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Evaluating Generative AI Tool Adoption and Its Effects on Academic Performance

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Abstract: There is an explosion of Generative AI tools used by students. The key topic is what factors influence the use of students' Gen AI tools and how they affect academic achievement in higher education. This study explores the factors influencing students' intention to use Generative AI tools and their impact on academic achievement. The research model was validated using survey data from 398 students in a bilingual higher education setting in Jordan. Structural Equation Modeling (SEM) analysis was performed using Amos 20 to test the research hypotheses. Further the authors test the study using 8 machine learning models (decision tree, SVM, Random Forest, Neural network, Linear Regression, kNN, Gradient boosting, and AdaBoost). The empirical results are offered. several key findings. First, the ease of use and compatibility both positively influence the attitude towards using Generative AI tools. Facilitating conditions positively influence perceived behavioral control. Attitude, subjective norms, and perceived behavioral control positively influence behavioral intention to use Gen AI tools. Finally, behavioral intention positively influences academic achievement.

Keywords: Generative AI, Academic Achievement, TAM, DTPB, Educational technology

1 Introduction

GenAI is short for Generative Artificial intelligence able to generate text, sound, images and other media by using generative AI models. Generative AI models learn patterns and structure of input training sets of data and then generate new data that has similar characteristics. GenAI is used for data analysis, software development, marketing, project management and education. Text generating abilities written [1], [2] or conversational [3] is evident in GenAI tool named ChatGPT created by Open AI. The training set includes research papers, books, and poems. As such there are a number of GenAI like Synthesia (video), AI Studios, GitHub Copilot, Jasper (marketing), Claude (chatbot), AlphaCode (code-generation), Bing AI (search), ChatSonic (chatbot), Amazon CodeWhisperer (code-generation), Bardeen (workflow automation), Cohere Generate (text, images, and audio) , DreamStudio (text, images, and audio), Writesonic (content creation), Bard (conversational tasks), QuillBot (writing assistant), Soundraw (sound), AI Query.

There are many advantages to GenAI other than saving time and money reported by blogs pre-prints and research papers [4] , [5]. GenAI Creates versatile content, enhances user experience, is efficient in automation, and is adaptable and context aware. Furthermore, personalization and customization, language translation and understanding, medical research and diagnosis, scientific research and exploration, entertainment and gaming, facilitation of design processes. Further Schonberger [6] discussed opportunities and risks of

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ChatGPT in Education i.e. developing digital literacy, support scholarly practices, automate student support, personalized learning support, encourage creativity, and generating text summaries. However, some concerns are presenting themselves i.e. bias and fairness [5], originality and creativity, computational resources, ethical considerations [7], limited adaptability, data privacy, and model reliability. Further Schonberger [6] listed the following challenges of ChatGPT in education: Misinformation, Difficulty in evaluating the results, Lack of consideration of current and scientific sources, Unclear authorship, and Biases.

The primary objective of this empirical study is to investigate and analyze the factors that influence students' intentions to use Generative AI tools. Additionally, the study aims to assess the impact of utilizing these tools on students' academic achievement within the context of Jordan. Through empirical research and data analysis, the study seeks to identify the determinants affecting students' adoption of Generative AI tools and to evaluate the correlation between their usage and academic achievement in the Jordanian educational setting.

The motivation of this research is the desire to comprehend, improve, and enhance the integration of Generative AI tools in Jordanian educational settings for the betterment of students' learning experiences and academic achievements. Understanding the factors that drive students' intentions to use these tools can aid in promoting the effective integration of technology in education. Further, identify how these tools contribute to enhancing students' academic performance. Discover potential barriers or challenges hindering the effective implementation of such technologies in the Jordanian educational context. the research could provide valuable insights for educational policymakers, institutions, and educators in Jordan. And will contribute to academic literature.

The importance of researching the factors influencing students' intention to use Generative AI tools and their impact on academic achievement in Jordan lies in several significant aspects: First, the research may guide educators and policymakers in effectively integrating technology into the educational process. Insights gained from the research can contribute to enhancing teaching methodologies and student learning experiences. Help tailor educational approaches to better suit students' preferences and improve engagement. Discover potential barriers and challenges hence design interventions. The research outcomes can guide educational policymakers in Jordan in formulating strategic plans and policies related to the integration of technology in the educational system. The research will add to the body of knowledge in educational technology and serves as a reference for future research and studies in this field.

The major contributions of the current research on factors influencing students' intention to use Generative AI tools and their impact on academic achievement in Jordan could encompass several key aspects: This research provides valuable experimental evidence regarding the adoption of Generative AI tools within the educational landscape in Jordan, addressing a notable gap that currently exists in the literature. It specifically and uniquely explores various factors that influence students' intentions to utilize these innovative tools and examines their subsequent impact on academic performance outcomes. This investigation considers Jordan's distinct cultural, social, and educational dynamics, ensuring that the findings are relevant and applicable to the local context. The research aims to contribute significantly to understanding how such advanced technologies can be integrated into the educational system effectively.

The research identifies factors influencing students' intentions to use Generative AI tools. It provides insights into key motivators and inhibitors affecting their adoption of innovative educational technologies. In addtion, the research explores how Generative AI tools impact students' academic achievement, revealing their potential effects on learning outcomes and whether they correlate positively or negatively with success in Jordan's education system.

The findings provide practical insights for educators, policymakers, and institutions in Jordan. Recognizing the factors affecting technology adoption and its influence on academic performance can aid in formulating strategies, improving curricula, and shaping policies to effectively integrate Generative AI tools in education. The research serves as a foundation for future studies in similar domains. It may inspire further investigations, longitudinal studies, or comparative analyses, encouraging a deeper exploration of the role of Generative AI tools in education and their effects on student learning and achievement.

2 LITERATURE REVIEW

Generative Artificial Intelligence (AI) tools have emerged as innovative technologies with significant potential to transform educational practices worldwide. Research in the field of educational technology emphasizes the importance of understanding factors influencing students' acceptance and utilization of these tools, as well as their impact on academic achievement. Many studies investigated the role of Generative Artificial Intelligence (AI) tools in the field of educational using deferent models like:, [5], [6], [7], [8], [9], [10], [11], [12], [13], [14] [15], [16], [17], [18], [19], [22].

A multitude of studies have investigated the Technology Acceptance Model (TAM) as a framework to comprehend users' acceptance of technological innovations in educational settings like [9], [10], [12], [13], [14] and [19], others used Unified Theory of Acceptance and Use of Technology (UTAUT) like [6] and [17], theory of planned behavior (TPB) like [19], and Latent Dirichlet allocation (LDA) like [18]. Other concentrated their effort on different domains of education like math, economics and programming in [11], or higher education [20], FinTech in [13], English language in [10]. Lo in the research [11] investigated the impact of ChatGPT on education with emphasis of ChatGPT role as assistant to teacher and tutor to students by examining the performance of ChatGPT across many domains: math, economics and programming. Tlili et al in the research [7] investigated ChatGPT in education by examining the case of ChatGPT through lenses of educational transformation, response quality, usefulness, personality and emotion, and ethics. Zhai in [5] investigated the user experience of ChatGPT as implications for education, the researcher suggested that ChatGPT will dive changes to the different aspects of education: learning goals, learning activities, and assessment and evaluation practices.

Liu in [10] investigated ChatGPT in learning English language by using TAM model. While Shaengchart in [9] investigated ChatGPT usage intention in higher education also using TAM. Tiwari et al. in [12] investigated the factor influencing the use of ChatGPT in education by using an expanded TAM model. Belanche et al. [13] studied AI in FinTech to understand robo-advisors and used TAM model. Rahman [14] Studied driver acceptance to support systems using TAM model. Le et al. [22] combined the TAM and UGT frameworks to investigate how Vietnamese students' views of ChatGPT and intrinsic needs affect their intentions to use it for education. Also, Schonberger [6] examines the opportunities and risks of artificial intelligence (AI) in the context of higher education, using ChatGPT as an example. generative Artificial Intelligence (AI) that can be applied to create various content such as text, code, audio, images and videos according to Korzynski et al. in [15].

Duong et al [16] investigated ChatGPT effort expectancy and performance expectancy of UTAUT model in higher education. Hidayat in [17] investigated the adoption of educators to ChatGPT using UTAUT model in education.Yang in [18] investigated public acceptance of ChatGPT with governmental services using Latent Dirichlet allocation (LDA) model. Abaddi in [19] investigated ChatGPT digital entrepreneurial intentions using technology acceptance model (TAM) and the theory of planned behavior (TPB). Su in [20] discussed the potential of ChatGPT for higher education of innovation and entrepreneurship in China. Yu in [8] contemplated the two extremes between banning ChatGPT or not in education.

However, within the Jordanian educational context, there is a scarcity of empirical research specifically examining Generative AI tools' acceptance and their influence on academic achievement among students. Given the unique cultural and educational landscape of Jordan, exploring these factors becomes imperative to inform educational practices and policies.

3 THEORETICAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

This research paper proposed a model reflected in Figure 1. The model is based on the theory of planned behavior (TPB) and decomposed theory of planned behavior (DTPB) used in many research papers. Further, the paper studied more than 24 research papers pertaining to generative AI tools [2], [3], [5], [6], [7], [9], [10], [11], [12], [15], [16], [17], [18], [22], [21], [23], [24], [25], [26], [27], [28] and [29]. Hence, the model consists of three types of variables: independent, mediating, and dependent. The independent variables include perceived risk (PR), ease of use (EU), compatibility (CT), subjective norm (SN), self-efficacy (SE), and facilitating conditions (FC). The mediating variables are attitude (ATT), perceived behavioral control (PBC), and behavioral intention (BI). The dependent variable is academic achievement (AA). As such, 9 hypotheses were developed based on the model described above, which is presented in the next section.

Schonberger [1] introduces and discusses the risks of using ChatGPT in higher education, including biases introduced through training data and potential limitations in linguistic diversity. The author found that ChatGPT offers personalized learning and immediate feedback, Challenges include accuracy, lack of human interaction, privacy and security issues, bias, discrepancies, over-reliance, plagiarism and cheating. Shaw et al. [2] The paper mentions that using ChatGPT in education poses a risk of producing misleading or erroneous texts due to its tendency to disregard facts or generate fake facts. The author found that ChatGPT can generate accurate texts like humans. ChatGPT may produce misleading or erroneous texts.

Sallam et al. [28] study showed that risk perception played a crucial role in shaping the attitude and usage of ChatGPT among healthcare students in Jordan. This highlights the importance of addressing potential biases in ChatGPT by the developers which can shape the attitude towards its use. Thus, the risk of technological flaws that could lead to cybersecurity threats and data breaches should be addressed properly. Derner and Batistič [26] discussed the security risks associated with ChatGPT, including malicious text and code generation, private data disclosure, fraudulent services, information gathering, and producing unethical content.

Sebastian [27] investigates the cybersecurity risks associated with ChatGPT and similar AI-based chatbots, including potential vulnerabilities that could be exploited by malicious actors. Mitigation methods are also suggested.Aghemo et al. [24] discusses the potential risks of using ChatGPT in scientific writing, including the possibility of introducing bias, the commodification of research, and the lack of transparency and reproducibility.Ferrara [30] discusses the challenges and risks associated with biases in generative language models like ChatGPT, emphasizing the importance of

developing responsible AI systems to minimize unintended consequences. Doshi et al. [25] mentions that ChatGPT can demonstrate prejudice and bias in its answers, perpetuating the biases present in the data it was trained on.
Based on the previous and in addition to [26], [27], [28], [29] the first hypothesis was developed:
H1. Perceived risk (PR) has a positive effect on attitude (ATT) toward using Generative AI Tool.
Perceived usefulness and Ease of use (EU) are both part of the original TAM model and used to study generative AI according to [13] in FinTech. [31] and [F3] studied the influence of EU on attitude (ATT) in E-wallet Apps. Based on the research work of : [1], [2], [3], [6], [29] H2 was developed.
H2. Ease of use (EU) has a positive effect on Attitude (AT) toward using Generative AI Tool.
As referenced in [32] and [33] "Compatibility is the degree to which the innovation fits with the potential adopter's existing values, previous experience and current needs" and based on the work of [32] the hypothesis (H3) was developed:
H3. Compatibility (CT) has a positive effect on attitude (AT) toward using Generative AI Tool.
Masa'deh et. al. [32] stated that "A subjective norm represents an individual's normative belief concerning a particular referent, weighted by the motivation to comply with that referent" , researchers [32] also examined the impact of subjective norm (SN) on behavioral intention (BI). Accordingly, the following hypothesis was formulated.
H4. Subjective norm (SN) has a positive effect on behavioral intention (BI) toward using Generative AI Tool.
Both self-efficacy and facilitating conditions are influences on perceived behavioral control (PBC). A definition of self-efficacy referenced by [32] states that self-efficacy "represents an individual's self confidence in his or her ability to perform a behavior". self-efficacy was referenced in [36] was defined as self-knowledge to use an object. It was further discussed in [2], [6] that self-efficacy influences PBC. Thus, H5 and H6 were developed.
H5. Self-efficacy (SE) has a positive effect on perceived behavioral control (PBC) toward using Generative AI Tool.
H6. Facilitating conditions (FC) has a positive effect on perceived behavioral control (PBC) toward using Generative AI Tool. according to [36] Attitude defined is an individual positive or negative feeling about performing the target behavior. Rahman et al [14] investigated the behavioral intention to adopt driver support systems. Tiwari [12] studied attitude influence on behavioral intention and their results supported the hypothesis. Therefore, H7 is proposed based on the work of [3], [1], [2], [6]:
H7. Attitude (ATT) has a positive effect on behavioral intention (BI) toward using Generative AI Tool.

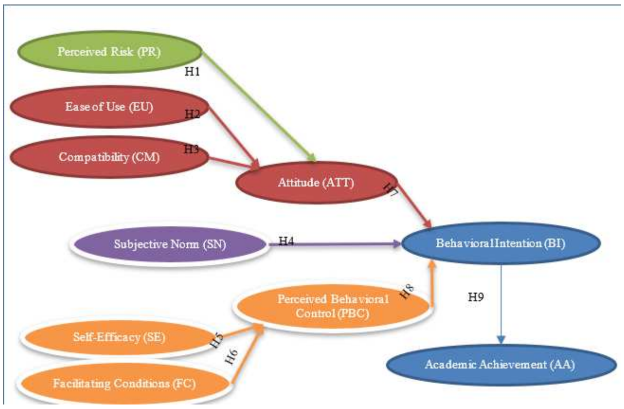

Fig. 1: The suggested model adopted from [34] based on DTPB [35]

Perceived behavioral control (PBC) according [37] refers to an individual's assessment of their capacity to successfully carry out an activity, considering both internal and external elements that may impact their control.
H8. Perceived behavioral control (PBC) has a positive effect on behavioral intention (BI) toward using Generative AI Tool.
Behavioral intention measures of the strength of one's intention to perform a specific behavior according to [36]. The research work of [3], [1], [2], [6], [29] suggested the following hypothesis.
H9. Behavioral intention (BI) has a positive effect on academic achievement (AA).

4 RESEARCH METHODS

This study investigates the total effect of using Generative AI (GenAI) on academic achievement (AA). It examines the influence of perceived risk (PR), ease of use (EU), and compatibility (CT) on attitude (ATT); self-efficacy (SE) and facilitating conditions (FC) on perceived behavioral control (PBC); and attitude (ATT), perceived behavioral control (PBC), and subjective norm (SN) on behavioral intention (BI). Additionally, it explores the impact of behavioral intention (BI) on academic achievement (AA). Given the limited research on this topic, the researchers proposed the research model shown in Figure 1 after an extensive development phase, leading to the formulation of the hypotheses. A questionnaire was then designed and tested, and data were collected from a convenience sample of 398 participants. The following sections—research context, measurement items, and participants and procedure—provide a detailed explanation of the survey design and research methodology.

4.1 Research context

As the world is shifting to computer-based learning and education, GenAI are becoming essential in the learning and teaching environment. The primary question explores the factors influencing students' behavioral intention to use GenAI and how the overall process impacts academic achievement. This study was conducted using the following approach.

4.2 Measurement items

To evaluate the proposed research model for this study, a questionnaire survey was designed. The survey items were adapted from previous studies. The model includes 10 direct and intermediate variables, along with 6 moderating variables: gender, age, education, university type, and GenAI.
The construct Perceived risk (PR) was measured by (3)items suggested by [38]; ease of use (EU) was measured by (3)items adopted from [38], [39]; compatibility (CT) was measured by (4) items [35], [38]. Subjective norm (SN) was measured by (3)items from [40], [38]. Self-efficacy (SE) was measured by (3)items from [35], [38]. Facilitating conditions (FC) was measured by (4)items [41], [38]. attitude (AT) was measured by (3)items from [40], [38], perceived behavioral control (PBC) [35], [38], and behavioral intention (BI), [40], [38], were each measured by (3)items. Academic achievement (AA) was measured by (7) items adopted from [42] and [43].

4.3 Participants and procedure

A web-based survey using Google Docs was prepared in Arabic and English. It employed a 5-point Likert scale from strongly disagree (1) to strongly agree (5). A panel of five academicians reviewed the survey, and feedback was incorporated. The questionnaire was then piloted on 25 GenAI users in Jordan to assess question clarity, leading to further revisions.
From November 24, 2023, to May 14, 2024, the survey was distributed to 398 GenAI users and students in Jordan. College professors shared it via email, WhatsApp, and Facebook academic groups to ensure student participation. Table 1 presents the demographic profile of respondents. Most were male and female students, aged 18 to under 28, with a bachelor's degree, attending public universities. They had good or excellent internet experience, and the majority used ChatGPT as their GenAI tool.

Table 1

5 DATA ANALYSIS AND RESULTS

5.1 Descriptive Analysis

To analyze the responses and assess respondents' attitudes toward each survey question, the mean and standard deviation were calculated. The mean represents the central tendency, while the standard deviation indicates data dispersion, reflecting variability [43], [44]. The level of each item was determined using the formula: (highest Likert scale point – lowest point) / number of levels = (5 - 1) / 5 = 0.80. The categories were defined as follows: • 1.00–1.80: Very low • 1.81–2.60: Low • 2.61–3.40: Moderate • 3.41–4.20: High • 4.21–5.00: Very high Items were then ranked based on their mean values. Tables 3 and 4 present the results.

Table 2

As shown in Table 2, the data analysis indicates that all research variables were applied at a high level, except for the respondent's PR, which was at a very low level. Which reflects that the students consider using generative AI as low risk. On the other hand, ease of use and perceived behavioral control are high.

5.2 SEM analysis

5.2.1 Measurement Model

Table 3 presents the mean, standard deviation, level, and order scores for each variable. It also highlights the properties of the final measurement model. Respondents perceive GenAI tools as low risk. For ease of use (EU2), they stated that GenAI does not require much mental effort. Regarding compatibility, they believe GenAI aligns with their study methods. Peer pressure influence is positive, with classmates being supportive of GenAI use. Regarding self-efficacy, Respondents expressed confidence in using GenAI without assistance. However, they also have access to support if needed.
Their attitude toward GenAI is positive, and they like the idea of using it. They feel in control of their GenAI usage. Their behavioral intention to use GenAI is high, and they believe it positively impacts their academic achievement. Composite Reliability (CR) measures the internal consistency of indicator variables loading on the latent variable.
If the Composite reliability is greater than 0.7 then the indicator variables loading on the latent variable have shared variance among them as shown in table 4 all CR of constructs are greater than 0.7. Cronbach's alpha of each of the constructs is of GOOD level since all ranged between 0.80 and 0.89 for PR, CM, ATT, PBC, and BI. Cronbach's alpha was acceptable reliability level for EUSN, SE, and of excellent reliability level for AA on the other hand it was questionable for FC.

Table 3

The goodness of fit index values of different factor

models as described by [44] and [45] like GFI (Goodness-of-fit Index); AGFI (Adjusted Goodness-of-fit Index); NFI (Normed Fit Index); CFI (Comparative Fit Index); RMR (Root Mean Square Residual); RMSEA (Root Mean Square Error of Approximation) were reflected using Amos 29 fitness model the authors report the following findings:
For the Default model, the discrepancy divided by degrees of freedom is 1244.910 / 503 = 2.475 which is less than 3 as recommended [46] and described as a good fit.
The CFI is 0.917 which is greater than 0.90 recommended by [47]. REMSEA is 0.061 is less than 0.08 as recommended by [48] and [49]. SRMR is 0.0706 which is less than 0.09 as recommended by [46]. The IFI is 0.918 which is greater than 0.90 as recommended by [49]. PNFI is 0.735 which is greater than 0.5 as recommended by [49]. PCFI is 0.775 which is greater than 0.5 as recommended by [49]. Hence, one can assume that the proposed model is fit.

5.2.2 Validity and reliability of Model

To demonstrate the model's validity and reliability the following was conducted and presented in Table 5. CR, AVE,$\mathbb{R}^2$, and Cronback Alpha, correlations of constructs were calculated using Amos 29 for all model's constructs. As for the Convergent validity as seen in Table 5 below AVE is greater than 0.5 and CR is greater than AVE. Reliability of SEM Model Composite Reliability CFA, All factor loadings are above 0.5 which is recommended as seen in table 4, where reliability is estimated by using the three CR [50], AVE [50], and Cronbach Alpha [51].
All measurements in the model have the required consistency reliability between the indicator variables and the measurements. All measurements' CR is above the recommended value 0.7, the average Variance Extracted (AVE) of each construct is less than the CR of each measurement. And all AVEs greater than 0.5. Cronbach alpha for all the measurements is above the recommended 0.7. Based on the CR and AVE results the measurement model is acceptable. Franke and Sarstedt [52] argued that the square root of AVE should exceed the correlation between model components. This study's latent variables met this requirement, confirming discriminant validity. Table 5 shows all AVEs are greater than squared interconstruct correlations and Cronbach's alpha values, proving the measurement scale's legitimacy. A high Cronbach's alpha coefficient further confirms the scale's validity. This outcome proves that discriminates validity was achieved.

Table 4

5.2.3 Structural Model

Structural equation modeling (SEM) was conducted using Amos 20 to test the study hypotheses. SEM enables simultaneous examination of all hypotheses, including direct and indirect effects. The results revealed that ease of use and compatibility had a positive and significant impact on attitude, leading to the acceptance of H2 and H3. However, perceived risk did not have an influence on attitude (B=-0.055); thus, H1 was rejected. As well as self-efficacy did not have influence on Perceived Behavioral Control, thus H5 was rejected.
Furthermore, facilitating conditions had a positive and significant effect on perceived behavioral control, leading to the acceptance of H6. Subjective norms, attitude, and perceived behavioral control also positively and significantly influenced behavioral intention, which in turn affected academic achievement, resulting in the acceptance of H4, H7, H8, and H9. Additionally, the coefficients of determination ($\mathbb{R}^2$) for the endogenous variables were 0.457 for attitude, 0.572 for perceived behavioral control, 0.677 for behavioral intention, and 0.674 for academic achievement, which indicates that the model does account for the variation of the proposed model. Table 6 provides a summary of the tested hypotheses.

Table 5

The first hypothesis pertaining to the influence of perceived risk(PR) on attitude (ATT) was reject in conflict of [53] , [54] , [18], [28], [32]. In other words, the students don't take risks seriously in their attitude towards the use of generative AI. Another fact found in this research shown in Table 3 is that the mean of this construct was the lowest found among other constructs. The research [21] agreed with the proposed hypothesis H2 perceived ease of use (EU) and attitude (ATT) was found to be insignificant among students for learning and education. This finding is in line with [12], [13], [22], [31], [32]., [53], [55] and [56].
Hence, the students' attitude towards using generative AI is easy to use. The third hypothesis which discussed the influence of compatibility influence on attitude was accepted and that is in line with the work of both [28] and [32]. Hence, students find that this innovation fits their values, previous experience and current needs. The fourth hypothesis of subjective norms(SN) influence on behavioral intention (BI)was accepted and agreed with the finding of [53], [13] and [32]. Hence, students' normative belief and motivation comply with behavioral intention to use generative AI.
The fifth hypothesis which discussed self-efficacy influence on perceived behavioral control (PBC) was rejected which does not agree with the work of [56] and [32]. Hence, students' self-confidence and ability to use generative AI was not founded in this research. Both [53], [32] supported the findings of this research regarding H6. The influence of facilitating conditions on perceived behavioral control (PBC).
Hence, students find the facilitating conditions are available to use generative AI. Alike [12], [57], [13] supported the findings of this research regarding H7. The

influence of Attitude on behavioral intention (BI). Hence, the students' attitude is positive reading their intention to use generative AI. In fact, according to the findings of this research the Coefficient value was the highest in the model as seen in Table 6.

Both [16], [32] supported the findings of this research regarding H8. The influence of perceived behavioral control (PBC) on behavioral intention (BI). The student perceived behavioral control as positive towards the intent to use generative AI. In cooperation [21] and [56] supported the findings of this research regarding H9. The influence of behavioral intention (BI) on Academic Achievement (AA). Further the students believe that using generative AI will affect positively their academic achievement. In fact, according to the findings of this research the Coefficient value was the second highest in the model as seen in Table 6.

6 MACHINE LEARNING TOOLS

The empirical findings revealed that ease of use and compatibility positively influence students' attitudes toward using Generative AI tools, while facilitating conditions significantly enhance perceived behavioral control. Furthermore, attitude, subjective norms, and perceived behavioral control were identified as significant predictors of students' behavioral intentions to use Generative AI tools, which, in turn, positively influence academic achievement. In terms of ML models [58], [59], [60], we prepare a set of Datasets with independent (features) and dependent (target) variables, such as PR, EU, and CM as independents and ATT as target, SE and FC as features while PBC as target, ATT, SN, and PBC as features and BI as target, and BI as single feature to predict AA.

The analysis of predictive model performance, based on metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and $\mathbb{R}^2$. Based on first dataset, Linear Regression (LR) as the best-performing model, achieving the lowest MSE (0.402), RMSE (0.634), and MAE (0.483), along with the highest $\mathbb{R}^2$ value (0.309), indicating the strongest fit to the data.

This suggests that LR effectively captures the linear relationships in the dataset. Gradient Boosting (GB) also showed strong performance, with an MSE of 0.462, RMSE of 0.680, and an $\mathbb{R}^2$ value of 0.207, demonstrating better generalization than most models except LR. k-Nearest Neighbors (kNN) exhibited moderate performance, with an $\mathbb{R}^2$ value of 0.184, while Support Vector Machine (SVM) showed adequate but less effective results, with an $\mathbb{R}^2$ value of 0.150. Artificial Neural Network (ANN), Random Forest (RF), and AdaBoost (AB) performed poorly, with low $\mathbb{R}^2$ values (0.061, 0.095, and 0.097, respectively), and higher error metrics.

The Decision Tree (DT) model demonstrated the worst performance, with the highest error values and a negative $\mathbb{R}^2$ value (-0.006), indicating overfitting and poor data modeling. Overall, LR outperformed all other models, likely due to the dataset's linear nature, while GB demonstrated competitive performance for capturing non-linear relationships. Other models, including ANN, RF, and DT, require further optimization to improve their performance.

Table 6

In second dataset, LR achieved the lowest MSE (0.2934) and RMSE (0.5416), as well as the highest $\mathbb{R}^2$ value (0.4722), indicating its effectiveness in capturing the variance in the dataset despite its simplicity. The kNN model followed closely with a competitive $\mathbb{R}^2$ value of 0.4257, suggesting its ability to provide robust predictions in non-linear data distributions.

In contrast, ensemble methods such as RF and GB achieved moderate performance, with RF achieving the lowest MSE among ensemble models (0.3261) and an $\mathbb{R}^2$ value of 0.4133, which underscores its strength in handling complex data structures. However, AB, despite its strong performance in precision and recall in classification tasks, demonstrated the highest MSE (0.3858) and RMSE (0.6211) in this regression task, accompanied by a relatively low $\mathbb{R}^2$ value (0.3059), indicating limitations in its regression capabilities.

ANN performed well with an $\mathbb{R}^2$ value of 0.3554 and relatively low MAE (0.4190), reflecting their potential for handling non-linear relationships. DT, though computationally inexpensive, showed limited predictive power with a lower $\mathbb{R}^2$ value (0.3277). SVM exhibited relatively high computational cost and delivered suboptimal results, with an $\mathbb{R}^2$ value of 0.3139 and a higher MAE (0.4678). The analysis reveals that while LR and kNN are more suited for datasets with linear or moderately complex relationships, ensemble methods such as RF and GB provide a balance between accuracy and complexity for more intricate data.

ANN offer promising performance but require higher computational resources, whereas SVM and DT may be less optimal for regression tasks. Model selection should align with the specific requirements of the application, prioritizing accuracy, computational efficiency, or interpretability as needed.

Table 7

The third dataset, LR emerged as the best-performing model, achieving the lowest MSE (0.3230), RMSE (0.5683), and MAE (0.4161), along with the highest $\mathbb{R}^2$ value (0.5427). These results highlight its strong ability to capture the linear relationships in the data, making it particularly suitable for datasets with minimal complexity. GB and RF followed as strong contenders among ensemble methods.

GB achieved an MSE of 0.3718 and an $\mathbb{R}^2$ value of 0.4736, while RF exhibited slightly better performance with an MSE of 0.3979 and an $\mathbb{R}^2$ value of 0.4366. These results underscore the efficacy of ensemble techniques in capturing non-linear relationships, albeit with higher

computational requirements. The kNN model demonstrated balanced performance with an $\mathbb{R}^2$ value of 0.4603 and relatively low MAE (0.4397), suggesting its robustness in capturing localized patterns in the data.
SVM performed moderately, achieving an $\mathbb{R}^2$ value of 0.4018 and an MAE of 0.4545, though it was outperformed by simpler models like kNN and LR. On the other hand, ANN exhibited the highest MSE (0.4712) and RMSE (0.6864), alongside a relatively low $\mathbb{R}^2$ value (0.3328). This indicates challenges in fitting the data effectively, potentially due to overfitting or inadequate parameter tuning. DT, while computationally efficient, recorded subpar performance with an MSE of 0.4601 and an $\mathbb{R}^2$ value of 0.3485, limiting their utility for this dataset.
Finally, AB performed moderately, with an MSE of 0.4258 and an $\mathbb{R}^2$ value of 0.3970, reflecting its average capacity to generalize to the data. Despite its effectiveness in classification tasks, AB's regression performance appears constrained in this context. Overall, LR and GB stand out as the most reliable models for this dataset, with the choice of model depending on specific application requirements, such as interpretability, computational efficiency, or handling of complex data structures. Further optimization of hyper-parameters, particularly for ANN and ensemble methods, could improve their performance.

Table 8

In last dataset, the DT and LR models demonstrated the best performance, achieving the lowest MSE (0.2734) and RMSE (0.5229), alongside the highest $\mathbb{R}^2$ values (0.5515), indicating their suitability for tasks prioritizing error minimization and model simplicity. GB emerged as a competitive alternative, with similar MSE (0.2755) and $\mathbb{R}^2$ (0.5482), suggesting its capability to balance accuracy and robustness. Conversely, the SVM performed poorly, with the highest MSE (0.4904) and RMSE (0.7003), potentially due to inadequate hyper-parameter tuning or incompatibility with the dataset's characteristics.
ANNs displayed moderate performance ($\mathbb{R}^2$ = 0.5359), with slightly higher errors, possibly indicating overfitting or sensitivity to hyper-parameter choices. The AB model underperformed compared to GB, which highlights the importance of selecting ensemble techniques that align with dataset complexity. These results emphasize that while simpler models like DTs and LR provide interpretable and reliable predictions, more complex models like GB and RF may offer competitive performance when computational resources allow.
Future research should focus on refining hyper-parameters and exploring advanced feature engineering techniques to further optimize model performance, particularly for underperforming models like SVM and AB. The results emphasize that while simpler models like DTs and LR deliver robust accuracy and interpretability, more complex models (e.g., ANN and GB) can offer marginally improved performance at the cost of increased computational complexity. The SVM's poor performance may stem from inadequate hyper-parameter tuning or data characteristics unsuited to its kernel-based approach.

Table 9

7 DISCUSSION AND CONCLUSIONS

The first hypothesis pertaining to the influence of perceived risk(PR) on attitude (ATT) was reject in conflict of [18], [28], [32], [53], [54]. In other words, the students don't take risks seriously in their attitude towards the use of generative AI.
Another fact found in this research shown in Table 3 is that the mean of this construct was the lowest found among other constructs. The research [21] agreed with the proposed hypothesis H2 perceived ease of use (EU) and attitude (ATT) was found to be insignificant among students for learning and education. This finding aligns with previous studies [12], [13], [22], [31], [32], [53], [55] and [56], supporting the consistency and validity of the results, Hence, the students' attitude towards using generative AI is easy to use. The third hypothesis which discussed the influence of compatibility influence on attitude was accepted and that is in line with the work of both [28] and [32].
Hence, students find that this innovation fits their values, previous experience and current needs. The fourth hypothesis of subjective norms(SN) influence on behavioral intention (BI)was accepted and agreed with the finding of [13], [32] and [53],. Hence, students' normative belief and motivation comply with behavioral intention to use generative AI.
The fifth hypothesis which discussed self-efficacy influence on perceived behavioral control (PBC) was rejected which does not agree with the work of [56] and [32]. Hence, students' self-confidence and ability to use generative AI was not founded in this research. Both [53], [32] supported the findings of this research regarding H6. The influence of facilitating conditions on perceived behavioral control (PBC). Hence, students find the facilitating conditions are available to use generative AI. Alike [12], [13], and [57] supported the findings of this research regarding H7.
The influence of Attitude on behavioral intention (BI). Hence, the students' attitude is positive reading their intention to use generative AI. In fact, according to the findings of this research the Coefficient value was the highest in the model as seen in Table 6.
Both [16], [32] supported the findings of this research regarding H8. The influence of perceived behavioral control (PBC) on behavioral intention (BI). The student perceived behavioral control as positive towards the intent to use generative AI. In cooperation [21] and [56] supported the findings of this research regarding H9. The influence of behavioral intention (BI) on Academic Achievement (AA). Further the students believe that using generative AI will affect positively their academic achievement. In fact, according to the findings of this

research the Coefficient value was the second highest in the model as seen in Table 6.

7.1 Theoretical Implications

This research established a connection between influencing factors of GenAI and academic achievement, a unique contribution, especially within a bilingual setting such as Jordan, where no prior studies have addressed this objective. Hence, this research will serve as a pedestal to other researchers, practitioners, as well as teachers, students and universities. University policy will have to adapt and develop new rules especially for plagiarism. Gen AI developers will have to accommodate the bias dilemma as well as sensitive data.
In the same token teachers and academicians will have to develop their own tools to detect plagiarism as well as bias and adapt assessment methods. Students should be more careful in using such software and develop their sense of writing rather than the copy and paste option.

7.2 Practical Implications

Some of the practical implications of this study are as follows: first, teacher and academic roles will evolve hence, rather than fight Gen AI one can leverage these tools. Second, Explore Gen AI in modeling more personalized learning pathways.
Third, addressing originality and accountability issues among users will be essential. As well as addressing the bias issues in Gen AI. More studies must be conducted to assess the impact of Gen AI on student learning and information retention and skill development. And conduct more studies on the impact of Gen Ai on students' motivation, engagement, interpersonal dynamic.

7.3 Limitations and Future Research Direction

This study used a quantitative method, collecting primary data through an online questionnaire from students. Future research could consider qualitative methods, like interviews, or a mixed-method approach for deeper insights. While this research focused on higher education, future studies could examine GenAI in secondary education, exploring the variables that influence high school students' and teachers' perceptions and behaviors toward GenAI tools.
The model does not include all potential factors that could shape students' attitudes toward Generative AI technologies, such as their comfort level with technology or personal experiences with AI, It also neglects the impact of social and cultural elements that could shape students' acceptance of such tools.The current study did not employ a control group design due to the respondents being spread across 29 universities in Jordan, As a future work, researchers could consider implementing a quasi-experimental design by selecting specific universities or regions within Jordan to serve as control and experimental groups.
The number of Gen AI tools is overwhelming, and the researchers cannot test and use all of them. Further, the use of GenAI comes with an expensive fee, many of the students cannot afford it. Integrating GenAI into the education environment entails logistical and pedagogical challenges. Hence the use of GenAI is not yet established among students in universities.
Therefore, future work may address and study the specific needs and concerns of students related to Generative AI. Also, investigate the effect of integrating AI tools into the education process.
Furthermore, study the human factors influencing the adoption of AI tools and their influence on educational outcomes. Detailed study that can concentrate on the Generative AI attributes can be conducted to explore further the factors influencing the adoption of AI tools and their influence on learning outcomes.
Future research should prioritize creating frameworks to address the ethical implications of AI in education. As GenAI tools are the study's outcome variable, additional studies could explore their impact on areas such as creative thinking, academic performance, scientific productivity, and research ethics. Moreover, future studies could investigate the nuances of GenAI use across different countries, enabling a deeper understanding of potential connections and unique patterns within varied cultural and socioeconomic contexts.

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References

[1] Quintans-Júnior, L.J.; Gurgel, R.Q.; De Souza Araújo, A.A.; Correia, D.; Martins-Filho, P.R. ChatGPT: The New Panacea of the Academic World. Revista Da Sociedade Brasileira De Medicina Tropical 2023, 56, doi:10.1590/0037-8682-0060-2023.
[2] Holland, B.J. ChatGPT 3.5 and 4. In Advances in library and information science (ALIS) book series; 2023; pp. 316–340.
[3] MSpitzer, M. ChatGPT. Nervenheilkunde 2023, 42, 192–199, doi:10.1055/a-1948-8785.

[4] Nadir, K. Generative AI: Advantages, Limitations, and Concerns that You Have to Know. GLEEMATIC A.I.
[5] Zhai, X. ChatGPT User Experience: Implications for Education. SSRN Electronic Journal 2022, doi:10.2139/ssrn.4312418.
[6] M. Schonberger, ChatGPT in Higher Education: The Good, The Bad, and The University, in 9th International Conference on Higher Education Advances (HEAd'23), Universitat Politècnica de València, Jun. 2023, pp. 331–338. doi: 10.4995/HEAd23.2023.16174.
[7] Tlili, A.; Shehata, B.; Adarkwah, M.A.; Bozkurt, A.; Hickey, D.T.; Huang, R.; Agyemang, B. What If the Devil Is My Guardian Angel: ChatGPT as a Case Study of Using Chatbots in Education. Smart Learning Environments 2023, 10, doi:10.1186/s40561-023-00237-x.
[8] Yu, H. Reflection on Whether Chat GPT Should Be Banned by Academia from the Perspective of Education and Teaching. Frontiers in Psychology 2023, 14, doi:10.3389/fpsyg.2023.1181712.
[9] Shaengchart, Y. A Conceptual Review of TAM and ChatGPT Usage Intentions Among Higher Education Students. Advance Knowledge for Executives (AKE) 2023, 2(3), No. 25
[10] Liu, G.; Ma, C. Measuring EFL Learners' Use of ChatGPT in Informal Digital Learning of English Based on the Technology Acceptance Model. Innovation in Language Learning and Teaching 2023, 1–14, doi:10.1080/17501229.2023.2240316.
[11] Lo, C.K. What Is the Impact of ChatGPT on Education? A Rapid Review of the Literature. Education Sciences 2023, 13, 410, doi:10.3390/educsci13040410.
[12] Tiwari, C.K.; Bhat, Mohd.A.; Khan, S.T.; Subramaniam, R.; Khan, M.A.I. What Drives Students toward ChatGPT? An Investigation of the Factors Influencing Adoption and Usage of ChatGPT. Interactive Technology and Smart Education 2023, doi:10.1108/itse-04-2023-0061.
[13] Belanche, D.; Casaló, L.V.; Flavián, C. Artificial Intelligence in FinTech: Understanding Robo-Advisors Adoption among Customers. Industrial Management & Data Systems 2019, 119, 1411–1430, doi:10.1108/imds-08-2018-0368.
[14] Rahman, M.M.; Strawderman, L.; Lesch, M.F.; Horrey, W.J.; Babski-Reeves, K.; Garrison, T. Modelling Driver Acceptance of Driver Support Systems. Accident Analysis & Prevention 2018, 121, 134–147, doi:10.1016/j.aap.2018.08.028.
[15] Korzynski, P.; Mazurek, G.; Altmann, A.; Ejdys, J.; Kazlauskaite, R.; Paliszkiewicz, J.; Wach, K.; Ziemba, E. Generative Artificial Intelligence as a New Context for Management Theories: Analysis of ChatGPT. Central European Management Journal 2023, 31, 3–13, doi:10.1108/cemj-02-2023-0091.
[16] Duong, C.D.; Bui, D.T.; Pham, H.T.; Vu, A.T.; Nguyen, V.H. How Effort Expectancy and Performance Expectancy Interact to Trigger Higher Education Students' Uses of ChatGPT for Learning. Interactive Technology and Smart Education 2023, doi:10.1108/itse-05-2023-0096.
[17] Hidayat-Ur-Rehman, I.; Ibrahim, Y. Exploring Factors Influencing Educators' Adoption of ChatGPT: A Mixed Method Approach. Interactive Technology and Smart Education 2023, doi:10.1108/itse-07-2023-0127.
[18] Yang, L.; Wang, J. Factors Influencing Initial Public Acceptance of Integrating the ChatGPT-Type Model with Government Services. Kybernetes 2023, doi:10.1108/k-06-2023-1011.
[19] Abaddi, S. GPT Revolution and Digital Entrepreneurial Intentions. Journal of Entrepreneurship in Emerging Economies 2023, doi:10.1108/jeee-07-2023-0260.
[20] Su, Y.; Liu, Z. A Study of ChatGPT Empowering College Students' Innovation and Entrepreneurship Education in the Context of China. International Journal of New Developments in Education 2023, 5, doi:10.25236/ijnde.2023.051301.
[21] Al-Mamary, Y.H.; Alfalah, A.A.; Shamsuddin, A.; Abubakar, A.A. Artificial Intelligence Powering Education: ChatGPT's Impact on Students' Academic Performance through the Lens of Technology-to-Performance Chain Theory. Journal of Applied Research in Higher Education 2024, doi:10.1108/jarhe-04-2024-0179.
[22] Le, T.M.D., Do, H.T.N., Tran, K.M., Dang, V.T. and Nguyen, B.K.H. Integrating Tam and UGT to explore students' motivation for using ChatGPT for learning in Vietnam. Journal of Research in Innovative Teaching & Learning 2024, https://doi.org/10.1108/JRIT-05-2024-0116
[23] Aghemo, A.; Forner, A.; Valenti, L. Should Artificial Intelligence-based Language Models Be Allowed in Developing Scientific Manuscripts? A Debate between ChatGPT and the Editors of Liver International. Liver International 2023, 43, 956–957, doi:10.1111/liv.15580.
[24] Spitzer, M. ChatGPT. Nervenheilkunde 2023, 42, 192–199, doi:10.1055/a-1948-8785.
[25] Doshi, R.H.; Bajaj, S.S.; Krumholz, H.M. ChatGPT: Temptations of Progress. The American Journal of Bioethics 2023, 23, 6–8, doi:10.1080/15265161.2023.2180110.
[26] Derner, E.; Batistič, K. Beyond the Safeguards: Exploring the Security Risks of ChatGPT. arXiv (Cornell University) 2023, doi:10.48550/arxiv.2305.08005.
[27] Sebastian, G. Do ChatGPT and Other AI Chatbots Pose a Cybersecurity Risk? International Journal of Security and Privacy in Pervasive Computing 2023, 15, 1–11, doi:10.4018/ijsppc.320225.
[28] Sallam, M.; Salim, N.A.; Barakat, M.; Al-Mahzoum, K.; Al-Tammemi, A.B.; Malaeb, D.; Hallit, R.; Hallit, S. Assessing Health Students' Attitudes and Usage of ChatGPT in Jordan: Validation Study. JMIR Medical Education 2023, 9, e48254, doi:10.2196/48254.
[29] Shaw, D.; Morfeld, P.; Erren, T. The (Mis)Use of ChatGPT in Science and Education. EMBO Reports 2023, 24, doi:10.15252/embr.202357501.
[30] Ferrara, E. Should ChatGPT Be Biased? Challenges and Risks of Bias in Large Language Models. arXiv (Cornell University) 2023, doi:10.48550/arxiv.2304.03738.
[31] Abdul-Halim, N.-A.; Vafaei-Zadeh, A.; Hanifah, H.; Teoh, A.P.; Nawaser, K. Understanding the Determinants of E-Wallet Continuance Usage Intention in Malaysia. Quality & Quantity 2021, 56, 3413–3439, doi:10.1007/s11135-021-01276-7.
[32] Masa'deh, R.; AlHadid, I.; Abu-Taieh, E.; Khwaldeh, S.; Alrowwad, A.; Alkhawaldeh, R.S. Factors Influencing Students' Intention to Use E-Textbooks and Their Impact on Academic Achievement in Bilingual Environment: An Empirical Study Jordan. Information 2022, 13, 233, doi:10.3390/info13050233.

[33] Srirahayu, D.P.; Nurpratama, M.R.; Handriana, T.; Hartini, S. Effect of Gender, Social Influence, and Emotional Factors in Usage of e-Books by Generation Z in Indonesia. Digital Library Perspectives 2021, 38, 263–282, doi:10.1108/dlp-12-2020-0129.

[34] Railean, E. Psychological and Pedagogical Considerations in Digital Textbook Use and Development; IGI Globals: Hershey, PA, USA, 2015. Available online: https://tinyurl.com/4bezvjwv(accessedon1December2021).

[35] Taylor, S.; Todd, P.A. Understanding information technology usage: A test of competing models. Inf. Syst. Res. 1995, 6, 144–176.

[36] Shen, S.; Xu, K.; Sotiriadis, M.; Wang, Y. Exploring the Factors Influencing the Adoption and Usage of Augmented Reality and Virtual Reality Applications in Tourism Education within the Context of COVID-19 Pandemic. Journal of Hospitality Leisure Sport & Tourism Education 2022, 30, 100373, doi:10.1016/j.jhlste.2022.100373.

[37] Bosnjak, M.; Ajzen, I.; Schmidt, P. The Theory of Planned Behavior: Selected Recent Advances and Applications. Europe's Journal of Psychology 2020, 16, 352–356, doi:10.5964/ejop.v16i3.3107.

[38] Hsiao, C.-H.; Tang, K.-Y. Explaining Undergraduates' Behavior Intention of e-Textbook Adoption. Library Hi Tech 2014, 32, 139–163, doi:10.1108/lht-09-2013-0126.

[39] Davis, F.D. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989, 13, 319–340.

[40] Ajzen, I. The theory of planned behavior. Organ. Behav. Hum. Decis. Processes 1991, 50, 179–211.

[41] Hao, Y.; Jackson, K. Student satisfaction toward e-textbooks in higher education. J. Sci. Technol. Policy Manag. 2014, 5, 231–246.

[42] Maqableh, M.; Rajab, L.; Quteshat, W.; Masa'deh, R.; TKhatib Karajeh, H. The Impact of Social Media Networks Websites Usage on Students' Academic Performance. Commun. Netw. 2015, 7, 159–171.

[43] Pallant, J. SPSS Survival Manual: A Step Guide to Data Analysis Using SPSS for Windows Version 12; Open University Press: Chicago, IL, USA, 2005.

[44] Sekaran, U.; Bougie, R. Research Methods for Business: A Skill-Building Approach, 6th ed.; Wiley: New York, NY, USA, 2013.

[45] Meyers L.S., Gamst G. & Guarino A.J. (2006) Applied Multivariate Research. Design and Interpretation. Sage Publications, Thousand Oaks, CA.

[46] Hair Jr., J.F., Black, W.C., Babin, B.J. and Anderson, R.E. (2009) Multivariate Data Analysis. 7th Edition, Prentice Hall, Upper Saddle River, 761.

[47] Bentler, P.M. Comparative Fit Indexes in Structural Models. Psychological Bulletin 1990, 107, 238–246, doi:10.1037/0033-2909.107.2.238.

[48] Byrne, B. M. (2001). Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. Mahwah, NJ: Lawrence Erlbaum Associates.

[49] Meyers L.S., Gamst G. & Guarino A.J. (2005) Applied Multivariate Research. Design and Interpretation 1st Edition. Sage Publications, Thousand Oaks, CA.

[50] Fronell, C.; Larcker, D. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. J. Mark. Res. 1981, 18, 39–50

[51] Cronbach, L.J. Coefficient Alpha and the Internal Structure of Tests. Psychometrika 1951, 16, 297–334, doi:10.1007/bf02310555.

[52] Franke, G.; Sarstedt, M. Heuristics versus Statistics in Discriminant Validity Testing: A Comparison of Four Procedures. Internet Research 2019, 29, 430–447, doi:10.1108/intr-12-2017-0515.

[53] Faqih, K.M.S. Factors Influencing the Behavioral Intention to Adopt a Technological Innovation from a Developing Country Context: The Case of Mobile Augmented Reality Games. Technology in Society 2022, 69, 101958, doi:10.1016/j.techsoc.2022.101958.

[54] Bedué, P.; Fritzsche, A. Can We Trust AI? An Empirical Investigation of Trust Requirements and Guide to Successful AI Adoption. Journal of Enterprise Information Management 2021, 35, 530–549, doi:10.1108/jeim-06-2020-0233.

[55] Abbasi, G.A.; Sandran, T.; Ganesan, Y.; Iranmanesh, M. Go Cashless! Determinants of Continuance Intention to Use E-Wallet Apps: A Hybrid Approach Using PLS-SEM and fsQCA. Technology in Society 2022, 68, 101937, doi:10.1016/j.techsoc.2022.101937.

[56] Awal, Md.R.; Haque, Md.E. Revisiting University Students' Intention to Accept AI-Powered Chatbot with an Integration between TAM and SCT: A South Asian Perspective. Journal of Applied Research in Higher Education 2024, doi:10.1108/jarhe-11-2023-0514.

[57] Kabra, G.; Ghosh, V.; Joshi, Y. Factors Influencing Adoption of Cloud Computing Services in HEIs: A UTAUT Approach Based on Students' Perception. International Journal of Business Information Systems 2023, 42, 103, doi:10.1504/ijbis.2023.128301.

[58] Abu-Taieh EM, AlHadid I, Abu-Tayeh S, Masa'deh RE, Alkhawaldeh RS, Khwaldeh S, Alrowwad AA. Continued intention to use of M-Banking in Jordan by integrating UTAUT, TPB, TAM and service quality with ML. Journal of Open Innovation: Technology, Market, and Complexity. 2022 Jul 13;8(3):120.

[59] AlHadid I, Abu-Taieh E, Alkhawaldeh RS, Khwaldeh S, Masa'deh RE, Kaabneh K, Alrowwad AA. Predictors for E-government adoption of SANAD App services integrating UTAUT, TPB, TAM, Trust, and perceived risk. International Journal of Environmental Research and Public Health. 2022 Jul 7;19(14):8281.

[60] Abu-Taieh E, AlHadid I, Masa'deh RE, Alkhawaldeh RS, Khwaldeh S, Alrowwad AA. Factors influencing YouTube as a learning tool and its influence on academic achievement in a bilingual environment using extended information adoption model (IAM) with ML prediction—Jordan case study. Applied Sciences. 2022 Jun 9;12(12):5856.

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