Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt

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Keywords

Performance expectancy, effort expectancy, demographics, chat-bot, behaviour intention, UTAUT

Abstract

Chat-bot as an (AI) technology has taken great attention in recent years and especially in the education sector. before applying such new technology. it is vital to Understand the determinates that affect the behaviour intention for a student to accept or reject this technology in higher education, to understand this behaviour intension, the current research applied the unified theory of acceptance and use of technology (UTAUT) with excluding for two moderators from the original model which are experience and Voluntariness of use. Additionally, this research excluded facilitating conditions and behaviour use as it aimed to investigate only the intension behaviour of the students. This study also aimed to examine the role of demographic factors (gender and age) effect on the model research independent variables and the behaviour intension variable. Therefore, the researcher put the objectives of the study that are represented in, developing a framework for the acceptance of chat-bot technology on the behaviour intension of students in higher education in Egypt. To achieve these objectives, the researcher collects data about the required variables by making a questionnaire. This questionnaire targeted students at the Arab academy for science and technology and maritime transport (AASTMT). AASTMT was selected because it represents one of the oldest private universities in Egypt that apply artificial intelligence technology in its educational system. The final sample consisted of 385 responses. data were analyzed through data testing, descriptive analysis, correlations, regression, and structural equation modelling (SEM). Results indicated a significant impact of performance expectancy, effort expectancy and social influence on students' behaviour intention to accept the chat-bot technology in their higher education in Egypt. Moreover, the results have shown that there is no moderating role of demographic factors (gender and age) proved in the relation between performance expectancy, effort expectancy, social influence, and behaviour intention.

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Introduction

Artificial Intelligence (AI) is one of the most transformative technology evolutions of our times and most sectors have started to explore how they can use this technology to improve their customer experience and streamline their business operations (Wang et al., 2018). AI opens up many opportunities in the education field and the possibility for higher education services to become scalable at an unprecedented rate for better education service, but it is critical to study the potential users' acceptance of this technology first. chat-bots technology in higher education has been widely researched and described in many previous studies like for example, (Winkler and Söllner, 2018) who described Chat-bots as conversational agents that primarily uses language and conversation to interact with humans and they mainly focused on what is called Chabot-mediated Learning (CML) which is a learning environment where the student uses chat-bots in their learning process to increase its quality and outcome.

Besides, providing individual support is considered the primary potential of CML since when the classrooms get bigger and individual assistant became more challenging, the chat-bots can provide support for both teachers and students (Winkler and Söllner, 2018), additionally, Literature on technology acceptance (Foon and Fah, 2011; Alharbi and Drew, 2014; Burns et al., 2017) provides solid models that researchers can employ and rely on in investigating specific technology acceptance among users.

Meanwhile, research studies on the acceptance of AI technology have generated interest for a lot of information system researchers. According to Al-Mamary et al. (2015), the UTAUT (Venkatesh et al. 2003) is the most popular model in the field of technology acceptance and it focuses on the technology factors for the successful implementation of information systems. The same perspective is reported in previous studies, for example, Sana'a (2016) stated that UTAUT is one of the most popular research models to predict the use and acceptance of information systems and technology by users based on certain factors that can be used with it. Hence, the current study has been used the original UTAUT model and applied the UTAUT (Venkatesh et al.2003) model to investigate the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt, also Age and Gender Demographics of the respondents are considered since it is the main scope here in this research to understand the relationship between respondents' demographics and the model variables.

Research questions

To provide an insight into the factors that influence the acceptance of chat-bot technology by higher education students, the following specific research questions are employed which are:

1- What are the significant variables affecting students' behaviour intention in Egyptian higher education to accept the use of chat-bot technology?

2- How do age and gender moderate performance expectancy, effort expectancy, social influence, facilitating conditions, anxiety and system interaction constructs to influence Egyptian higher education students' behavioural intention of chat-bot technology?

Literature review

A new model for higher education is a must, however, learning is not a receipt degree anymore, as technology and machines are continuing to surpass their old boundaries within time, humans must also continue to hone their mental skills, capacities, and technological knowledge to cope with this change. AI technology is expected to help many students, professors, administrative staff in universities and researchers all around the world. Thus, there is a huge need to take the help of this technology in the higher education sector (Menon et al., 2014; Stefan and Sharon, 2017). In all developing and developed countries, the concerned governments want to enhance the quality of their education (Chatterjee et al., 2020). This enhancement can be reached by adopting modern technology like AI in this sector (Cremer and Bettignies, 2013). Investigating a future technology like AI needs a well understanding of the factors that will lead to its acceptance or rejection from the potential users, previous Studies suggested that intentions will generally determine the individuals' actual behaviours (e.g., Cronan et al., 2018).

Chat-bots in education promise to have a significant positive impact on learning success and student satisfaction. A small number of studies have already shown successfully implemented chat-bots in learning scenarios (Kerly et al., 2007; Dutta, 2017; Huang et al., 2017). According to Chrisinger (2019), mentioned that AI-enabled Chat-bot could help to answer individual students' queries with accuracy as the technology matures. These AI-powered chat-bots can provide immediate answers to the students outside of the regular classes, help them search for study resources on the internet and know their results quickly and conveniently.

Few chat-bots’ examples have been applied in higher education to assist the student in their study process, apart from this application in the spectrum of online courses (Brinton et al., 2015). Additionally, Lidén and Nilros (2020) in their study investigated the students’ perceived benefits and limitations of chat-bots in higher education, by exploring the relative advantage, complexity, and compatibility of different chat-bot functionality, the study suggested that it is preferable to start with little functionality and then successively improve as small implementations with basic AI functionality are more accepted and useful to students compared to complex AI functionality.

Past studies found that private universities are more likely to adopt information technology in education like for example Yasmeen et al. (2015) who conducted a comparative study of the availability and Use of Information Technology in the Subject of Education in Public and Private Universities of Islamabad and Rawalpindi, the study concluded that the availability of equipment in education departments of private universities are better than public universities, Accordingly, the current research focused on an Egyptian private education university which is AASTMT and collect the questionnaires data from its higher education students.

Egypt has made an enormous stride in improving basic and secondary education like Teacher training, girls' education, community involvement and Information and Communication Technology in the classroom. These are a few of the areas that the Egyptian Government has worked to improve often in collaboration with the donor community (Kozma, 2004, pp. 11-12). However, the level of commitment has not been as strong at the higher education level, many issues factor into the poor quality of the higher education system (Holmes, 2008). Research studies in the education sector have previously applied the UTAUT model to identify the determinants of students' acceptance and use of various technologies in many countries (Khechine et al., 2014) To adapt the original UTAUT model in the educational context, many external variables have been added to ensure a better understanding of technology acceptance by students.

In many ways, the reason for selecting the UTAUT model is that it includes and combined the other eight technology acceptance models (Venkatesh et al., 2003). Also, the integrated constructs of the UTAUT model have characterized those constructs utilized in earlier different models. In this sense, the UTAUT is considered as an all-inclusive model for synthesizing acceptance attitude and behaviour for adopting AI (Carter and Belanger 2005). Many studies in the literature highlighted the moderating role of age and how it affected the users’ behaviour intention for information technology. (Khasawneh and Ibrahim, 2012), mentioned that moderating role of the age variable is among the most significant demographic characteristics and is considered a significant factor in technological adoption in the universities among academic staff.

Additionally, Alshboul et al. (2018) stated that young academic staff may be more or even most familiar with Information and Communication Technology in the education system especially those who use computers during their college studies or those who receive higher education degrees from any developed country. Moreover, Gender moderating role in the UTAUT model has been proven in many previous studies of its effect on the behavioural intention to use information technology. Maldonado et al.

(2011) and Magsamen-Conrad et al. (2015) studies found that gender moderating role affects the behaviour intention to use information technology.

Conceptual Framework

Based on the research questions and according to the literature review that has been previously discussed, the independent variables of the current research are performance expectancy, effort expectancy, social influence. the demographic moderators (age and gender) affect this relation compared to other studies findings. On the other hand, the dependent variable is the students' Behavior intention to accept or reject chat-bot AI technology in their higher education.

Figure 1 was constructed by the researchers to illustrate the original UTAUT model after excluding two moderator variables (experience and Voluntariness of use), facilitating conditions and behaviour used to examine the model variables' significance.

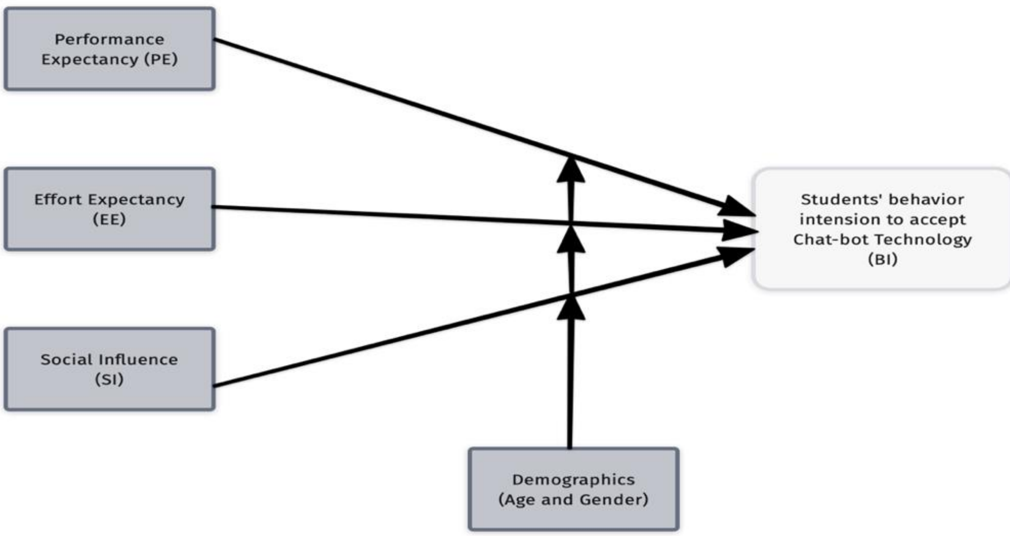


Figure 1: Proposed UTAUT Research Model

Methodology

The current research employed the survey method through the questionnaire as a data collection method to explore the perceived influence of technology acceptance constructs in the participants' behavioural intentions of Chat-bot technology adoption in higher education. The current study contributed to the quantitative methodological strategy by establishing an acceptable level of validity and reliability among study variables. The quantitative method used in the current research study allowed the researchers to measure each construct significance in the UTAUT model and determine which independent variable has the most effect on the student's behaviour intention. It was most appropriate to use the quantitative method to measure the relationships among the research variables of the original UTAUT original model in the context of higher education, as the quantitative methodology was the better choice for studies that attempt to understand relationships among variables (Creswell, 2009). For the current research, AASTMT was selected as the targeted population as it is one of the largest and oldest private universities with over more than 30 years in the education field. Additionally, AASTMT launched a new campus in El Alamein city, the College of AI to be the first of its kind in the region.

The College of AI was established to cope with the 4th Industrial Revolution where AI is its main pillar (www.aast.edu) which is the intended technology that the current research study investigates the students' behaviour intension about. According to AASTMT students' affairs year 2020, the total number of enrolled students in all programs (undergraduate and post-graduate) at the academy Miami, Al Alamain and Aboukeer branches are 5000 students. Accordingly, the target population of this research study is defined as all the AASTMT students enrolled in under and postgraduate programs in the academy for the academic year 2020-2021, as they are currently enrolled students who can participate in the survey. This target population includes students from all genders, age groups and degrees. The researcher selected the sample size for the population based on the time participants were available. This research study is based on investigating AI technology in higher education; thus, it has been assured that sample and population are being relevant to this area of research.

Sekaran and Bougie (2016) showed different ways to choose the right sample size and cited the work of (Krejcie and Morgan, 1970) table which greatly simplified the size decision. According to this table, when N= 5000 is the targeted P in this research study, then the right sample size (S= 357) will statistically represent the targeted population. The current research study used the structural equation model, according to Deng et al. (2018), many scholars have studied sample size issues in SEM and factor analysis. They stated that many Earlier types of research noted that reasonable results could be obtained in SEM analyses when N is <200 (Gerbing and Anderson, 1985), or at least above 100 (Boomsma, 1985).

They cited the work of Bentler and Chou (1987) who noted that sample size N should instead be considered relative to the number of parameters Q, and the ratio of N: Q can be as low as 5:1 for normally distributed data, and 10:1 for random distributions. Accordingly, the sample size of the current study is 385 students of the AASTMT which is an optimal size for the analyses that were to be used in testing the study’s hypotheses and answer the research questions as according to Hair et al. (2010), they stated the minimum acceptable sample size for quantitative research is (N = 354). A Stratified random sampling technique has been adopted for the process of sampling in the current research study. According to Sekaran and Bougie (2016), this technique is a probability sampling design that first divides the population into meaningful, non-overlapping subsets, and then randomly chooses the subjects from each subset. The current research study split the higher education total population in Egypt into segments or strata, the higher education students at the AASTMT university first and then split into the undergraduate strata and postgraduate strata for the interest of the current empirical research interest.

Gathering the data in this study was a very challenging step due to the pandemic situation of the COVID-19 virus which hit the world and it was so dangerous and impossible to distribute it hand to hand and collect it back. The data collection process was performed during the education year 2020/2021 by distributing a direct link for the survey for AASTMT students on google drive via students' group's social media platforms like WhatsApp groups, AASTMT Facebook pages through students group admins and another part was also distributed through professors' zoom lectures by providing the survey direct link to fill it out and submit. A total of 500 questionnaires were distributed among the AASTMT students in three branches (Miami, Al Alamain and Aboukeer),116 questionnaires were dropped out from the data collected due to uncheck and missing values. Accordingly, 385 students were included and used in the data analysis process. The data collected from the questionnaire have been well revised properly for any unengaged responses and data entry errors. After that, to properly analyze the UTAUT factors, the researcher applied the Confirmatory Factor Analysis (CFA) technique to develop latent factors in the

UTAUT model. These factors have been used for Path analysis via Structural Equation Modeling (SEM) stage.

Findings

According to data analysis and testing the research variables significant on behaviour intension and the moderating role of demographics variable on the research model, the researchers concluded the following

Descriptive Analysis of Respondents Profile

Table 4-1 represents the respondents' profiles that have participated in this study. The research has employed an online survey technique in collecting all the information in regards to this study. Therefore, in this section, the explanation about gender, age, and learning experience is introduced with specific statistics obtained from the data collection approaches. In total, it shows that the total sample that participated in this research is N=385. It is observed that males contribute the highest percentage with 66% (N=254), meanwhile, female respondents are about 34% (N=131). Additionally, most of the respondents who participated in this research are within the age range from 18 to 22 with 59.2% (N=228). Moreover, most of the respondents had a 0 to 3-year learning experience with 53% (N=204).

Table 4- 1: Descriptive Statistics of Respondents Profile

Item	Category	Frequency (N=385)	Percent %
Gender	Male	254	66.0
	Female	131	34.0
Age	18-22	228	59.2
	23-27	75	19.5
	Above 28	82	21.3
Learning Experience	0- 3 years	204	53.0
	More than 3 years	181	47.0

Table 4-2 shows the correlation matrix for the relationship between Performance Expectancy, Effort Expectancy, Social Influence, Technology Anxiety, and Behavior Intention. It was observed that:

There is a significant relationship between Performance Expectancy and Behavior Intention, as the corresponding P-value is less than 0.05 (P-value = 0.000). Also, there is a positive moderate relationship between Performance Expectancy and Behavior Intention, as the corresponding correlation coefficient lies between 0.3 and 0.5 (r = 0.535).

There is a significant relationship between Effort Expectancy and Behavior Intention, as the corresponding P-value is less than 0.05 (P-value = 0.000). Also, there is a positive moderate relationship between Effort Expectancy and Behavior Intention, as the corresponding correlation coefficient lies between 0.3 and 0.5 (r = 0.464).

There is a significant relationship between Social Influence and Behavior Intention, as the corresponding P-value is less than 0.05 (P-value = 0.000). Also, there is a positive moderate relationship between Social Influence and Behavior Intention, as the corresponding correlation coefficient lies between 0.6 and 0.8 (r = 0.610).

Table 4- 2: Correlation between Research Variables and Behavior Intention

		1.	2.	3.	4.
1. Performance Expectancy	Pearson Correlation	1			
	Sig. (2-tailed)				
	N	385			
2. Effort Expectancy	Pearson Correlation	.292**	1		
	Sig. (2-tailed)	.000			
	N	385	385		
3. Social Influence	Pearson Correlation	.546**	.416**	1	
	Sig. (2-tailed)	.000	.000		
	N	385	385	385	
	Sig. (2-tailed)	.000	.000	.000	
	N	385	385	385	
4. Behavior Intention	Pearson Correlation	.535**	.464**	.610**	1
	Sig. (2-tailed)	.000	.000	.000	
	N	385	385	385	385

Table 4-3 shows the SEM analysis for the impact of the Research Variables on Behavior Intention. It could be observed that:

There is a significant impact of Performance Expectancy on Behavior Intention, as the corresponding P-value is less than 0.05 (P-value = 0.000). Also, there is a positive impact of Performance Expectancy on Behavior Intention, as the corresponding estimate is greater than zero (Estimate = 0.211).

There is a significant impact of Effort Expectancy on Behavior Intention, as the corresponding P-value is less than 0.05 (P-value = 0.000). Also, there is a positive impact of Effort Expectancy on Behavior Intention, as the corresponding estimate is greater than zero (Estimate = 0.342).

There is a significant impact of Social Influence on Behavior Intention, as the corresponding P-value is less than 0.05 (P-value = 0.000). Also, there is a positive impact of Social Influence on Behavior Intention, as the corresponding estimate is greater than zero (Estimate = 0.420).

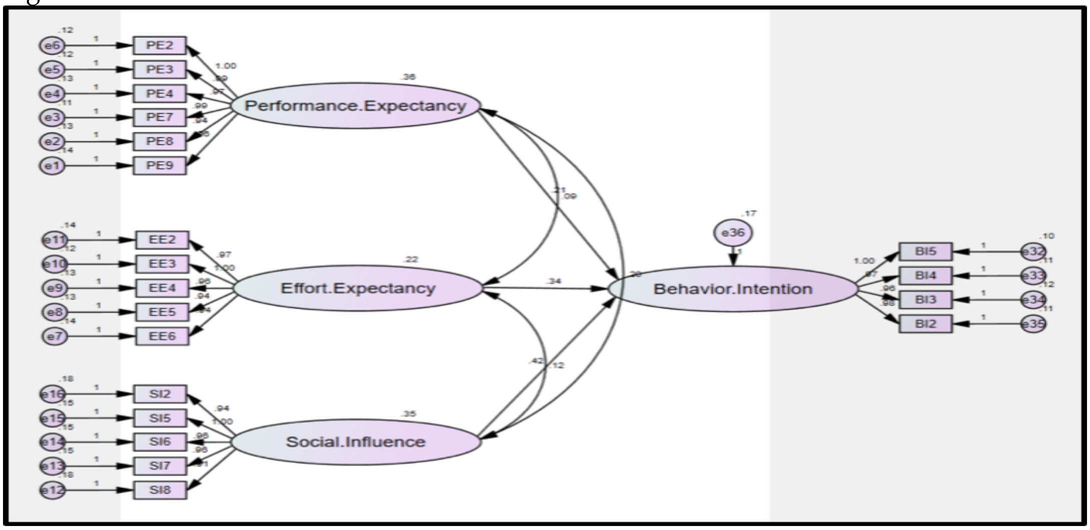
Furthermore, the R square is 0.519, which means 51.9% of the variation in the Behavior Intention can be explained by the model.

Table 4-3: SEM Analysis of Research Variables on Behavior Intention

			Estimate	P	R^2
Behavior Intention	<---	Performance Expectancy	.211	***	
Behavior Intention	<---	Effort Expectancy	.342	***	.519
Behavior Intention	<---	Social Influence	.420	***	

The model fit indices: CMIN/DF = 1.135, GFI = 0.954, CFI = 0.996, AGFI= 0.942, and RMSEA = 0.019 are all within their acceptable levels. The SEM model conducted for the effect of the Research Variables on Behavior Intention is illustrated in Figure 4-4.

Figure 4- 4: SEM for the effect of Research Variables on Behavior Intention



This section investigates the moderation role of Gender in the relationship between Research Variables and Behavior Intention. To test the moderation role, the interaction effect is computed by multiplying the centralized values of the independent variable with that of the moderator. The moderation role is then tested by investigating the significant effect of the computed interaction variable. Table 4-5 shows the SEM analysis of the moderation role of Gender between Research variables and Behavior Intention. It could be observed that:

There is an insignificant effect of the interaction variable between Performance Expectancy and Gender on Behavior Intention, as the corresponding P-value is more than 0.05 (P-value = 0.152). Therefore, there is an insignificant moderation role of Gender in the relationship between Performance Expectancy and Behavior Intention.

There is an insignificant effect of the interaction variable between Effort Expectancy and Gender on Behavior Intention, as the corresponding P-value is greater than 0.05 (P-value = 0.939). Therefore, there is an insignificant moderation role of Gender in the relationship between Effort Expectancy and Behavior Intention

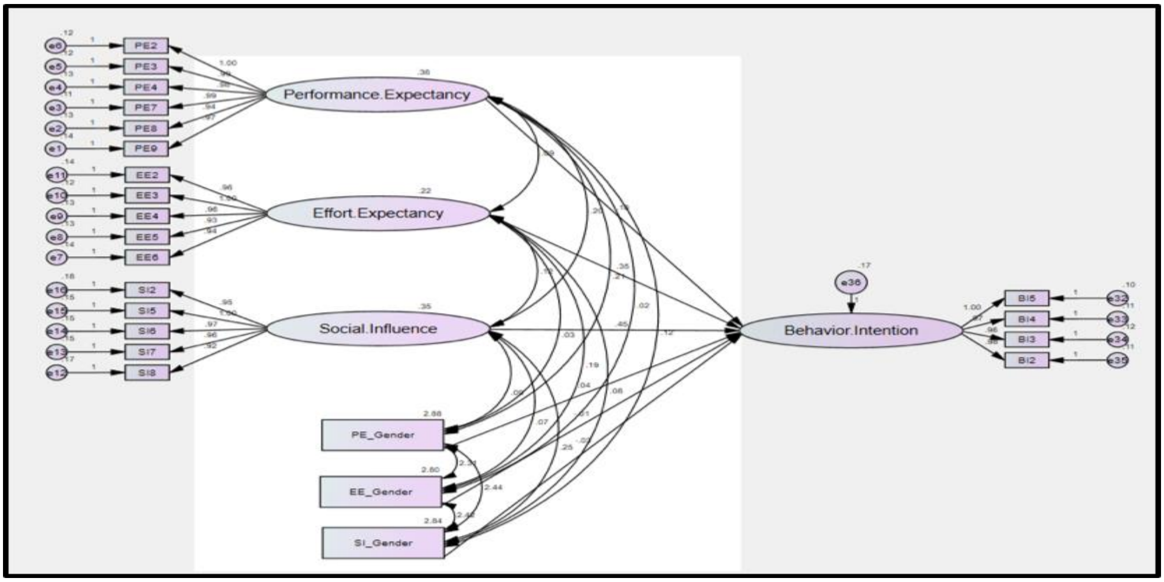
There is an insignificant effect of the interaction variable between Social Influence and Gender on Behavior Intention, as the corresponding P-value is greater than 0.05 (P-value = 0.524). Therefore, there is an insignificant moderation role of Gender in the relationship between Social Influence and Behavior Intention.

Table 4-5: SEM Analysis for the Moderation role of Gender between Research Variables and Behavior Intention

			Estimate	P	R^2
Behavior Intention	<---	Performance Expectancy	.182	.002	.521
Behavior Intention	<---	Effort Expectancy	.350	***	
Behavior Intention	<---	Social Influence	.447	***	
Behavior Intention	<---	PE*Gender	.040	.217	
Behavior Intention	<---	EE*Gender	-.007	.849	
Behavior Intention	<---	SI*Gender	-.031	.418	

The model fit indices: CMIN/DF = 1.079, GFI = 0.952, CFI = 0.998, AGFI= 0.937, and RMSEA = 0.014 are all within their acceptable levels. The SEM model conducted for the moderation role of Gender between Research Variables and Behavior Intention is illustrated in Figure 4-5.

Figure 4- 5: SEM for Moderation role of Gender between Research Variables and Behavior Intention



Concerning the moderation role of Age in the relationship between Research Variables and Behavior Intention. To test the moderation role, the interaction effect is computed by multiplying the centralized values of the independent variable with that of the moderator. The moderation role is then tested by investigating the significant effect of the computed interaction variable. Table 4-6 shows the SEM analysis of the moderation role of Age between Research variables and Behavior Intention. It could be observed that:

There is an insignificant effect of the interaction variable between Performance Expectancy and Age on Behavior Intention, as the corresponding P-value is more than 0.05 (P-value = 0.062). Therefore, there is an insignificant moderation role of Age in the relationship between Performance Expectancy and Behavior Intention.

There is an insignificant effect of the interaction variable between Effort Expectancy and Age on Behavior Intention, as the corresponding P-value is greater than 0.05 (P-value = 0.403). Therefore, there is an insignificant moderation role of Age in the relationship between Effort Expectancy and Behavior Intention

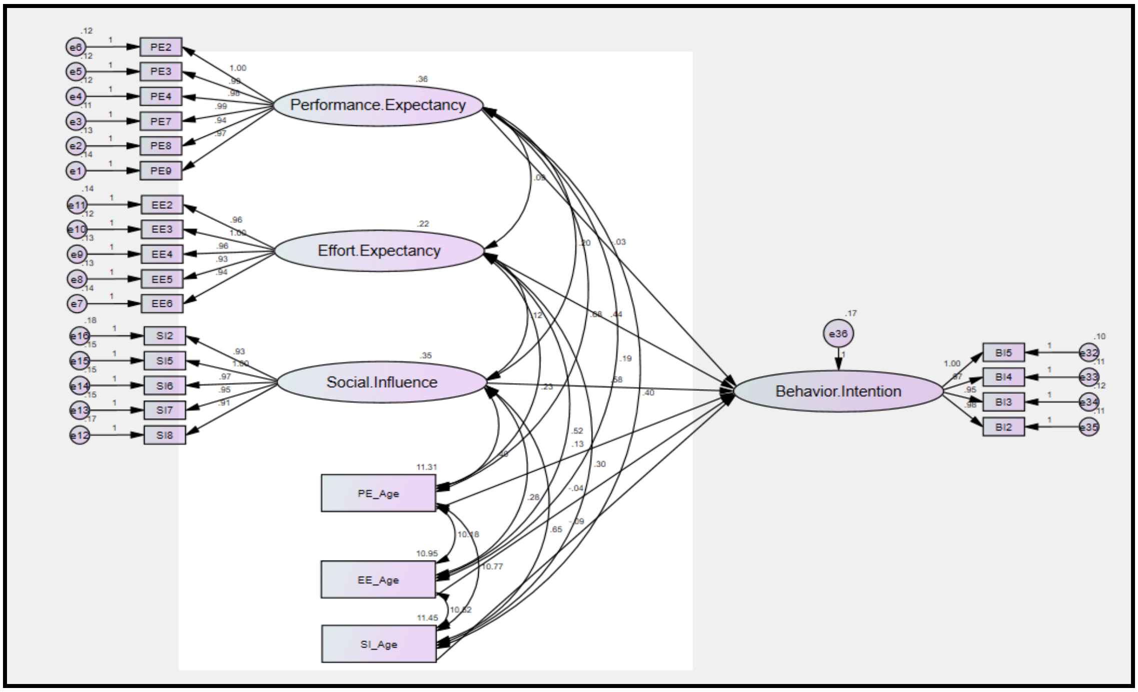
There is an insignificant effect of the interaction variable between Social Influence and Age on Behavior Intention, as the corresponding P-value is greater than 0.05 (P-value = 0.244). Therefore, there is an insignificant moderation role of Age in the relationship between Social Influence and Behavior Intention

Table 4- 6: SEM Analysis for the Moderation role of Age between Research Variables and Behavior Intention

			Estimate	P	R^2
Behavior Intention	<---	Performance Expectancy	-.028	.825	.532
Behavior Intention	<---	Effort Expectancy	.443	***	
Behavior Intention	<---	Social Influence	.579	***	
Behavior Intention	<---	PE*Age	.133	.024	
Behavior Intention	<---	EE*Age	-.044	.414	
Behavior Intention	<---	SI*Age	-.092	.171	

The model fit indices: CMIN/DF = 1.122, GFI = 0.950, CFI = 0.997, AGFI= 0.935, and RMSEA = 0.018 are all within their acceptable levels. The SEM model conducted for the moderation role of Age between Research Variables and Behavior Intention is illustrated in Figure 4-6.

Figure 4- 6: SEM for Moderation role of Age between Research Variables and Behavior Intention



Conclusion and Recommendations

The current research study aimed to investigate the acceptance of the AASTMT students' higher education for chat-bot technology Additionally, it aims to investigate the moderating role of age and gender between the independent and dependent model variables.

The Results of this research study indicated a significant impact of performance expectancy, effort expectancy, and social influence on students' behaviour intention. while there is no moderating role of demographic factors (age and gender) proved in the relation between performance expectancy, effort expectancy, social influence, and behaviour intention.

This research indicated some important recommendations that the researcher provides for each policy and decision-makers as well as for future research. The first recommendation of this study is suggested to decision-makers, which is providing suitable training and courses to students aiming to teach them how to use chat-bots technology in their educational process. The second recommendation provided to decision and policymakers is utilizing Chat-bots technology in higher education, which helps in encouraging students to use Artificial Intelligence technologies. The final recommendation suggested to decision-makers is to provide suitable training to lecturers to teach them how to use AI applications as a teaching method that satisfy the needs of each student.

Limitations and Direction for Future Research

Further research needs an investigate and add other new variables to the UTAUT model that may affect the adoption of chat-bot technology and its influence on behaviour intention. Additionally, the researcher suggests future recommendations to the future research, which are making studies that include the same variables but in a longer period and on a larger sample. Finally, the researcher recommends making comparative studies between Egypt and other developing countries to observe if the same results will be concluded or not.

References

Al-Mamary YH, Shamsuddin A, Hamid A, Aziati N. Investigating the key factors influencing management information systems adoption among telecommunication companies in Yemen: the conceptual framework development. International Journal of Energy, Information and Communications. 2015;6(1):59-68.

Alharbi, S. and Drew, S. (2014). Using the Technology Acceptance Model in Understanding Academics' Behavioural Intention to Use Learning Management Systems. International Journal of Advanced Computer Science and Applications, 5(1).

Alshboul, Khaled & Bardai, Barjoyai & Alzubi, Mohammad. (2018). the moderating effects of demographic factors in the usage of e-government services among jordanian citizens. International Journal of Humanities and Social Science. 6. 184-199.

Bentler, P. M., and Chou, C.-P. (1987). Practical issues in structural modelling. Social. Methods Res. 16, 78–117. DOI: 10.1177/0049124187016001004.

Boomsma, A. (1985). Nonconvergence, improper solutions, and starting values in LISREL maximum likelihood estimation. Psychometrika50, 229–242. DOI: 10.1007/BF02294248.

Brinton, C., Rill, R., Sangtae, H., Mung, C., Smith, R. & Ju, W. (2015). Individualization for Education at Scale: MIIC Design and Preliminary Evaluation. IEEE Transactions on Learning Technologies, 8(1), pp.136–148.

Burns, M.E., Houser, M.L. and Farris, K.L. (2017). Theory of planned behaviour in the classroom: An examination of the instructor confirmation-interaction model. Higher Education, 75(6), pp.1091–1108

Carter, L., and F. Belanger, "The utilization of e-government services: citizen trust, innovation and acceptance factors" Information Systems Journal, (15:1), 2005

Chatterjee, S. and Bhattacharjee, K.K. (2020). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. Education and Information Technologies, 25(5), pp.3443–3463.

Chrisinger, D. (2019). The solution lies in education: Artificial intelligence & the skills gap. On the Horizon, 27(1), 1–4. https://doi.org/10.1108/OTH-03-2019-096.

Cremer, D., & Bettignies, H. C. (2013). Pragmatic business ethics. The Leadership Maestro, 24(2), 64–67. https://doi.org/10.1111/j.1467-8616.2013.00938.x.

Creswell, J.W., 2009. Mapping the field of mixed methods research.

Cronan, T. P., Mullins, J. K., & Douglas, D. E. (2018). Further understanding factors that explain freshman business student's academic integrity intention and behaviour: Plagiarism and sharing homework. Journal of Business Ethics, 147(1), 197–220.

Dutta, D. 2017. Developing an Intelligent Chatbot Tool to assist high school students in learning general knowledge subjects. Georgia Institute of Technology. Atlanta

Foon, Y. S., & Fah, B. C. Y. (2011). Internet banking adoption in Kuala Lumpur: An application of UTAUT model. International Journal of Business and Management, 6(4), 161–167

Gerbing, D. W., and Anderson, J. C. (1985). The effects of sampling error and model characteristics on parameter estimation for maximum likelihood confirmatory factor analysis. Multivariate Behav. Res. 20, 255–271. DOI: 10.1207/s15327906mbr2003_2

Hair, Joseph & Black, William & Babin, Barry & Anderson, Rolph. (2010). Multivariate Data Analysis: A Global Perspective.

Holmes, Mary. (2008). Higher education reform in Egypt: Preparing graduates for Egypt's changing political economy. Education, Business and Society: Contemporary Middle Eastern Issues. 1. 175-185. 10.1108/17537980810909797.

Huang, J.-X., Lee, K.-S., Kwon, O.-W., & Kim, Y.-K. 2017. A chatbot for a dialogue-based second language learning system. CALL in a climate of change: adapting to turbulent global conditions: 151

Kerly, A., Hall, P., & Bull, S. 2007. Bringing chatbots into education: Towards natural language negotiation of open learner models. Knowledge-Based Systems, 20(2): 177–185.

Khasawneh, M., & Ibrahim, H. (2012). A model for Adoption of ICT in Jordanian Higher Education Institutions: An Empirical Study. Journal of e-Learning & Higher Education, 2012, c1-10.

Khechine, H., Pascot, D., Lakhal, S., & Bytha, A. (2014). UTAUT model for blended learning: The role of gender and age in the intention to use webinars. Interdisciplinary Journal of ELearning and Learning Objects, 10, 33-52. Retrieved from
http://www. ijello.org/Volume10/IJELLOv10p033-052Khechine0876.pd

Kozma, R. (2004). Technology, economic development, and educational reform: Global changes and an Egyptian response. Arlington, VA: Pal-Tech.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30, 607-610.

Lidén, A. and Nilros, K. (2020). Perceived benefits and limitations of chatbots in higher education. [online] Available at: http://www.divaportal.org/smash/get/diva2:1442044/FULLTEXT01.pdf.

Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., & Dowd, J. (2015). Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. Computers in Human Behavior, vol. 50, pp.186-196.

Maldonado, Ursula & Khan, Gohar & Moon, Junghoon & Rho, Jae. (2011). E-learning motivation and educational portal acceptance in developing countries. Online Information Review. 35. 66-85. 10.1108/14684521111113597.

Menon, R., Tiwari, A., Chhabra, A., & Singh, D. (2014). Study on the higher education in India and the need for a paradigm shift. Procedia Economics and Finance, II, 1, 886–871.
https://doi.org/10.1016/S22125671(14)00250-0.

Sana'a Y. A critical review of models and theories in field of individual acceptance of technology. International Journal of Hybrid Information Technology. 2016;9(6):143-58

Sekaran, U. and Bougie, R., 2016. Research methods for business: A skill-building approach. John Wiley & Sons.

Stefan, A. D. P., & Sharon, K. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. Research and Practice in Technology Enhanced Learning, 1, 313. https://doi. org/10.1186/s41039-017-0062-8.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D.: User acceptance of information technology: Toward a unified view. MIS Quarterly 27(3), 425–478 (2003).

Wang, Y., Forbes, R., Cavigioli, C., Wang, H., Gamelas, A., Wade, A., Strassner, J., Cai, S. and Liu, S., 2018. Network management and orchestration using artificial intelligence: Overview of ETSI ENI. IEEE Communications Standards Magazine, 2(4), pp.58-65.

Winkler, R. & Söllner, M. (2018). Unleashing the Potential of Chatbots in Education: A State-Of-The-Art Analysis. Academy of Management Annual Meeting (AOM). Chicago, USA.

Yasmeen, S., Alam, M.T., Mushtaq, M. and Alam Bukhari, M. (2015). Comparative Study of the Availability and Use of Information Technology in the Subject of Education in Public and Private Universities of Islamabad and Rawalpindi. SAGE Open, 5(4), p.215824401560822.