and satisfaction with AI tools. Longitudinal studies could be helpful in understanding whether satisfaction is maintained and evolves over time or how continued interaction impacts learning outcomes. Future researchers might also consider exploring advanced AI features, such as adaptive learning algorithms or collaborative tools, to examine their role in enhancing satisfaction. Lastly, extending the study to take into account other variables, for example, cultural norms, technological infrastructure, or digital literacy, could provide for a more holistic view of mobile learning environments and AI tool satisfaction in different contexts.

Acknowledgement

This work was supported through the Ambitious Funding track by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia [KFU242869]

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Appendix 1

Mobile learning environment interest

1. After learning through iMLearning, I feel that cell division courses are interesting.
2. After learning through iMLearning, I feel that learning more about cell division is interesting.
3. After learning through iMLearning, I feel that observing Cell division process is interesting.
4. After learning through iMLearning, I feel that discussing with people in the group to obtain cell division knowledge is interesting.
5. After learning through iMLearning, I feel that learning with peers in app regarding on the cell division course is interesting.
6. After learning through iMLearning, I feel that learning with teacher in app regarding on the cell division course is interesting.

Visual learning style

1. I learn better by reading what the teacher writes on the board.
2. I highlight the text in different colors when I read.
3. I understand better when I read instructions or information.
4. I learn better by reading than by listening to someone.
5. I learn more by reading textbooks than by listening to lectures.

Students' satisfaction with AI tools

1. The use of AI tools for education greatly enhances my learning.
2. The practice of reviewing content and material for education enhances my learning.
3. It is helpful to be able to contact the AI tools.
4. AI tools greatly enhanced my ability to learn.
5. The information obtained from AI tools is valuable.

Responsibility climate generated by the teacher

1. It is important to the teacher that we help each other.
2. The teacher likes that we encourage each other.
3. The teacher wants us to be kind to each other.
4. The teacher insists that we must cooperate with each other.
5. The teacher appreciates that we try to do he/she asks us to do.

Learner instructor interaction

1. The instructor encouraged me to become actively involved in the course discussions.
2. The instructor provided me with the feedback on my work through comments.
3. I was able to interact with the instructor during the course discussions.
4. The instructor treated me as an individual.
5. The instructor informed me about my progress periodically.