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AI ADOPTION IN UNIVERSITY SETTINGS: A TECHNOLOGY READINESS AND UTAUT-BASED MODELS OF MEDIATING MECHANISMS

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ABSTRACT

This study is an extension of literature concerning the effectiveness of learning using AI technologies, focusing on the factors affecting behavioral intention of students towards such use in the context of Jordan higher educational institutions. The sample, consisting of 282 university students from Jordanian university was selected through convenience sampling, after which, data was gathered from them. Data was analyzed using Partial Least Squares-Structural Equation Modeling to test the formulated hypotheses. Based on the obtained results, efforts, social influence, perceived risk, and technology readiness had significant effects on behavioral intention of students towards AI technology but this significance was not found for performance expectancy and facilitated conditions. Moreover, the findings indicated that attitudes had a significant mediating effect on perceived risk, social influence, and behavioral intention but efforts, performance expectancy, facilitating conditions, technology readiness had no such mediating effect. The study has several practical and theoretical implications, the top of which is the extension of theoretical models of UTAUT and other technology readiness models and the enhancement of AI practices among the learning process of students.

KEYWORDS: Artificial Intelligence, University, Education, Students, Mediation.

1. INTRODUCTION

Different fields have witnessed the increasing role of technology and AI in human activity in light of data availability and real-time processing (Raffaghelli et al. 2022; Busnatu et al. 2022; Almaiah et al. 2022; Jdaitawi & Kan'an, 2022; Al-Mawadieh et al., 2025; Al-Mawadieh & Hashem, 2025; Al-Momani et al., 2025). This phenomenon paves the way for future opportunities of leveraging AI among technology developer and education professional circles (Alteeq et al. 2024; Han et al. 2025). Nevertheless, the AI adoption level among higher education institutions still lacks the evidence needed, with outcomes differing on the basis of environment, leading to mixed results.

Recent studies indicated the inevitable adoption of AI among institutions of higher learning, where such institutions have been investing effort and resources to improving personalized student support using AI technology (Raffaghelli et al. 2022). However, AI adoption is generally a detailed process that can be affected by various factors, mainly when it comes to behavioral intentions of the relevant stakeholders in the educational field. Hence, technology models are applicable to the investigation, such as, the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) (Sohn & Kwon, 2020). The model's factors are not only predictors of individual inclination towards new technology use but also readiness of decision-makers to take up the required actions that give way to the AI era of institutions (Anh et al., 2024; Tunmibi & Okuonghae, 2023).

The use of AI in improving learning experience in the field of education is well-known (Xu, 2024), with educators making use of AI technologies in day-to-day lives in the form of voice assistances in their homes, correcting grammar, completing sentries, and writing essays for work, and developing automated trip planning on their mobile devices (Gardona, Rodriguez & Ishmael, 2023). Learners can obtain the required information and experience an enriching learning process through the use of AI apps (Kamalov, Calonge & Gurrib, 2023). There are different AI-enabled learning systems versions like videos, interactive simulations and text-based materials that can be tailor-made in real-time to individual student's learning progress and unique personality (Calend, 2024). AI-related work in education (i.e., Wang & Wang, 2024) revealed that the AI systems use has opened up avenues for innovation of traditional education, and it seems that it has a potential role in learning improvement and facilitation (Labadze, Grigolia & Machaidze, 2023).

Despite the past literature on the role of AI in improving learning, further studies are needed to examine the AI development in learning strategies, and this holds particular truth in the context of developing nations (Ali et al., 2024; Han, Mustafa & Kharuddin, 2025). This literature gap is also evident in the users' intentions towards AI technologies adoption and their actual use of it–in other words, a notable gap exists in the theoretical integration concerning the adoption of AI technologies and innovation (Kim, Balzquez & Oh, 2024). Consequently, more studies need to be carried out to investigate the adoption of AI technologies in the context of higher education institutions (Mohsin et al., 2024; Southworth et al., 2023). Indubitably, the examination and understanding of the factors driving and hindering AI adoption in higher education institutions will be valuable in such institutions for developing strategies to enhance the learning process and quality of students.

2. THEORETICAL AND HYPOTHESES DEVELOPMENT MODEL

The changes in higher education wrought by IT and its innovations and the behavioral aspects of their usage are significant factors (Hassanzadeh et al., 2012; Batucan et al., 2022). Teo (2011) suggested that technology acceptance refers to the person's willingness to accept technology to achieve several tasks. Although, more recently AI technologies implemented various based on several theories and models to achieve their objectives, limitations also were highlighted in information systems studies. For instance, Alateeq et al. (2024) and Wu (2011), reported that TAM model showed difficulties in tackling emerging solutions/service and lead to inconclusive outcomes (Garaca, 2011; Legris et al., 2003). Moreover, UTAUT model and its variables (performance expectation, effort expectancy, social influence and facilitating conditions) have been used in investigating technological innovations in higher education has also been evidence (Halili & Sulaiman, 2018; Venkatesh et al., 2003; Venkatesh et al., 2011; Venkatesh et al., 2012).

Moreover, the above four variables have been evidenced in previous studies and in UTAUT as effective in predicting individual's intention towards AI technology use (Venkatesh et al., 2016; Milicevic et al., 2024; Gao et al., 2021). Despite the UTAUT has been effective in examining the use and acceptance of technological innovations in an integrative manner owing to its synthesis of eight prominent technology acceptance models (Sobaih et al., 2024; Venkatesh et al., 2003), it has still been criticized and suggestions for additional variables have been made along the same lines. Studies recommended shifting away from the sole focus of the abilities of users and considering the perceived risks of technology, its functionality and the requirements of the tasks (Al-Adwan, 2023; Yang, Asaad & Dwivedi, 2017).

In other studies (Zhang et al., 2021; Wu et al., 2022), the risks stemming from AI application in education were mentioned as a concern. Conceptually, perceived risks are those risks that are related to the pre-prediction or pre-expectations of people concerning the behavioral outcome before the behavior is carried out (Bauer, 1960). In this regard, two main perceived risk factors are examined in this study, which are time risk and psychological risk–the remaining risk types are excluded to avoid overlapping among the theories' factors. Risks have a general negative effect on the willingness towards face recognition technology adoption (Wei et al., 2021) and in this study, perceived risks, namely time and psychological risks, are proposed to have significant effect on the willingness of the students to adopt AI technologies in their learning process. Chatterjee and Bhattacharjee (2020) are one of the few authors who suggest perceived risks as a novel variable to be examined with UTAUT model. Therefore, this study proposed perceived risks to influence the behavioral intentions of students to adopt AI technology.

Additionally, the Technology Readiness Index (TRI) has been used to achieve future events (2005) as well as to assess students' preparedness and intention for using AI technology in the learning process (e.g., Sanusi, Ayanwale & Chiu, 2024; Shirahada et al., 2019; Tang et al., 2021). **Thus, this study proposes the following hypotheses**

- Effort expectancy is positively related to the students' intention towards AI technologies use.
- Facilitating conditions are positively related to the students' intention towards AI technologies use.
- Performance expectation is positive related to the students' intention towards AI technologies use.
- Perceived risks are positively related to the students' intention towards AI technologies use.
- Technological readiness is positively related to the students' intention towards AI technologies use.
- Social influence is positively related to the students' intention towards AI technologies use.

In AI research, the use of UTAUT in its original format, with additional variables or different variables is apparent, making an all-inclusive paradigm for the integration of the acceptance, attitudes and behaviors and AI adoption (Nimo & Ravishanka, 2024; Chatterjee & Bhattacharjee, 2020a). However, based on recent studies by Dwivedi et al. (2021), Rana et al. (2017), and Rana et al. (2016), the attitudes of individuals need to be included in UTAUT as it is the core to shedding light on behavioral intention.

In previous studies, attitude has been suggested as a mediating variable in determine using technology (e.g., Alhumaid et al., 2023; Gao et al., 2021; Cox et al., 2019; Venkatesh et al. (2003). In the same line, Krishanan et al. (2017) contended that attitude mediates in the relationship between behavioral intention and other factors and thus, in this study, it is proposed that behavioral intention is influenced by performance expectancy and the other examined factors through the mediation of attitude. **Therefore, it is proposed that**

- Effort expectancy is positively related to the attitude of students.
- Facilitating conditions are positively related to the attitude of students.
- Performance expectancy is positively related to the attitude of students.
- Perceived risks are positively related to the attitude of students.
- Technological readiness is positively related to the attitude of students.
- Social influence is positively related to the attitude of students.
- Attitude mediates the relationship between performance expectancy and students' behavioral intention to use AI technologies.
- Attitude mediates the relationship between effort expectancy and students' behavioral intentional to use AI technologies.
- Attitude mediates the relationship between social influence and students' behavioral intention to use AI technologies.
- Attitude mediates the relationship between facilitating conditions and students' behavioral intention to use AI technologies.
- Attitude mediates the relationship between perceived risks and students' behavioral intention to use AI technologies.
- Attitude mediates the relationship between technological readiness and students' behavioral intention to use AI technologies.

3. METHODOLOGY

This study's main objective is to examine the influence of factors on the behavioral intentions of students to use AI technologies in their learning process and it focuses particularly on Jordanian university students. This study used quantitative approach using survey tool to collect data from the study participants which has been suggested in literature (Venkatesh et al., 2012; Jdaitawi et al., 2024).

3.1. Participants

The population of the study consists of Jordanian students who enrolled at the university levels who familiar with technology as well willing to participate in current study. A total of 282 students participated in this study, whose age ranged from 18 to 22 years old in accordance with Hair et al. (2010) and Loehlin (1992) who supported a number of 200-250 participants to be used in PLS-SEM analysis. Prior to initiating the study, the approval of the Ethics Committee of Irbid National was obtained in order to proceed in distributing the copes of survey questionnaire. Upon obtaining such approval, the authors made contact with the departments' faculties for the distribution of the survey through a hyperlink. As mentioned, the students' selection was based on their voluntary participation, and this was obtained through their verbal agreement. They were assured that the data and feedback that they provide will be kept private and confidential.

3.2. Measurements

The questionnaire survey for data collection was distributed to the participants and within the survey, there were variable scales adopted from relevant literature (Venkatesh et al., 2012; Strzelecki, 2023) to measure performance expectation, effort expectation, social influence and facilitating conditions. This measurement held true for perceived risks (Wu, Zhang, Li, & Liu, 2022; Kumar & Bajaj, 2016) , students attitudes towards using AI (Sanusi et al., 2024), readiness of scale (Sanusi et al., 2024; Keramati et al., 2011), and lastly, students' behavioral intention to use AI (Choi et al., 2023). A total of 38 items were used to measure the above seven factors gauged on a five-point Likert scale (1-5), where 1 denotes strongly disagree and 5 denotes strongly agree. The items in the survey, adopted from past studies, were tweaked in the survey to align them with the objectives of the study. The first section of the survey was dedicated to obtaining the participants' demographic information including age, gender and computer experience, while the second one included item measured on a Likert scale to take the respondents' perceptions concerning the influence of factors on the students' behavioral intention to use AI technology.

3.3. Validity and Reliability of the Measurement Model

The items reliability were tested using Cronbach's Alpha coefficient, composite reliability test and factor loading coefficient analysis. The acceptable criterion in view of the factor loading coefficient of items was over 0.40 at an excellent level, of the CR values of items was over 0.60 to be considered to be consistent, and the same was followed for Cronbach's Alpha coefficient. The study also tested convergent validity using the Average Variance Extracted (AVE), with the condition that they exceed 0.50. Data was entered into SPSS and PLS-SEM and tested through descriptive analysis to obtain their mean and standard deviation values. Regression analysis was also used to test the formulated hypotheses, and the results are presented in Table 1.

Table 1: Construct Validity and Reliability Measurements.

Variable	α	CR	AVE
Attitude	0.885	0.885	0.813
effort expectancy	0.937	0.937	0.841
facilitated condition	0.903	0.903	0.775
Behavioural Intention	0.895	0.896	0.826
performance expectancy	0.915	0.919	0.799
Perceived risks	0.905	0.911	0.681
technology readiness	0.876	0.884	0.729
social influence	0.891	0.891	0.821

Based on the tabulated values, the constructs obtained acceptable Cronbach's alpha scores that are as follows - behavioral intention to use AI technology (0.895), social influence (0.891), performance expectancy (0.915), effort expectancy (0.937), facilitated conditions (0.903), perceived risks (0.905), technology readiness (0.876), technology awareness (0.894), and attitude (0.885) and lastly, voluntariness of use (0.912). The constructs' convergent validity scores were also acceptable at over 0.60, while their

CR illustrated good construct internal consistency with the following scores–behavioral intention to use AI technology (0.896), social influence (0.891), performance expectancy (0.919), effort expectancy (0.937), facilitated conditions (0.903), perceived risks (0.911), technology readiness (0.884),and attitude (0.885). The AVE and constructs validity were found to be converging. The model fit indices also presented accepted values as shown in Table 2.

Table 2: Model Fit Indices.

Indices	Saturated Model	Minimum Cutoff
SRMR	0.046	0.08
Chi-Square	1491.350	---
NFI	0.839	>0.80

4. RESULTS

The results for the initial PLS-SEM's evaluation of the students' attitude are presented in Figure 1 and Table 3. It is evident from the table that the following results were obtained for the constructs–perceived risks, social influence and technology readiness had a significant effect on the attitudes of students to use AI technologies (β = 0.421, p= 0.000, β = 0.212, p= 0.000, and β = 0.212, p= 0.024 respectively). On the other hand, effort expectancy, facilitated conditions and performance expectancy had no significant effects (β = 0.093, p= 0.217, β = -0.006, p= 0.931, and β = 0.031, p= 0.667 respectively). These insignificant effects are presented in Figure 1 with values over 0.05. As for behavioral intentions to use AI technologies as a learning tool in educational institutions, Figure 1 reveals the following results–efforts expectancy, perceived risks, social influence, and technology readiness significantly affect behavioral intention of students (β = 0.160, p= 0.026, β = 0.260, p= 0.000, β = 0.103, p= 0.045, and β = 0.225, p= 0.031 respectively), while facilitated conditions and performance expectancy had no such effect (respectively), with insignificant values exceeding 0.05. Moreover, Figure 1 also supports the significant influence of attitudes over the behavioral intention of students towards using AI technologies (β = 0.230, p= 0.001).

The final model of the study indicating that the most significant factors driving students' attitudes include perceived risks (β = 0.421) and social influence (β = 0.212) and the top factor that is significant to behavioral intention to use AI technologies is attitude of students (β = 0.230). Behavioral intentions of the students were also driven by perceived risks (β = 0.260), technology readiness (β = 0.225), efforts expectancy (β = 0.160) and social influence. On the whole, perceived risks and attitude of students were the top significant constructs driving behavioral intention towards AI technologies use in their learning process.

Table 3: Result of Direct Hypothesis Testing.

Structural Path	B and t-value	Decision
H1: Effort Expectancy–Attitude	0.093, p=0.217	Not Supported
H2: Facilitated Conditions–Attitude	-0.006, p=0.931	Not Supported
H3: Performance Expectancy–Attitude	0.031, p=0.667	Not Supported
H4: Perceived Risks–Attitude	0.421, p=0.000	Supported
H5: Social Influence–Attitude	0.212, p=0.000	Supported
H6: Technology Readiness–Attitude	0.212, p=0.024	Supported
H7: Effort Expectancy–Behavioral Intention	0.160, p=0.026	Supported
H8: Facilitated Conditions–Behavioral Intention	-0.069, p=0.284	Not Supported
H9: Performance Expectancy–Behavioral Intention	0.057, p=0.618	Not Supported
H10: Perceived Risks–Behavioral Intention	0.260, p=0.000	Supported
H11: Social Influence–Behavioral Intention	0.103, p=0.045	Supported
H12: Technology Readiness–Behavioral Intention	0.225, p=0.031	Supported
H13: Attitude–Behavioral Intention	0.230, p=0.001	Supported

With regards to the mediating analysis results, Table 4 indicates inconclusive findings, with the following; efforts expectancy, facilitated conditions, performance expectancy, technology readiness have no statistically significant indirect effect on behavioral intention through attitude (H: p= 0.021>0.05; H: p= -0.001>0.05; H: p= 0.007>0.05; and H: p= 0.049>0.05 respectively), while perceived risks and social influence have statistically significant indirect effect on behavioral intention through attitude (H: p= 0.097<0.05 and H: p= 0.049<0.05 respectively). In other words, attitude partially mediates the effect of the study variables on behavioral intention to use AI technologies and on the whole, the findings provide insight into the AI use dynamics, stressing on direct as well as indirect effects contribution towards driving intentions of students towards AI technologies usage in their learning process.

Table 4: Result of Mediating Effect Hypothesis Testing.

Structural Path	Direct Effect	Indirect Effect	Total Effect	t-value	p	Decision
H14: EE-AT-BI	0.093	0.021	0.114	1.122	0.262	Not Accepted
H15: FC-AA-BI	-0.006	-0.001	0.007	0.083	0.934	Not Accepted
H16: PE-AA-BI	0.031	0.007	0.038	0.397	0.692	Not Accepted
H17: PR-AA-BI	0.421	0.097	0.518	2.989	0.003	Accepted
H18: SI-AA-BI	0.212	0.049	0.261	1.804	0.071	Not Accepted
H19: TR-AA-BI	0.212	0.049	0.261	2.701	0.007	Accepted

Added to the above findings, the R2 and R2 adjusted values reveal the explanatory power of the structure model, and in this regard, attitude had R-squared value of 0.778, which means that 77% of the variance in attitude is explained by the model's independent variables. As for the R-squared adjusted value, it is 0.773, supporting a consistent model that is well-fitted, considering the absence of unnecessary predictors inflating the explanatory power. Along the same line, behavioral intention to use AI obtained R-squared value of 0.79, which means that 78% of the variance in behavioral intention is explained by the model's independent variables. With an R-squared adjusted value of 0.78, the model's consistency and fit are supported, with no predictors increasing its explanatory power.

5. DISCUSSION

This study tested the formulated hypotheses proposing that efforts expectancy influence the attitudes and behavioral intention of students towards using AI technologies in their university learning. The results rejected the hypotheses as an insignificant influence was found on attitudes and behavioral intention. This may be explained by the students' difficulty in handling AI applications, and they had low perceptions of their importance, or it may have fallen short of being consistent with their learning activities and requirements. This result of this study is inconsistent with previous studies by Xu, Chen and Zhang (2024), who evidenced attitudes and behavioral intention to be influenced by effort expectancy. Therefore, the results rejected hypotheses and 1 and 7.

Based on the results, facilitating conditions did not significantly influence attitudes and behavioral intention. This may be because of limited students' skills in using the AI applications. However, the results of the current study supported Bervell et al. (2022) results which indicated insignificant influence between facilitation conditions and actual use of AI technologies, but it against other studies who evidenced that facilitating conditions significantly influence the behavioral intention (e.g., Hunde et al., 2023; Cortez et al., 2024). Thus, the study rejected hypotheses 2 and 8.

Moving on to the next examined construct, namely performance expectancy and its influence over the attitudes and behavioral intention of students to use AI technologies, the result also found insignificant influence on both. This result may be attributed to the lack of belief among students concerning the usefulness of AI technologies in learning success and in enhancing their learning efficiency and quality. Hence, only if the students perceive that AI technology is useful in their learning then there will be the likelihood that their attitude and behavioral intention towards its use will be enhanced. The result may also be attributed to the fact that the students who participated are only in their first and second year of university learning and were not as familiar with the potential of AI tools. This result is inconsistent with those reported by past studies (Xu, Chen & Zhang, 2024; Milicevic et al., 2024), who revealed the significant influence of performance expectancy on the students' attitudes and their behavioral intention towards using AI technologies. This result rejected the formulated hypotheses 3 and 9.

The next tested hypotheses involved the influence of perceived risks on the students' attitudes and behavioral intention to use AI in their learning process, and the result showed significant effects, which supports hypotheses four and ten. The students were of the consensus that using AI brings about their learning and helps in completing tasks in the period required. Compared to traditional learning methods, they agreed that AI use completes tasks in a way that lessens the pressure on their psychological state and in turn, makes them less nervous and hence enable them to complete their tasks. This result is in contrast to Khan and Khan (2019), Wu et al. (2022), and Davis and Venkatesh (1996), who revealed that psychological risk has a significant influence over the students' willingness towards adopting AI technologies.

The study also proposed the influence of social influence over the attitudes and behavioral intention of university students towards using AI technology. The analysis results indicated support for the hypothesis, and this may be related to the instructors' influence over their students' use of AI technology. This result is supported by (Jdaitawi et al., 2024; Wu et al., 2022; Salleh, 2016), who evidenced the direct significant influence of social influence factor over the willingness of students to adopt technology tools in the activities of learning. Concerning the technology readiness hypothesis, the result revealed that technology readiness is to influence both the behavioral intentions of students and their attitudes. The results, however, supported by Nouraldeen (2022), Masry-Herzallah, and Watted, (2024), and Anh et al. (2024) who supported the argument that technology readiness has positive impact on the adoption of AI and its usefulness. The results also supported previous studies (Fomani, 2023; Dwivedi et al., 2017) result that indicated a positive relation between students' attitudes and their intention behavioral to use AI technology.

Moving on to the indirect effects tested in this study, following the recommendations of past literature on students' behavioral intentions – the study found attitude to have a partial mediating effect on relationship between the variables and behavioral intention towards AI tools use. In particular, attitude was found to have a positive mediating effect on perceived risks and behavioral intention, and on social influence and behavioral intention, supporting both H17 and H19. On the other hand, attitude was not found to have the same mediating effect on the relationship between efforts expectancy and behavioral intention, performance expectancy and behavioral intention, facilitated conditions and behavioral intention, and technology readiness and behavioral intention, resulting in the rejection of H14, H15, H16 and H18. These results stress the need for the satisfactory perception of students and their practical use of AI technology to have a positive evaluation of its entirety. The insignificant results may be attributed to the difference in the students' academic tasks and groups, with students having different levels of familiarity and knowledge and it may have generated different learning attitudes and learning experiences when it comes to AI technologies use. This may be adopted as an extended investigation in future studies in the UTAUT context. These results present additional empirical evidence supporting UTAUT and extend the UTAUT literature domain concerning AI technologies use at the university level.

5.1. Implications

This study has several implications for theory, the first of which is the development and validation of the framework using UTAUT, TRI and perceived models to shed light on the influence of behavioral intention towards AI technologies. The second implication is the study findings providing empirical evidence of AI technology use on the university level, particularly in the context of Jordan academic settings. The third theoretical implication is the extension of past literature comprising of studies by Bhat et al. (2024), Han et al. (2025), Kim et al. (2024), Rana et al. (2024), Graeme et al. (2024), and Nimo and Ravishanka (2024), who called for additional factors to be examined based on their influence on behavioral intention of students towards using AI technologies in learning. The study minimized the literature gap in literature concerning students' behavioral intention towards using AI technology through the use of UTAUT with technology readiness. The results of this study indicated that UTAUT factors of efforts expectancy, perceived risks, social influence, and attitudes, along with technology readiness were top predictors of behavioral intention of students towards using AI technologies. Another contribution is the testing of mediating effects of variables, among which attitudes partial mediation on the relationship between the variables and behavioral intention of students towards AI was supported. The study provided additional empirical evidence of the under-examined mediating variables in the UTAUT domain and in the university context.

The study implications are not limited to theory as the study also contributes to the practical education practices in Jordan universities and those of developing nations. Practical implications for educator and policy-maker circles are presented concerning the AI implementation success in universities. Educators are recommended to attend training sessions to develop their technology skills and knowledge for effective AI technology implementation in both teaching and learning for the students' enhanced learning experiences and outcomes. Lastly, policymakers can lend support to the financing and resource assistance for the development and implementation of AI tools and resources in the field of education.

6. CONCLUSION

In sum, this study extends literature and supports prior findings concerning university students' behavioral intention towards using AI technologies in the process of learning. The study revealed that the influence of the examined independent variables namely, effort expectancy, performance expectancy, and facilitated conditions had not significant effects on the students' attitudes towards AI technology use in learning. The study also revealed that remaining examined independent variables namely, perceived risk, technology readiness, and social influence had significant effects on the attitudes of students towards AI technologies. The study also examined effort expectancy, perceived risks, social influence, technology readiness, attitudes, facilitating conditions and performance expectancy and found them to be significant with the exception of the last two variables. The study found significant mediating effect from attitude on the relationship between perceived risk, social influence and behavioral intention of students towards AI technology but not on the relationship between efforts expectancy, performance expectancy, facilitated conditions, technology readiness and behavioral intentions of students towards AI technology.

6.1. Limitations and Future Directions

This study and its findings significantly contribute to enriching the AI literature in the education field but despite such contributions, the study has its limitations, the first of which is the use of the quantitative method of data collection and analysis. In this regard, future studies may adopt a longitudinal study instead, with a mixed approach (both quantitative and qualitative method) to delve into the students' perceptions on the use of AI to complete their learning and academic tasks. Another study limitation is its sole context, which is the university institutions and as such, for a broader generalizability of findings, future studies can replicate the study in different educational levels and contexts. Moreover, the study is also limited in the examined variables as other additional variables may have a hand in influencing AI behavioral intentions among students aside from the ones included in the investigation. Future studies can focus on additional variables like students' characteristics like age, gender, university type, technological factors and students' different experience levels for a more nuanced investigation.

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