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Analyzing Students' Attitudes and Behavior Toward Artificial Intelligence Technologies in Higher Education

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***Abstract:** In this study, we aim to contribute to the existing literature on the implementation of artificial intelligence (AI) in education. We explore the factors that impact the behavior and attitude of students toward the use of AI in higher education. We employed a quantitative approach using a wide range of adoption theories and models, including the unified theory of acceptance and use of technology model. We formulated hypotheses and verified the conceptual model. A questionnaire was used to collect data from 350 students. The structural equation model (SEM) was applied to estimate the relationship between dependent and independent variables. Based on SEM results, we found that despite perceived risk negatively impacting students' attitudes, the factors of performance expectancy and facilitating conditions significantly influenced students' attitudes and their behavioral intention to use AI in education. The results also show that effort expectancy does not significantly influence attitudes toward AI use in higher education. Research limitations are discussed at the end of this study.*

***Keywords:** Artificial Intelligence; Education; Students' Attitude; Behavior*

I. INTRODUCTION

One definition of artificial intelligence (AI) is computers' ability to "perform cognitive tasks" that are normally associated with human thinking, in particular in problem-solving and learning [1]. In recent years, AI is being increasingly used in education, mainly because of the advances that have occurred in technology, implying that technology can be used to enhance learning and research. Reference [2] noted that one of the most common and important applications of AI is by teachers in a formal classroom setting, where they use information and communications technology (ICT) to present material to their students. An important feature of AI technology is that it can be used to customize learning materials to meet individuals' needs, thereby enabling personalized learning approaches [3, 4]. From the teaching perspective, intelligent computer systems provide a hugely valuable service by reducing heavy workloads in environments where the amount of work is a burden on the teaching staff.

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The efficiency that computer systems provide improves the quality of the education offered. In higher education, libraries powered by AI can enhance the learning experiences of students by providing them with a personalized learning approach. However, the AI technology currently available may not be fully developed for this application and more development time may be needed [5, 14, 15].

Chatbots are useful tools that can meet students' individual needs, and thus, provide valuable support [4, 5]. They are particularly beneficial for use outside the normal classroom time, as students can employ them to gain answers to any questions that they may have [6, 9]. Furthermore, AI technologies can be used in an educational context to provide assistance with administrative tasks such as student admissions and generate smart content [2, 7]. Textbooks can be digitalized using AI technologies and digital learning interfaces can be configured throughout the educational system. This is particularly true in higher education, where the number of students has continuously increased over the past few decades, leading to a very high workload for teaching staff. AI is one of the modern technologies that can help reduce this increasing burden [3, 9, 10].

Despite the above-mentioned benefits of AI technology, it is not always accepted by teaching staff, administrative staff, or students, suggesting that its benefits are not being utilized to the full extent possible [10, 11]. This is an issue that should be addressed, but to the best of our knowledge, the research on the implementation of AI technology in Saudi higher education is scant [12, 13, 16].

Several researchers have reported that educational outcomes are more effective when using AI to assist learning than with traditional learning that is teacher-centered [2, 3,5, 12, 24–26]. This development has been recognized and the use of AI in education is being accorded a high priority in Saudi Arabia because of the importance of education in Saudi Arabia's Vision 2030. A paradigm shift in the administration and teaching departments within higher education is essential. The priority should be ensuring that students receive a high-quality education that is up-to-date and the best that can be offered [6, 18, 19]. One of the critical elements of this development should be the incorporation and implementation of effective technological solutions and tools, with AI being one among them [6, 20, 21]. Generally, the models and concepts related to the willingness and desire of users to employ AI-powered solutions originate from various fields such as psychology, data mining and analytics, and sociology [22, 30, 31].

Several drivers of models and theories for the synthesis of user acceptance behavior exist, with researchers tending to select one or two of these that are most suited to their study, neglecting the rest. In our case, we illustrate that the unified theory of acceptance and use of technology (UTAUT) model is capable of explaining approximately 70% of the variation in behavioral intention compared to 17% to 53% of the variation in other models and theories. Therefore, this model is considered to be the best when exploring and predicting the intentions of users about using emerging technologies such as AI [6, 32]. This model has been updated by several researchers by integrating it with other models and constructs [33].

II. LITERATURE REVIEW

Providing students the opportunity to learn on their own with the assistance of AI technology will benefit them enormously. Students at all levels will have their needs for a new and innovative approach that can be tailored to the needs of each student [3, 6, 27]. With the implementation of ICT and AI, education in Saudi Arabia will be high in quality and flourish [23, 27]. The goal to improve education is shared by developing and developed countries alike, and one of the cornerstones of achieving it is through the application of modern technology such as AI, which can not only be used for direct teaching but also improve systems for developing students' abilities and assessing and providing feedback on their work. The aim of improving the quality of education offered by implementing technological tools is a common theme across the globe [24, 28, 29].

Reference [8] conducted a study among online learning students in China based on the UTAUT model and perceived risk to develop a suitable method for evaluating e-learning products that employ AI. The authors' recommendations were theoretical and the study showed how to create and promote AI-based e-learning programs, considering users' experiences and goals. The program controller can better balance experiences and requirements using this method.

In addition, a university online management system was analyzed by [30] to gauge the level of student acceptance. The study was based on the UTAUT and structural equation model (SEM) and employed a pre- and post-usage experimental design with 839 participants. Of these, 347 filled in a questionnaire before and after using the online management system to enable the researchers to assess if and how their acceptance levels changed over time. The study was conducted in the academic year 2019–20. The results provided guidance for incorporating AI systems into higher education virtual classrooms, highlighting that the adoption of the early warning system had a disconfirmation effect.

Reference [13] developed a theoretical framework based on the technology acceptance model (TAM) to assess students' use of AI-based voice assistants as part of their learning. Data collected from 300 university students were analyzed using PLS-SEM and the resulting model was validated. The study reported that perceived ease of use (PEOU), trust, and enjoyment influence perceived usefulness (PU) and that PEOU is significantly affected by trust in technology and enabling factors. Contrary to expectations, building a conducive environment, ensuring security, and the subjective norm were not factors that influenced PU. Similarly, enjoyment and subjective norms did not alter PEOU. This study helped in better understanding the principal factors that affect students' use of voice assistants while studying.

Reference [3] reported that AI was a valuable tool that could lend strong support to innovative education policies. This exploratory study collected data from students from HE institutions in India to evaluate their acceptance of AI use in education. The data were analyzed using SmartPLS software and their study illustrated how AI chatbots can facilitate the provision of personalized assistance to students who require solutions to specific problems. The authors contended that the applications have a high degree of accuracy and can offer services to students outside of regular school hours. They further argued that AI chatbots could play critical roles in addressing administrative challenges as well as admission queries. The findings demonstrated that perceived risks and effort expectancy significantly affect the attitudes of stakeholders concerning the adoption of AI, whereas performance expectancy has a limited impact on attitude.

In a study conducted by [17], a questionnaire was developed to assess student's level of awareness and perceptions of AI-enabled and mobile learning-based systems in higher education institutions. The results provided insights into how students viewed the use of these technologies in HE. They were familiar with these types of systems and used them often. Given this familiarity, the study assumed that they will be quick to adopt new AI-powered systems as they emerge, even when they are at the research stage. Table I provides a summary of important research articles on AI.

TABLE I. SUMMARY OF SELECTED RESEARCH ON AI

Author Name and Year	Research Aim	Research Methods	Research Findings	Limitations
Zhu & Ren, 2022	To analyze the impact of AI on role cognition in Taiyuan City's education system.	Questionnaire survey method.	The learning of AI-assisted courses is dependent on course role cognition.	The questionnaire data collection methods may have resulted in data duplication and the collection of inaccurate views from respondents.

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Author Name and Year	Research Aim	Research Methods	Research Findings	Limitations
Chatterjee & Bhattacharjee, 2020	To explore the techniques that stakeholders would use to adopt AI in India.	Research survey.	The perceived risks and effort expectancy significantly affect the attitudes of stakeholders concerning the adoption of AI. Performance expectancy has a limited impact on attitude.	The study results are not generalizable as all inputs were received from non-adopters of AI technology. The adoption of AI technology in India is limited.
Chen et al., 2020	To conduct a comprehensive systematic review of significant studies on the application of AI in education.	Systematic review.	The effect of AI on education has attracted increasing interest. Applications of deep learning in educational contexts are limited. Natural language processing has been adopted in the educational sector. Studies that evaluate AI technologies in the context of educational theories are limited.	Most of the studies reviewed are position studies in which researchers expressed personal views on issues related to AI in education. The number of studies that conducted a bibliographic analysis of AI in education was limited.
Rahman et al., 2022	To understand the relevance and challenges associated with the adoption of AI in the Malaysian banking industry.	In-depth interviews and questionnaires.	The challenges to AI adoption include limited infrastructure, poor expertise, and non-existent regulatory frameworks.	Data collected from interviews are largely subjective and may be influenced by factors that were not assessed by the researchers in the study.
Bu, 2022	To redefine the teacher's fundamental duties and advocate for the sensible application of AI technology in the educational context.	Literature review.	The integration of AI in education is critical, given its capacity to facilitate education advancement. Learners and instructors must adjust to their roles in education by adapting to the new educational environment, which is characterized by the integration of AI into learning.	While the views presented were evidence-based, a one-sided argument in support of AI regulation was promoted.
Zheng & Khalid, 2022	To propose a conceptual framework for the adoption of enterprise resource planning and business intelligence systems (ERPBI).	Literature review.	Many major companies use AI as a factor for competitive growth. Small and medium enterprises in Asia understand the critical role of ERPBI in institutional management.	The sole focus on technological factors limits the generalizability of the findings, given the existence of other elements that affect technology adoption in the business environment.

III. METHODOLOGY AND CONCEPTUAL FRAMEWORK

A. Methodology

We employed a self-administrated structured questionnaire for data collection. The questionnaire was distributed online (using the Blackboard system) to undergraduate students in a Business Administration College at Taif University, a Saudi government university. All undergraduate students qualified as participants (random sampling). The participants were informed that any personal details collected, such as their names and university ID, would be anonymized so that they would not be identifiable from the published research. The use of their data only for research purposes was also confirmed.

The quantitative questionnaire comprised 33 questions related to the use of AI in higher education. It focused on analyzing students' attitudes and their behavioral intention regarding the use of AI services to deliver personalized content to the students. The questionnaire also asked the students about the perceived risks of using AI in higher education. The students were contacted using the Blackboard system, a learning management system adopted at Taif University, and asked if they would be willing to participate in completing the questionnaire.

The students were requested to return their completed questionnaire within 30 days, that is, by the end of September 2022. A total of 500 questionnaires were sent out and 350 completed forms were returned and included in the data analysis. On average, the questionnaire was completed by students in 5 to 10 minutes. The questions were adapted from similar surveys published in the literature and were validated by the supervisors.

From the 350 questionnaires returned, 304 were usable—the responses were excluded if the participants had been at the university for less than six months (n = 21) and if some questions had not been answered (n = 25). The minimum sample size required for meaningful analysis was 200, based on the SEM sample size criteria. Therefore, the 304 valid responses in this study were sufficient for 80% statistical power.

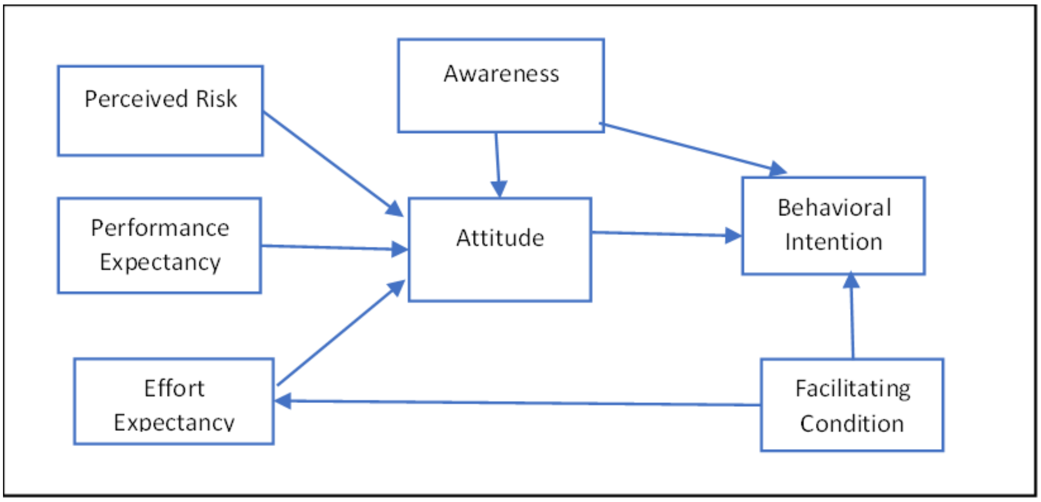

Fig. 1. Conceptual framework.

B. Conceptual Framework

Following a review of the extant literature, we decided to adopt the UTAUT model for constructing the study's conceptual framework. UTAUT was chosen because it possesses a more effective explanatory power than other models or theories [34]. Furthermore, it encompasses the other eight existing models and has consistently been found to be an effective model for synthesizing the acceptance behavior and attitude of stakeholders toward the adoption of AI technology [35]. The UTAUT model has four exogenous factors: performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI). SI was not considered in this study because the participants were literate undergraduate students.

Additionally, UTAUT was chosen as the model for this study because it encompasses the other eight current models. It is therefore viewed as a complete model for the synthesis of attitude (ATT) and acceptance behavior toward the adoption of AI technologies [35]. In this study, we show that ATT can be used as a moderator when assessing the intentions of users regarding technology acceptance. Previous studies have employed ATT as a mediator variable between behavioral intention (BI) and PE, EE and BI, and EE and BI. Following the literature, the two constructs of awareness (AWR) and perceived risk (PR) were also included as crucial exogenous factors. Past studies have reported a direct relationship between FC, and BI and EE [36]. Therefore, we hypothesized that PE, PR, and EE would directly impact BI via ATT (see Fig. 1). FC and AWR have been shown to influence adoption through BI [37]. In this study, we explore whether students' attitudes and behavior influence the exogenous constructs.

Having explained why we selected PR, PE, EE, FC, ATT, AWR, and BI to understand students' attitudes and their behavior toward artificial intelligence technologies in higher education, we now discuss each one in more detail and formulate our hypotheses.

1) *Perceived risk*

PR can be defined as a belief that the achievement of a goal will involve some type of loss [38]. Reference [39] defined it as a mixture of uncertainty about how severe the loss might be, and uncertainty over which action is the best to take next. It is a significant factor in the study of user behavior as it impacts the first steps in decision-making [40]. Several studies have examined how the PR of using new forms of technology is affected by TAM and UTAUT [41, 38]. PR is a construct in the UTAUT model, and unlike the other four constructs, it has a negative influence on the adoption of technology. It combines behavioral and environmental risks. Based on the above discussion, we hypothesize that:

H1: PR has a negative influence on students' attitudes toward AAHE.

2) *Performance expectancy*

PE is defined as the extent to which a user believes that a new piece of technology will help to achieve a noticeable improvement in their performance [38]. Together with PU of the TAM, PE is regarded as a critical influencing factor of attitude toward the use of technology, having a positive and significant influence [36]. It also has a positive and significant impact on BI with regard to AAHE. PE, PU, relative advantage, and outcome expectancy, as employed in adoption theories, have a high level of similarity [41]. The following hypothesis is based on these findings:

H2: PE has a constructive and positive influence on students' attitudes toward AAHE.

3) *Effort expectancy*

EE is defined by [44] as a user's belief in the level of ease of utilizing a system effectively, regardless of its complexity. If technology is user-friendly, the EE will be low and the technology will be easy to adopt. Most users intend to use technology that is easy to utilize, flexible, and helps them to achieve their goals. Reference [42] reported that EE is an important influencing factor concerning the intention to use. Extant studies confirm that related to technology adoption, EE and PEOU can strongly predict attitude [43]. Based on this evidence, we propose the following hypothesis:

H3: EE has a positive impact on student's attitudes toward AAHE.

4) *Facilitating conditions*

FC is defined as the extent to which a person believes that the technical and organizational framework exists to support the use of the system. The absence of FC inhibits positive intentions to use a new technology [38].

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In this study, FC refers to the existence of resources that will support the adoption and usage of AI technology. Researchers have reported that FC has a significant impact on BI [38, 44, 45], as well as the acceptance of AI technology [46, 47]. Based on the above, we posit the following hypotheses:

H4: FS has a positive impact on EE.

H5: FC has a positive impact on students' behavior.

5) Awareness

Previous studies have reported that the UTAUT variables and others variables such as AWR can predict the BI of potential users [48, 49], although these studies have been conducted in the field of m-commerce, rather than education [50]. In this study, AWR refers to the participant's knowledge and awareness of AAHE. Reference [51] reported that one of the main reasons why more people do not use AI systems is that they are unaware of them and the benefits they offer. Researchers have found that the more individuals know about technology, that is, the higher their level of expertise, the more likely they are aware of innovations.

AWR is an important driver of acceptance, as the more people know about a system, the more likely they are to use it [52]. However, AWR is still not fully understood, particularly with regard to emerging technologies such as AAHE. The lack of knowledge and awareness dissuades some people to utilize them. References [53–55] reported that a lack of AWR reduced the intention to use AI systems, highlighting the need for more research into AAHE. Users are often hesitant to access or use AI-based services because they are unfamiliar with new technologies, or may not even be aware that they exist [55]. Previous studies have investigated the link between BI and AWR and found that AWR significantly influences people's intention to employ technology [53, 54]. Therefore, we propose the following hypotheses:

H6: Students' awareness has a positive impact on their attitude toward AAHE.

H7: Students' awareness has a positive impact on their behavior.

6) Attitude

ATT is defined as an individual's feelings, positive or negative, toward the target activity [47]. Reference [44] defined ATT toward technology as how an individual responds emotionally to an ICT system. ATT has been reported to influence motivation to use and actual usage over time [38]. ATT is commonly evaluated by examining how people feel about a certain behavior; if they have a positive attitude toward something, they will derive pleasure and convenience from its use. ATT is also part of the latest UTAUT model as a mediator of the interactions between BI and interpersonal beliefs; indeed, it is an important construct in relation to BI. Considering all the evidence discussed above, we hypothesize that:

H8: Students' attitude has a constructive and positive impact on their behavior.

IV. RESEARCH RESULTS

We analyzed data in five stages. Factor analysis was conducted using SPSS 25 software, followed by Cronbach's alpha reliability tests, to assess internal consistency. When satisfactory results were achieved, confirmatory factor analysis (CFA) was performed using SPSS Amos 22.0 tool. The model was tested for several types of validity: discriminate, convergent, and composite. SEM was employed to assess the relationship between the dependent and independent variables. Each hypothesis was rejected or supported according to the results obtained from the SEM.

A. Exploratory Factor Analysis

Two tests were utilized to confirm the suitability of the data for factor analysis: Kaiser–Meyer–Olkin (KMO) and Bartlett's tests. The two tests have different cut-off points for suitability—in KMO, the suggested minimum value is 0.7, and the data scored 0.863, confirming suitability. In Bartlett's test, PCA with Kaiser normalization and varimax rotation was employed, which confirmed that all 33 items could be used for the factor analysis. All the items scored higher than the cut-off point of < 0.5; therefore none were excluded. The total average variance of the 33 items was greater than the suggested minimum of 60 (65.31) and the items were allocated to 7 groups. The PCA results are presented in Table II.

TABLE II. RESULTS OBTAINED THROUGH FACTOR EXTRACTION OF THE ITEMS

Variables	Factor Loadings	Eigen Value	% Variance
AT1	0.769	7.254	21.982
AT2	0.755		
AT3	0.778		
AT4	0.794		
EE1	0.776	3.705	11.228
EE2	0.781		
EE3	0.778		
EE4	0.797		
EE5	0.806		
BI1	0.776	2.614	7.920
BI2	0.704		
BI3	0.772		
BI4	0.751		
BI5	0.774		
PE1	0.801	2.423	7.344
PE2	0.767		
PE3	0.783		
PE4	0.769		
PE5	0.771		
FC1	0.701	2.310	7.000
FC2	0.707		
FC3	0.774		
FC4	0.757		
FC5	0.718		
PR1	0.812	1.892	5.734
PR2	0.787		
PR3	0.794		
PR4	0.803		
AW1	0.777	1.355	4.107
AW2	0.834		
AW3	0.802		
AW4	0.721		

B. Reliability Tests

Cronbach's alpha was employed to test the reliability, or internal consistency, of the seven test items (seven components). The range of possible values of α is between 0 to 1, with 0 indicating no relationship between the items and 1 indicating large covariance.

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A value of α = 0.7 is considered acceptable. In this study, all the values were > 7, implying that they could all be employed in the next stage of the analysis (see Table III).

TABLE III. RESULTS OBTAINED VIA CRONBACH'S ALPHA FOR T COMPONENTS

Component	Items	Cronbach's Alpha	No of Items
1	PR1 PR2 PR3 PR4	0.850	4
2	PE1 PE2 PE3 PE4 PE5	0.857	5
3	FC1 FC2 FC3 FC4 FC5	0.832	5
4	EE1 EE2 EE3 EE4 EE5	0.866	5
5	AW1 AW2 AW3 AW4	0.816	4
6	AT1 AT2 AT3 AT4 AT5	0.866	5
7	BI1 BI2 BI3 BI4 BI5	0.863	5

C. Confirmatory Factor Analysis

CFA was employed in this study to evaluate the relationship between the latent and observed variables. CFA can be used to hypothesize relationships between variables and verify the hypothesized structure. A model was developed based on this study's hypotheses, and the validity of this model was then verified using CFA. Fig. 2 visualizes this study's model.

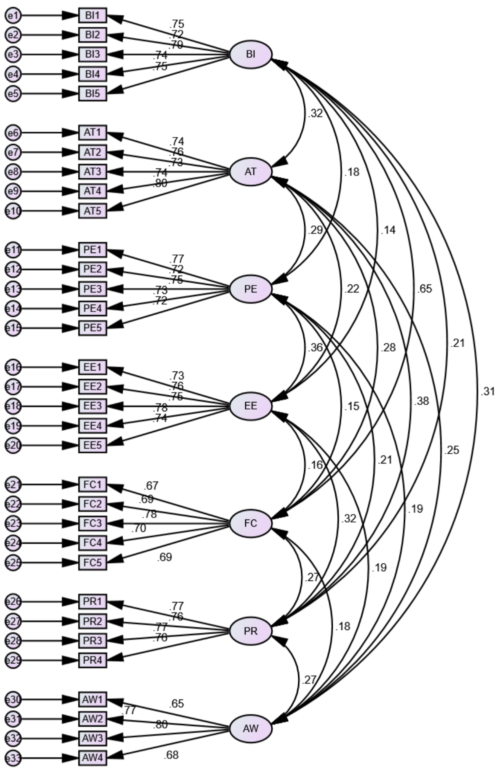

Fig. 2.CFA for Hypotheses Confirmation.

Table IV shows how each measure loads on a specific factor, confirming how the measured variables represent the constructs employed to verify the reliability and validation of the study model. The covariance between the latent variables is significant (p-values = < 0.05).

TABLE IV. COVARIANCE AND CORRELATION ESTIMATION BETWEEN THE LATENT VARIABLES

			Estimate	S.E.	C.R.	P	Estimate
BI	<-->	AT	0.198	0.033	6.056	***	0.325
BI	<-->	PE	0.120	0.033	3.597	***	0.182
BI	<-->	EE	0.086	0.030	2.886	.004	0.144
BI	<-->	FC	0.335	0.036	9.378	***	0.645
BI	<-->	PR	0.134	0.033	4.059	***	0.208
BI	<-->	AW	0.158	0.028	5.630	***	0.311
AT	<-->	PE	0.203	0.037	5.487	***	0.289
AT	<-->	EE	0.141	0.033	4.326	***	0.222
AT	<-->	FC	0.154	0.030	5.177	***	0.279
AT	<-->	PR	0.261	0.038	6.837	***	0.380
AT	<-->	AW	0.137	0.029	4.719	***	0.252
PE	<-->	EE	0.246	0.038	6.508	***	0.356
PE	<-->	FC	0.087	0.031	2.845	.004	0.145
PE	<-->	PR	0.156	0.038	4.068	***	0.209
PE	<-->	AW	0.113	0.031	3.701	***	0.193
EE	<-->	FC	0.085	0.028	3.058	.002	0.156
EE	<-->	PR	0.215	0.036	5.898	***	0.318
EE	<-->	AW	0.100	0.028	3.613	***	0.188
FC	<-->	PR	0.158	0.032	5.002	***	0.270
FC	<-->	AW	0.081	0.024	3.324	***	0.175
PR	<-->	AW	0.154	0.031	4.953	***	0.269

All the factors are significantly correlated. The SEM results are chi-square = 1087.884, degree of freedom = 474, and probability level = 0.000. However, other hypotheses possess the minimum discrepancy (chi-square/degree of freedom) of 2.295. The norm is that a model is considered to be significant if the minimum discrepancy < 5. Furthermore, the comparative fit index = 0.927 and the root mean square error of approximation = 0.048, indicating that this model is fit and acceptable.

D. Reliability and Validity Tests

The analysis results confirm that the composite reliability for all of the variables is > 0.7, which is considered good. In addition, the AVE for all variables > 0.5; thus they all have convergent validity. They also all possess a value for discriminant validity that is greater than the corresponding correlation; therefore, all the variables have a good level of discrimination (see Table V).

TABLE V. RESULTS OF RELIABILITY AND VALIDITY TESTS

Discriminant Validity								Composite Reliability Test	Convergent Validity
	BI	AT	PE	EE	FC	PR	AW	CR	AVE
BI	**0.749**							0.864	0.56
AT	0.325	**0.752**						0.867	0.566
PE	0.182	0.289	**0.739**					0.857	0.546
EE	0.144	0.222	0.356	**0.751**				0.866	0.564
FC	0.645	0.279	0.145	0.156	**0.708**			0.833	0.501
PR	0.208	0.38	0.209	0.318	0.27	**0.766**		0.85	0.586
AW	0.311	0.252	0.193	0.188	0.175	0.269	**0.731**	0.82	0.534

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E. Path Analysis of SEM

SEM was developed using SPSS Amos 22 software to perform path analysis. SPSS Amos Graphics software was used to create Fig. 3, which illustrates the relationships between all the variables. Those with a high value significantly influence the dependent variables. In this model, only one variable, that is EE, which has a p-value of 0.160, higher than 0.05, does not significantly impact ATT.

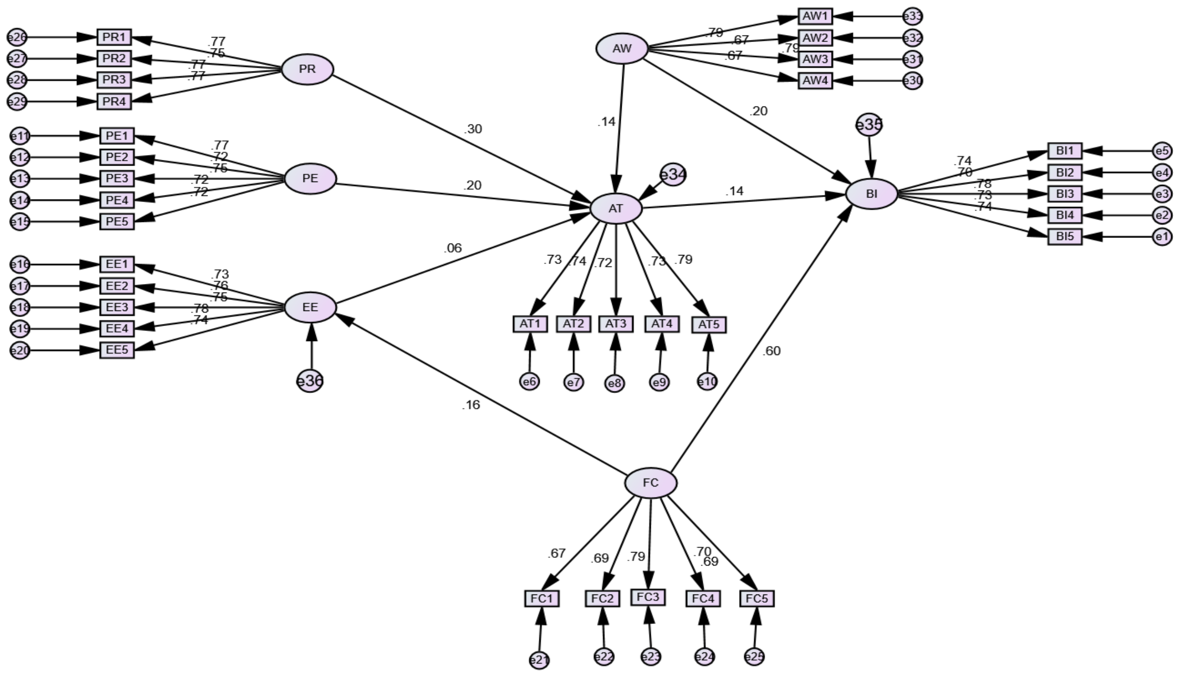

Fig. 3.SEM-The Path Diagram with Standardized Parameters.

V. DISCUSSION

This is the first study to evaluate the adoption of AI technology in HEIs in Saudi Arabia. We employed the UTAUT model, which normally contains four constructs: EE, PE, FC, and SI. The first two of these represent the technological context, while the latter two represent the implementation context. As HEIs are increasingly utilizing the functions of AI, investigating the factors that can affect the adoption and use of AI technology in these educational establishments is extremely important. To augment the UTAUT model to better suit the environment of HEIs, the constructs of AWR and ATT were added as mediating variables. As the number of existing studies on the use and adoption of AI in Saudi Arabian educational establishments is limited, our study makes a valuable contribution to this field. Our new theoretical model helps us to evaluate attitudes and perceptions of a fairly recent technology. The inclusion of PR as an exogenous variable strengthens our theoretical model. How FC influences EE is not considered in either the UTAUT model or our extension. The implication of this is that system resources, the accessibility of infrastructure, and expertise work together to facilitate the use of AI in higher education via FC. Given that we as a society cannot control whether stakeholders accept or adjust to the use of AI in their educational or administrative duties, the exogenous variable SI is not included in this theoretical model. Moderators are also not included in our theoretical model, which we regard as a great benefit as these moderators would not have any significant effect. The fact that these moderators are not present renders this theoretical paradigm unique. The endogenous variables, BRI and ATT, also proved a valuable addition to our theoretical model as they have comparable explanatory power.

VI. CONCLUSION

In this study, we aimed to analyze students' attitudes and behavior regarding the use of AI in higher education. To achieve this, we added new constructs, AWR and PR, to the UTAUT model as exogenous factors. The findings show that the variables AWR and ATT are important as ATT has a large influence over students' BI with regard to AI technology. Therefore, we can conclude that officials in higher education believe that AI technology is very useful in terms of influencing people's behaviors and intentions because it is widely employed in Saudi HEIs. Our model also shows that ATT is influenced by the antecedents, EE and PE. This highlights the important role of stakeholders in overcoming technological difficulties, as both these constructs are connected to technological challenges. This result indicates that administrators, developers, and designers in higher education systems must pay more attention to the usability of AI systems. They should not be afraid of admitting any issues they encounter, because then these can be overcome and the technology utilized and adopted more widely. Authorities must also be committed to informing developers of essential user needs.

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In other words, the technology selected for using education must consider primarily the needs and demands of users. Similarly, users must also be well informed about the capabilities of any new systems. Information on system use and capabilities can be disseminated through live demonstrations, booklets, etc. Finally, to reduce the PR of using AI technology, security and privacy issues must be seriously considered, and users of the system should be assured that their data will be protected from security breaches and cyber fraud. If users are reassured of this, the usage of AI in higher education in Saudi Arabia will undoubtedly boost.

LIMITATIONS AND FUTURE WORK

One of the limitations of the study is that it utilizes the quantitative method of a questionnaire survey. In the future, researchers could use other data collection methods to collect more in-depth data. Future research could also include parameters other than those used here, which are known to affect the usage of AI in higher education. The inclusion of these components would increase the explanatory power of the model. Finally, the sample size in the study was small, and therefore, the results cannot be generalized to Saudi Arabian higher education as a whole. Future work could be carried out on a larger sample to increase the generalizability of the findings.

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