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THE MODERATING EFFECT OF VOLUNTARINESS OF USE AND TECHNOLOGY AWARENESS ON STUDENTS' BEHAVIORAL INTENTION TO USE AI TECHNOLOGIES

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ABSTRACT

This study aimed at identifying the moderating effect of Voluntariness of use and Technology Awareness on students' behavioral intention to use AI technologies. The sample, consisting of 282 university students from Saudi university and where 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 had significant effects on behavioral intention of students towards AI technology but this significance was not found for performance expectancy. Also, technology awareness and voluntariness of use had no moderating effect between the variables and behavioral intention towards AI technology. The study has several practical and theoretical implications, the top of which is the extension of technology theoretical models and the enhancement of AI practices among the learning process of students.

KEYWORDS: Artificial Intelligence (AI) Technologies, Behavioral Intention, Technology Awareness, Voluntariness of Use

1. INTRODUCTION

Artificial intelligence (AI) is a rapidly evolving field of technology that involves the development of intelligent machines that can perform tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, and making decisions based on data (Ndalu, 2025; Owan, et al., 2023). AI refers to the field of computer science that involves creating computer programs capable of imitating intelligent behavior and ideally enhancing human-like abilities (Naqvi, 2020). However, AI has been increasingly integrated and used in many sectors (Garcia-Madurga & Grillo-Mendez, 2023; Mohebbi, 2025), and the educational sector is no exception (Nguyen, 2025; Owan et al., 2023). 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.

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 (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. Thus, this study proposes the following hypotheses;

- Effort expectancy is positively related to the students' intention towards AI technologies use.
- Performance expectation is positive 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 some other technology adoption studies, the major role of VOU in influencing the relationship between antecedents and behavioral intention (BI) (Han et al., 2025; Ramllah & Nurkhin, 2020). Following the logic behind the finding, the moderating influence of VOU is proposed. Aside from the major UTAUT determinants of behavioral intention, this research added technology awareness, which is defined by Collins (2007) as the level to which students have the likelihood to be familiar with AI. Technology awareness was also proposed by Abubakar and Ahmad (2013) as a moderating factor on the relationship between intention and its predictors and thus, it is proposed that UTAUT independent variables' significance influence over behavioral intention is moderated by technology awareness because individuals with higher technology awareness level are more likely to adopt AI compared to their counterparts with lower technology awareness level (Abubakar & Ahmad, 2015; Milicevic et al., 2024). On the basis of the above, the following hypotheses about technology awareness are proposed;

- Voluntariness of use moderates the influence of social influence on students' behavioral intention to use AI technologies.
- Voluntariness of use moderates the influence of technology readiness on students' behavioral intention to use AI technologies.
- Technology awareness moderates the influence of performance expectancy on students' behavioral intention to use AI technologies.
- Technology awareness moderates the influence of expectancy on students' behavioral intention to use AI technologies.
- Technology awareness moderates the influence of social influence on students' behavioral intention to use AI technologies.

This research demonstrates the perspectives of students on the factors affecting their behavioral intention towards using AI technologies through an extended UTAUT model with additional factors in a mandatory learning environment. This work is theoretically underpinned by past works (Bhat et al., 2024; Han et al., 2025; Kim et al., 2024). These studies have similarly been conducted in the education sector as mentioned in the reviewed literature. Based on these studies, the study developed the conceptual model and formulated the relevant hypotheses. Based on the author's best knowledge, this is a pioneering work on behavioral intention towards AI using UTAUT predictors, mediated by technology readiness and moderated by AI awareness and voluntariness of use. This study is an attempt to minimize the gap in literature concerning AI use in education in the Saudi context. The following sections present the methodologies adopted to achieve the objectives, the results and the discussion. The research concludes with several implications.

2. 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 Saudi 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).

2.1. Participants

The population of the study consists of Saudi's 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 and the Dean of Scientific Research of Prince Norah University 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.

2.2. 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, and social influence. This measurement held true for perceived risks (Wu, Zhang, Li, & Liu, 2022), technology awareness (Collins, 2007; Raub & Blunschi, 2014), voluntaries of use scale (Moore & Benbasat, 1991), and lastly, students' behavioral intention to use AI (Choi et al., 2023). A total of 22 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.

2.3. Validity and Reliability of the Measurement Model

The item's 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. 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), technology awareness (0.894), 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), technology readiness (0.884), technology awareness (0.897), and voluntariness of use (0.938). The AVE and constructs validity were found to be converging. The model fit indices also presented accepted values as shown in Table 2.

Table 1: Construct Validity and Reliability Measurements.

Variable	α	CR	AVE
effort expectancy	0.937	0.937	0.841
Behavioural Intention	0.895	0.896	0.826
performance expectancy	0.915	0.919	0.799
social influence	0.891	0.891	0.821
technology awareness	0.894	0.897	0.811
voluntariness of use	0.912	0.938	0.802

Table 2: Model Fit Indices.

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

3. RESULTS

The results for the initial PLS-SEM's evaluation of the students' attitude are presented in Table 3. It is evident from the table that the following results were obtained for the constructs – as the behavioral intentions to use AI technologies as a learning tool in educational institutions, Table 3 reveals the following results – efforts expectancy, and social influence significantly affect behavioral intention of students (β = 0.160, p= 0.026, β = 0.103, p= 0.045, respectively), while performance expectancy had no such effect (respectively), with insignificant values exceeding 0.05. Added to the above findings, the R2 and R2 adjusted values reveal the explanatory power of the structure model, and in this regard, 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.

Table 3: Result of Direct Hypothesis Testing.

Structural Path	B and t-value	Decision
H1: effort expectancy- behavioral intention	0.160, p= 0.026	Supported
H2: performance expectancy - behavioral intention	0.057, p= 0.618	Not supported
H3: social influence - behavioral intention	0.103, p= 0.045	Supported

The analysis of the main-effect relationships was followed by the testing of the moderating effects of technology awareness and voluntariness of use. The model was tested based on the previous criteria and found satisfactory findings. The results present the coefficients and significant levels. The main effects (with no moderation effects) coefficient levels are presented and these involved the direct impacts of effort expectancy, social influence, performance expectancy on behavioral intention. On the other hand, presents the effects with the addition of the moderators, and these are referred to as simple effects (Hair et al., 2017). The latter are positive interaction effects, and with this in mind, if the mean values of technology awareness and voluntariness of use increase by a standard deviation, then the independent variables and behavioral intention increase by 0.126 (0.105 + 0.073), 0.178 (0.145 + 0.033) and 0.103 (0.101 + 0.002) respectively. Similarly, if the mean values of technology awareness and voluntariness of use increase by a standard deviation, then the relationship between independent variables and behavioral intention increases to 0.250 (0.229 + 0.021) and 0.118 (0.040 + 0.078) respectively. Notably, in contrast to simple effects, interaction effects obtained p-values exceeding 0.05, with f2 values obtained not reaching 0.05 or higher which is considered to be a weak effect moderation size (Becker et al., 2023). In other words, no significant moderating effects were found for both technology awareness and voluntariness of use between efforts expectancy, performance expectancy, social influence and behavioral intention towards AI technology use.

4. DISCUSSION

This study tested the formulated hypotheses proposing that efforts expectancy influence the behavioral intention of students towards using AI technologies in their university learning. The results rejected the hypotheses as an insignificant influence was found on 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 that efforts expectancy influence on behavioral intention. Therefore, the results rejected the hypothesis.

Moving on to the next examined construct, namely performance expectancy and its influence on behavioral intention of students to use AI technologies, the result also found insignificant influence. 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. 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. The study also proposed the influence of social influence on 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.

With regards to the moderating effects, technology awareness and voluntariness of use were found to have insignificant moderating effects on the study variables relationship with behavioral intention towards AI technologies in their learning, and thus the results rejected the moderating hypotheses. The results are indicative of the fact that whether AI use is voluntary or mandatory, no significant moderating influence of social influence can be found on behavioral intention, which challenges assumptions of past studies like Venkatesh et al. (2003) and Han, Mustafa and Khatuddin (2025), calling for more studies to examine the contextual factors influencing the voluntariness of technology adoption (Han et al., 2025). It indicates that the behavioral intention of students is generally influenced by their perceptions of AI technologies in terms of its ease in academic tasks completion.

These results present empirical evidence in terms of the moderating variables of UTAUT while extending the UTAUT research scope considering university students' adoption of AI tools and technologies in learning.

4.1. Implications

This study has several implications for theory, the first of which is the development of 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. The contribution is the testing of moderating effects of variables, among which is the lack of moderating effects of technology awareness and voluntariness of use on the same. The study provided additional empirical evidence of the under-examined moderating variables in the university context. Practical implications for educator and policy-maker circles are presented concerning the AI implementation success in universities.

5. 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 no significant moderating effect was found from technology awareness on the relationship between efforts expectancy, performance expectancy, facilitated conditions, social influence, and behavioral intentions of students towards AI technology. Lastly, voluntariness of use also had no significant moderate effect on the relationship between social influence, technology readiness and behavioral intention of students towards AI technology.

5.1. Limitations and Future Directions

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 mixed methods. 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.

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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