

Exploring the Role of Generative AI in Enhancing Mobile Learning Adoption: A Case Study with Notion

Souha SERRAR, (Ph.D)

*L-QUALIMATE-DS Laboratory
 Faculty of Legal, Economic and Social Sciences Marrakech
 Cadi Ayyad University of Marrakech, Morocco*

Younes LAFRAXO, (PES)

*Professor of Higher Education, Laboratoire L-QUALIMATE-DS
 Faculty of Legal, Economic and Social Sciences Marrakech
 Cadi Ayyad University (UCA) of Marrakech, Morocco*

Correspondence address :	Faculté des Sciences Juridiques, Economiques et Sociales Marrakech Laboratoire fédératif LQUALIMAT-GRTE-DROIT- SOCIETE (L-QUALIMAT-GRTE-DS) +212 (0) 5 24 30 30 32 +212 (0) 5 24 30 33 95 contact.fsjes@uca.ac.ma
Disclosure Statement :	Authors are not aware of any findings that might be perceived as affecting the objectivity of this study and they are responsible for any plagiarism in this paper.
Conflict of Interest :	The authors report no conflicts of interest.
Cite this article :	SERRAR, S., & LAFRAXO, L. (2025). Exploring the Role of Generative AI in Enhancing Mobile Learning Adoption: A Case Study with Notion. <i>International Journal of Accounting, Finance, Auditing, Management and Economics</i> , 6(6), 727–739.
License	This is an open access article under the CC BY-NC-ND license

International Journal of Accounting, Finance, Auditing, Management and Economics - IJAFAME

ISSN: 2658-8455

Volume 6, Issue 06 (2025)

Exploring the Role of Generative AI in Enhancing Mobile Learning Adoption: A Case Study with Notion

Abstract:

The rapid advancement of Generative Artificial Intelligence (GenAI) offers new opportunities for enhancing mobile learning adoption, particularly through platforms like Notion. However, adoption remains inconsistent among university students. This study examines the factors influencing the adoption of Notion enhanced with GenAI functionalities, using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. Data were collected from 90 university students and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that Performance Expectancy (PE) is the most significant predictor of Behavioral Intention (BI), highlighting the importance of AI-driven features such as automated content generation and personalized learning recommendations. In contrast, Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) do not significantly influence adoption, suggesting that digital familiarity reduces perceived barriers. The study extends the UTAUT model to the context of AI-enhanced mobile learning tools. It recommends emphasizing productivity-enhancing features and intuitive AI automation to increase adoption. Future research should explore longitudinal effects, cross-cultural differences, and additional motivational drivers.

Keywords : Generative Artificial Intelligence, Mobile Learning Adoption, Notion, UTAUT model, Technology acceptance.

Classification JEL : I21 ; O33 ; C88

Paper type : Empirical Research

1. Introduction

The rapid evolution of mobile learning (m-learning) has significantly reshaped the educational landscape, providing students with flexible and personalized access to learning materials beyond traditional classroom settings. Digital platforms like Notion have emerged as powerful tools for enhancing productivity, knowledge management, and collaborative learning. However, despite the availability of such tools, the adoption of mobile learning technologies remains inconsistent, influenced by factors such as perceived ease of use, usefulness, and institutional support (Patterson, Frydenberg, & Basma, 2024).

Recent advancements in Generative Artificial Intelligence (GenAI) have introduced new opportunities for enhancing mobile learning experiences. AI-powered tools offer automated content generation, intelligent task organization, real-time assistance, and personalized learning recommendations, potentially reducing cognitive load and increasing engagement (Bouteraa, Bin-Nashwan, & Al-Daihani, 2024). GenAI also enables a personalized learning experience by tailoring educational content to individual students' needs, thereby improving learning efficiency and engagement (Khlaif, Ayyoub, & Hamamra, 2024). However, the extent to which these AI-driven features influence students' acceptance of digital learning tools is still underexplored (Zaim et al., 2024).

This study investigates the role of Generative AI in mobile learning adoption, using Notion as a case study. It examines how AI-enhanced functionalities impact students' perceptions and intentions to adopt Notion as an educational tool. To achieve this, the study applies the Unified Theory of Acceptance and Use of Technology (UTAUT) framework to analyze the key determinants of students' behavioral intentions toward AI-enhanced educational tools.

This study aims to evaluate the factors influencing the adoption of Notion in a mobile learning environment, with a specific focus on the role of Generative AI-driven features. The main objectives are:

To analyze how performance expectancy, effort expectancy, social influence, and facilitating conditions shape students' willingness to adopt Notion, based on the UTAUT model (Venkatesh et al., 2003).

This study aims to examine how AI-driven automation influences students' perceptions of usability, efficiency, and engagement; to empirically validate the adoption of Notion through the lens of technology acceptance theories; and to provide actionable recommendations for universities and educators on effectively integrating AI-powered mobile learning platforms into academic curricula (Joma et al., 2024; Al Mamun & Hasan, 2024; Saihi, Ben-Daya, & Hariga, 2024).

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), is widely used to explain technology adoption behavior, identifying four primary factors influencing behavioral intention: performance expectancy, defined as the degree to which a student believes that using a digital tool will enhance academic performance; effort expectancy, referring to the perceived ease of use of the technology; social influence, representing the extent to which individuals perceive encouragement from peers, professors, or institutions; and facilitating conditions, which relate to the availability of technical infrastructure, training, and institutional support for technology adoption.

Numerous studies have confirmed that performance expectancy is the strongest predictor of mobile learning adoption (Patterson, Frydenberg, & Basma, 2024). However, the introduction of Generative AI in educational tools is modifying traditional adoption patterns, making AI-driven automation and personalized learning features more relevant (Aryuni & Candra, 2024). This study extends the UTAUT model by incorporating AI-powered functionalities to assess their influence on students' technology acceptance.

This research contributes to both theoretical and practical discussions on mobile learning adoption and AI-enhanced education. The study provides empirical validation of the UTAUT model in the context of AI-driven mobile learning tools and offers insights into how Generative AI influences students' perceptions of usability, efficiency, and engagement.

From a practical perspective, the study highlights the importance of emphasizing AI-driven functionalities, such as automation and personalized recommendations, in promoting adoption. Recommendations for universities include providing AI-enhanced tools with clear instructional support, showcasing AI-powered benefits, and integrating digital literacy programs to optimize student engagement (Joma et al., 2024).

2. Literature Review

The UTAUT (Unified Theory of Acceptance and Use of Technology) model, proposed by Venkatesh et al. (2003), is one of the most widely used theoretical frameworks for analyzing technology acceptance. It is the result of the consolidation of eight pre-existing models, including TAM, TRA, and DOI. The model is based on four determining variables: performance expectancy, effort expectancy, social influence, and facilitating conditions. These variables influence behavioral intention to use, which is modulated by four moderators: gender, age, experience, and willingness to use.

In order to better capture the complexity of adoption behaviors in emerging technological contexts, numerous studies have proposed extensions to the UTAUT model in the context of mobile learning (M-Learning). For example, Chand et al. (2022) analyzed 77 empirical studies and enriched the model with seven new constructs: interaction, self-efficacy, motivation, satisfaction, attitude, digital literacy, and non-functional requirements (Chand et al., 2022).

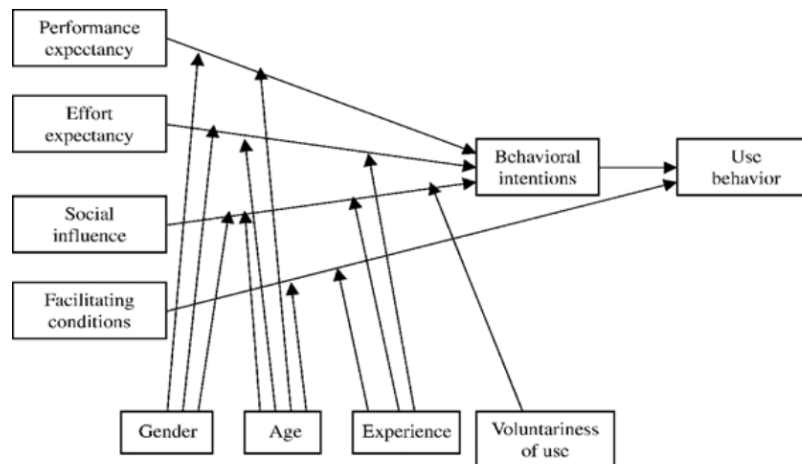
Other studies have incorporated variables such as perceived compatibility, mobile anxiety, service quality, and perceived innovation in order to better explain adoption intention among students in a university context (Faqih, 2022). Alowayr (2021) proposed an extension focused on intrinsic motivation, mobile self-efficacy, and perceived satisfaction, obtaining a significant predictive capacity for the extended model ($R^2 = 0.738$) (Alowayr, 2021).

Several empirical studies have validated, with nuances, the applicability of the UTAUT model to M-Learning. Performance expectancy, perceived effort, and hedonic motivation are regularly identified as significant predictors of usage intention (Yang, 2013), (Talan et al., 2024). However, studies have also highlighted that the relationships between the model's variables can be modulated by cultural and geographical context, which limits the universality of the model without prior adaptation (Akinbode et al., 2018), (Thomas et al., 2013). A recent meta-analysis conducted by Zhu and Huang (2023), based on 35 empirical studies, revealed that the factors most strongly correlated with the intention to adopt M-Learning are performance expectancy, attitude, perceived enjoyment, learning autonomy, and facilitating conditions (Zhu & Huang, 2023).

The UTAUT model is based on four fundamental constructs (Venkatesh et al., 2003) (Figure 1) that explain the acceptance and use of technologies. Performance expectancy refers to the extent to which an individual believes that using a technology will improve their performance. Effort expectancy refers to the perceived ease of use of the technology. Social influence refers to the user's perception of the importance that their friends and family or their environment attach to the use of the technology. Finally, enabling conditions encompass the technical and organizational resources perceived as necessary for effective use. These relationships are moderated by demographic and contextual variables such as age, gender, previous experience, and willingness to use. Numerous studies have proposed extensions to the initial model, adding variables such as self-efficacy, intrinsic motivation, technological compatibility, satisfaction, and attitude toward use. These enhancements aim to better capture the complexity of acceptance

behaviors in specific contexts, while maintaining the robust explanatory structure of the original model.

Figure 1: Theoretical framework, from Venkatesh et al. 2003

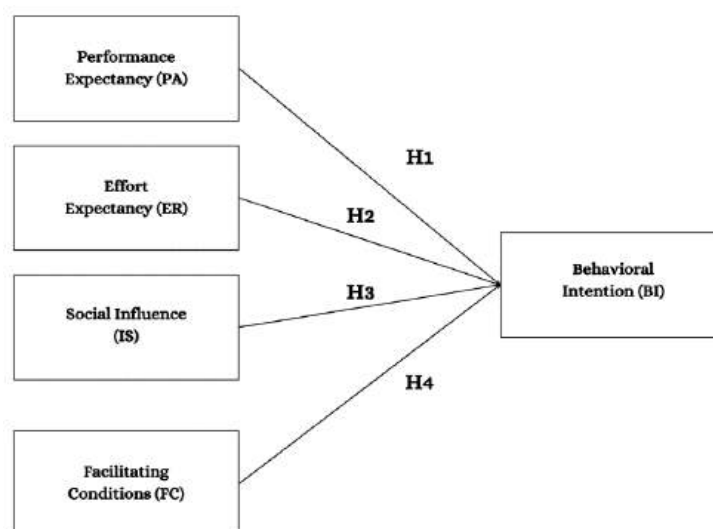


3. Research Model & Items

The items were adapted from previous studies validated in educational technology adoption research (Venkatesh et al., 2003; Khlaif, Ayyoub, & Hamamra, 2024). The questionnaire was pre-tested with a pilot group of 15 students to ensure clarity, validity, and reliability.

This model visualizes the hypothesized relationships between UTAUT constructs and Behavioral Intention, providing a basis for hypothesis testing through PLS-SEM analysis (Figure 2)

Figure 2: Conceptual framework, Adapted from Venkatesh et al. 2003



Source: Authors

The following table presents the detailed measurement items for each construct:

Table 1: Research Items

Construct	Code	Measurement Item
Performance Expectancy (PE)	PA1	Using Notion improves my productivity.
	PA2	Using Notion helps me accomplish my daily tasks.
	PA3	Notion helps me organize my notes and projects efficiently.
Effort Expectancy (EE)	ER1	Learning to use Notion is easy for me.
	ER2	It would be easy for me to become proficient at using Notion.

	<i>ER3</i>	I find Notion's interface clear and understandable.
Social Influence (SI)	<i>IS1</i>	People important to me think I should use Notion.
	<i>IS2</i>	Positive perceptions of Notion by my social circle encourage me.
	<i>IS3</i>	My peers use Notion and encourage me to use it as well.
Facilitating Conditions (FC)	<i>CF1</i>	I have the technological resources needed to use Notion.
	<i>CF2</i>	I have the necessary skills to use Notion.
	<i>CF3</i>	If I encounter problems, I can get help with Notion.
Behavioral Intention (BI)	<i>IC1</i>	I am motivated to learn how to use Notion soon.
	<i>IC2</i>	I intend to use Notion in the near future.
	<i>IC3</i>	I have planned to use Notion soon.

Source: Authors

4. Methodology

This study adopts a quantitative research design grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) model to investigate the factors influencing the adoption of Notion as a mobile learning platform enhanced with Generative AI functionalities. The UTAUT model is chosen for its effectiveness in predicting technology adoption through four key constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) (Venkatesh et al., 2003). It is particularly relevant for studying AI-enhanced educational tools (Patterson, Frydenberg, & Basma, 2024).

4.1. Research design

The study follows a cross-sectional survey design, using an online questionnaire distributed to university students who use Notion for academic purposes. The questionnaire measures students' behavioral intentions and their perceptions of AI-enhanced functionalities, such as automated content generation, intelligent task management, and personalized learning recommendations.

To test the hypotheses, Partial Least Squares Structural Equation Modeling (PLSSEM) is employed using SmartPLS 4.0, suitable for analyzing complex causal relationships in exploratory research (Hair et al., 2019). The model integrates Generative AI components within the UTAUT framework to evaluate their impact on students' behavioral intentions.

4.2. Sample and Procedure

The target population for this study consists of university students using Notion as a mobile learning tool. An online survey was distributed through university networks, social media platforms, and student forums, employing a non-probabilistic convenience sampling technique to reach respondents familiar with Notion's AI-enhanced features.

A total of 90 valid responses were collected, meeting the minimum sample size requirement for PLS-SEM analysis, as recommended by Hair et al. (2019). The sample is diverse, including students from different academic disciplines and educational levels, thus ensuring a comprehensive understanding of user perceptions. Participants were informed about the study's objectives, and informed consent was obtained to ensure ethical compliance.

The demographic distribution of the respondents is as follows:

Gender: 55% female, 45% male.

Age Range: 18-25 years (70%), 26-30 years (20%), and above 30 years (10%).

Educational Level: Undergraduate (60%), Graduate (30%), and Postgraduate (10%).

The online survey was designed using Google Forms and distributed through university mailing lists and social media channels. To ensure relevant user experience, respondents were required to have at least three months of experience using Notion.

This prerequisite ensured that participants' perceptions were based on substantial user interaction with the platform.

4.3. Measurement Instrument

The study utilizes a structured questionnaire adapted from validated scales within the UTAUT framework. The instrument measures the following constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), and Behavioral Intention (BI). Each construct is measured using multiple items on a 5-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

4.4. Data Analysis

The data was analyzed using SmartPLS 4.0, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM). This method is appropriate for testing complex causal relationships and predictive models in exploratory research (Hair et al., 2019). The analysis follows a two-step approach: Measurement model analysis:

- Reliability and validity tests: Cronbach's alpha and Composite Reliability (CR) were calculated to assess the internal consistency of the constructs. Cronbach's alpha values above 0.6 indicate acceptable reliability (Hair et al., 2019).
- Convergent validity: Evaluated using the Average Variance Extracted (AVE), which should be above 0.50 (Nunnally & Bernstein, 1994). All constructs showed AVE values greater than 0.5, confirming convergent validity.
- Discriminant validity: Assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT) to ensure that constructs are empirically distinct.

4.5. Structural Model Analysis:

- Path coefficients and hypotheses testing: The significance of path coefficients was evaluated using the Bootstrapping method with 5000 resamples. Hypotheses were tested for direct and moderating effects.
- Coefficient of determination (R^2): Analyzed to measure the explained variance of the endogenous constructs. In this study, R^2 for Behavioral Intention was 0.411, indicating a moderate explanatory power.
- Effect size (f^2): Calculated to determine the magnitude of influence between constructs.
- Predictive relevance (Q^2): Evaluated using the Stone-Geisser criterion to assess the predictive accuracy of the model.

This comprehensive approach ensures a rigorous examination of the proposed model, offering empirical insights into how Generative AI functionalities influence the adoption of Notion as a mobile learning tool.

5. Results

5.1. Descriptive Outcomes

The study collected data from 90 university students who use Notion as a mobile learning tool, ensuring that participants had at least three months of experience with the platform. The sample was obtained using a non-probabilistic convenience sampling technique, distributed through university networks and social media platforms.

The demographic distribution of the respondents is as follows: 55% female and 45% male. The majority of respondents are aged between 18-25 years (70%), followed by 26-30 years (20%) and above 30 years (10%). Regarding educational level, 60% are undergraduates, 30% are graduates, and 10% are postgraduates. The participants also come from various fields of study, including Humanities (35%), Sciences (30%), Business (20%), and Engineering (15%). This diverse sample composition provides a comprehensive representation of student perceptions across different academic disciplines and educational levels.

5.2. Validity and Reliability tests

The Measurement Model was evaluated using SmartPLS 4.0 to assess convergent and discriminant validity. Convergent validity was examined using Factor Loadings, Composite Reliability (CR), and Average Variance Extracted (AVE). All factor loadings exceeded the recommended threshold of 0.70, indicating good individual item reliability. Composite Reliability (CR) values ranged from 0.838 to 0.884, exceeding the minimum acceptable level of 0.70, confirming internal consistency. The Average Variance Extracted (AVE) values ranged from 0.635 to 0.753, confirming that more than 50% of the variance is explained by each construct's indicators.

Table 2: Individual item loadings

Construct	Items	Loading
Facilitating Conditions (FC)	CF1	0.798
	CF2	0.898
Effort Expectancy (EE)	ER1	0.704
	ER2	0.858
	ER3	0.882
Social Influence (SI)	IS1	0.871
	IS2	0.808
	IS3	0.862
Behavioral Intention (BI)	IC1	0.789
	IC2	0.867
	IC3	0.728
Performance Expectancy (PE)	PA2	0.881
	PA3	0.854

Source. Survey data (2024)

All loadings are above 0.70, confirming individual item reliability according to Chin (1998).

Table 3: Validity and reliability results

Construct	Cronbach's Alpha	Composite Reliability (CR)
Performance Expectancy (PE)	0.673	0.859
Effort Expectancy (EE)	0.784	0.858
Social Influence (SI)	0.806	0.884
Facilitating Conditions (FC)	0.622	0.838
Behavioral Intention (BI)	0.713	0.838
Construct	Cronbach's Alpha	Composite Reliability (CR)
Performance Expectancy (PE)	0.673	0.859
Effort Expectancy (EE)	0.784	0.858

Source. Survey data (2024)

Cronbach's Alpha values confirm internal consistency for all constructs, with values above 0.60. Composite Reliability (CR) confirms internal consistency, exceeding 0.70 for all constructs. Average Variance Extracted (AVE) values are above 0.50, confirming convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait Ratio (HTMT). The square root of each AVE was higher than the correlation with other constructs, confirming discriminant validity. HTMT ratios were all below 0.85, supporting discriminant validity.

5.3. Structural Model Analysis

The Structural Model was evaluated using PLS-SEM to test the hypothesized relationships between constructs. The analysis included Path Coefficients to determine the strength and significance of the relationships between constructs, Coefficient of Determination (R^2) to

measure the explained variance of Behavioral Intention (BI), and Effect Size (f^2) and Predictive Relevance (Q^2) to assess the impact and predictive power of the model.

Table 4: Structural model results

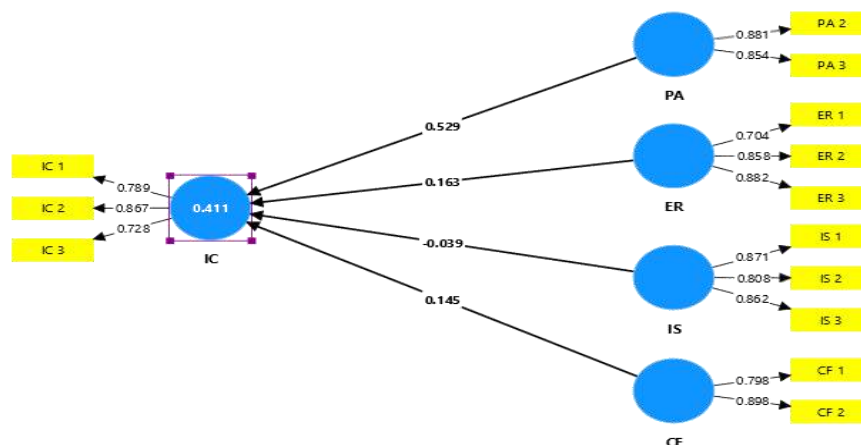
Hypothesis	Path coefficient (β)	t-value
H1: Performance expectancy $\rightarrow$ Behavioral intention	0.529	5.822
H2: Effort expectancy $\rightarrow$ Behavioral intention	0.163	1.589
H3: Social influence $\rightarrow$ Behavioral intention	-0.039	0.385
H4: Facilitating conditions $\rightarrow$ Behavioral intention	0.145	1.358
Hypothesis	Path coefficient (β)	t-value

Source. Survey data (2024)

Performance Expectancy (PE) positively and significantly influences Behavioral Intention (BI) ($\beta = 0.529$, $p < 0.001$), supporting H1. Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) do not significantly influence Behavioral Intention (BI), leading to the rejection of H2, H3, and H4.

The model explains 41.1% of the variance in Behavioral Intention (BI), indicating a moderate explanatory power. Performance Expectancy shows a large effect size, while the other constructs show negligible effects. The Stone-Geisser criterion confirms that the model has predictive relevance for Behavioral Intention (Figure 3).

Figure 3: The UTAUT model in Smart PLS 4 software presenting the results of the bootstrap technique



Source: Authors

6. Analysis and Discussion

6.1. Results Interpretation

The results of this study provide valuable insights into the factors influencing the adoption of Notion as a mobile learning platform enhanced with Generative AI functionalities. The findings reveal that Performance Expectancy (PE) is the most significant predictor of Behavioral Intention (BI), confirming H1. This suggests that students are more likely to adopt Notion when they perceive it as beneficial for productivity, task management, and academic performance. This is consistent with the UTAUT model, which posits that users are more likely to adopt a technology when they expect it to enhance their performance (Venkatesh et al., 2003). The significant impact of PE highlights the importance of AI-enhanced features such as automated content generation, intelligent task organization, and personalized learning recommendations, which improve learning efficiency and engagement.

However, Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) do not significantly influence Behavioral Intention (BI), leading to the rejection of H2, H3, and H4. The non-significant impact of Effort Expectancy indicates that students do not perceive

ease of use as a major barrier, possibly because they are already familiar with digital platforms and accustomed to exploring new applications independently. This suggests that AI-enhanced automation is perceived as intuitive and does not require significant learning effort. The non-significant effect of Social Influence suggests that students make independent decisions about technology adoption based on individual preferences and perceived usefulness, rather than relying on peer or social pressure. This finding is consistent with previous studies that indicate a decreasing influence of social factors on technology adoption among digitally literate users (Joma et al., 2024). The non-significant impact of Facilitating Conditions indicates that students do not rely heavily on institutional support or technical resources, possibly due to the availability of abundant online resources, tutorials, and community support.

The Coefficient of Determination (R^2) indicates that the model explains 41.1% of the variance in Behavioral Intention (BI), reflecting a moderate explanatory power. This suggests that while the UTAUT constructs provide a substantial explanation of Notion adoption, other factors such as perceived enjoyment, habit, or personal innovativeness may also play a role.

6.2. Comparatively to the Literature

This study contributes to the theoretical understanding of technology adoption by extending the UTAUT model to include Generative AI functionalities, providing a comprehensive framework to evaluate AI-enhanced mobile learning platforms. The findings confirm the continued relevance of Performance Expectancy as a primary determinant of adoption while highlighting the diminished role of Effort Expectancy, Social Influence, and Facilitating Conditions for digitally native students. This contributes to the growing body of literature on digital learning adoption and AI-enhanced educational tools, offering new insights into how AI-driven automation and personalization influence student engagement and behavioral intentions.

From a practical perspective, the findings provide actionable insights for educational institutions, technology developers, and policymakers. To promote the adoption of Notion and similar AI-enhanced learning platforms, developers should emphasize features that enhance productivity, facilitate effective task management, and provide personalized learning experiences. Educational institutions should demonstrate the performance benefits of AI functionalities through hands-on workshops, user testimonials, and targeted communication strategies that highlight productivity gains. Additionally, developers should focus on seamless user experiences and intuitive AI-driven automation to minimize cognitive load and reduce the perceived learning curve.

Given the non-significant impact of Social Influence and Facilitating Conditions, marketing strategies should focus on individual productivity gains and personal empowerment rather than peer influence or institutional endorsements. Furthermore, educational institutions should encourage self-directed learning and digital literacy by providing access to online resources, community support, and peer-to-peer learning networks.

These insights are particularly relevant for universities and educators seeking to integrate AI-powered educational tools into academic programs. By emphasizing productivity benefits and personalized learning pathways, institutions can enhance student engagement and maximize the educational impact of AI-enhanced platforms.

7. Conclusion

This study investigated the factors influencing the adoption of Notion as a mobile learning platform enhanced with Generative AI functionalities using the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The findings reveal that Performance Expectancy (PE) is the most significant predictor of Behavioral Intention (BI), confirming that students are more likely to adopt Notion when they perceive it as beneficial for productivity, task management, and academic performance. This highlights the importance of AI-enhanced

features such as automated content generation, intelligent task organization, and personalized learning recommendations, which positively impact learning efficiency and engagement. In contrast, Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) do not significantly influence Behavioral Intention (BI). The non-significant impact of Effort Expectancy suggests that students do not perceive ease of use as a barrier, likely due to their familiarity with digital platforms. This indicates that AI-enhanced automation is perceived as intuitive and does not require significant learning effort. The non-significant effect of Social Influence suggests that students make independent decisions about technology adoption based on personal preferences and perceived usefulness rather than peer or social pressure. Similarly, the non-significant impact of Facilitating Conditions indicates that students rely on self-directed learning resources and community support rather than institutional assistance.

The Coefficient of Determination (R^2) shows that the model explains 41.1% of the variance in Behavioral Intention (BI), indicating a moderate explanatory power. This suggests that while the UTAUT constructs provide substantial explanation, other factors such as perceived enjoyment, habit, or personal innovativeness may also influence the adoption of Notion.

These findings contribute to the theoretical understanding of technology adoption by validating the UTAUT model in the context of Generative AI-enhanced mobile learning platforms, offering empirical evidence that Performance Expectancy is the most influential factor, while Effort Expectancy, Social Influence, and Facilitating Conditions are less relevant for digitally literate students.

Despite its contributions, this study has several limitations. First, the sample was obtained using a non-probabilistic convenience sampling technique, which may limit the generalizability of the findings. The study was conducted with 90 university students from diverse academic disciplines, but the results may not be applicable to other user groups, such as professional learners or users from different cultural contexts. Future studies should consider larger and more diverse samples to enhance generalizability.

Second, this study employed a cross-sectional survey design, capturing students' perceptions at a single point in time. This limits the ability to examine longitudinal changes in technology adoption behaviors. Future research should adopt a longitudinal approach to investigate how students' perceptions and behavioral intentions evolve over time as they become more familiar with Notion and its AI-enhanced features.

Third, the study focused on the UTAUT constructs of Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, without considering other potential factors such as perceived enjoyment, habit, or personal innovativeness. Future research should expand the theoretical framework to include these variables, offering a more comprehensive understanding of the motivational and behavioral drivers influencing mobile learning adoption. Fourth, the study relied on self-reported data collected through an online questionnaire, which may be subject to social desirability bias or self-perception bias. Future studies could incorporate objective usage data or experimental designs to validate the findings and provide more accurate insights into students' behavioral intentions and actual usage patterns.

Finally, this study focused on Notion as a case study, which may limit the applicability of the findings to other AI-enhanced mobile learning platforms. Future research should investigate other platforms with different AI functionalities to examine whether the identified patterns hold across diverse learning tools.

This study opens several avenues for future research. First, future studies should explore the longitudinal effects of Generative AI functionalities on mobile learning adoption. Investigating how students' perceptions and behavioral intentions evolve over time as they become more familiar with AI-driven features would provide deeper insights into sustained technology acceptance.

Second, future research should expand the theoretical framework by integrating additional constructs such as perceived enjoyment, habit, and personal innovativeness.

This would offer a more holistic understanding of the motivational and behavioral drivers influencing mobile learning adoption, particularly in the context of AI-enhanced educational tools.

Third, future studies could investigate the moderating effects of demographic variables such as age, gender, educational background, and digital literacy on the relationships between UTAUT constructs and Behavioral Intention. Understanding how different user groups perceive and adopt AI-enhanced mobile learning tools would enable more targeted design and marketing strategies.

Fourth, future research should adopt mixed-methods approaches, combining quantitative surveys with qualitative interviews or focus groups. This would provide richer insights into the underlying reasons and contextual factors influencing students' technology adoption decisions.

Fifth, future studies should explore the cross-cultural validity of the findings by examining the adoption of Notion and similar AI-enhanced learning platforms in different cultural contexts. Comparative studies would provide insights into how cultural differences impact students' perceptions, behavioral intentions, and usage patterns.

Finally, future research should investigate the educational impact of AI-enhanced functionalities on learning outcomes, student engagement, and academic performance. This would provide a more comprehensive evaluation of the pedagogical value of Generative AI in mobile learning environments.

Références :

- (1). Akinbode, M., Mayowa, A., Okuboyejo, S. R., & Adeniji, C. (2018). Adoption and use of mobile learning in higher education: The UTAUT model. *Proceedings of the 2018 International Conference.*
- (2). Al Mamun, M. A., Hasan, M.: Engineering Students' Adoption of Generative AI: The Role of Social Influence and Cognitive Processes. In: *ASCILITE 2024 International Conference on Digital Learning*, pp. 1–12. ASCILITE Publications (2024).
- (3). Alowayr, A. (2021). Determinants of mobile learning adoption: Extending the unified theory of acceptance and use of technology (UTAUT). *The International Journal of Information and Learning Technology.*
- (4). Aryuni, M., Candra, S.: Analysis Factors Affecting Student Intention to Use Generative Artificial Intelligence in E-Learning. In: *2024 International Conference on Digital Learning*, pp. 45–58. IEEE, New York (2024).
- (5). Bouteraa, M., Bin-Nashwan, S. A., Al-Daihani, M.: Understanding the Diffusion of AIGenerative (ChatGPT) in Higher Education: Does Students' Integrity Matter?. *Computers in Human Behavior* 152, 106–119 (2024).
- (6). Chand, S., Kumar, B., Goundar, M. S., & Narayan, A. (2022). Extended UTAUT model for mobile learning adoption studies. *International Journal of Mobile and Blended Learning.*
- (7). Chin, W. W.: The Partial Least Squares Approach to Structural Equation Modeling. In: Marcoulides, G. A. (ed.) *Modern Methods for Business Research*, pp. 295–336. Lawrence Erlbaum Associates, Mahwah (1998).
- (8). Faqih, K. (2022). Investigating the adoption of an innovation using an extended UTAUT model: The case of mobile learning technology. *Journal of Theoretical and Applied Information Technology*, 100.
- (9). Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M.: *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. Sage Publications, Thousand Oaks (2019).

- (10). Joma, A., Bsharat, T., Khaldi, M., Sanmugam, M.: Drivers of Acceptance of Generative AI Through the Lens of the Extended Unified Theory of Acceptance and Use of Technology. SSRN, <https://papers.ssrn.com/sol3/Delivery.cfm?abstractid=4969172>, last accessed 2025/02/19.
- (11). Khlaif, Z. N., Ayyoub, A., Hamamra, B.: University Teachers' Views on the Adoption and Integration of Generative AI Tools for Student Assessment in Higher Education. *Education Sciences* 14(10), 122–135 (2024).
- (12). Nunnally, J. C., Bernstein, I. H.: *Psychometric Theory*. 3rd edn. McGraw-Hill, New York (1994).
- (13). Patterson, A., Frydenberg, M., Basma, L.: Examining Generative Artificial Intelligence Adoption in Academia: A UTAUT Perspective. *Issues in Information Systems* 25(2), 90– 102 (2024).
- (14). Saihi, A., Ben-Daya, M., Hariga, M.: The Moderating Role of Technology Proficiency and Academic Discipline in AI-Chatbot Adoption within Higher Education: Insights from a PLS-SEM Analysis. *Education and Information Technologies* 29(4), 567–584 (2024).
- (15). Talan, T., Doğan, Y., & Kalinkara, Y. (2024). Digital natives' mobile learning adoption in terms of UTAUT-2 model: A structural equation model. *Innoeduca. International Journal of Technology and Educational Innovation*.
- (16). Thomas, T., Singh, L., & Gaffar, K. (2013). The utility of the UTAUT model in explaining mobile learning adoption in higher education in Guyana. *International Journal of Education and Development Using Information and Communication Technology*, 9, 71–87.
- (17). Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
- (18). Yang, S. (2013). Understanding undergraduate students' adoption of mobile learning model: A perspective of the extended UTAUT2. *Journal of Convergence Information Technology*, 8(10), 969–979.
- (19). Zaim, M., Arsyad, S., Waluyo, B., Ardi, H., Al Hafizh, M.: AI-powered EFL Pedagogy: Integrating Generative AI into University Teaching Preparation Through UTAUT and Activity Theory. *Computers and Education: Artificial Intelligence* 5, 35–50 (2024).
- (20). Zhu, Z., & Huang, W. (2023). A meta-analysis of mobile learning adoption using extended UTAUT. *Information Development*.