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USING A MODIFIED VERSION OF THE TECHNOLOGY ACCEPTANCE MODEL TO EXPLAIN WHY SOCIAL SCIENCE UNIVERSITY STUDENTS IN GREECE USE CHATGPT: AN APPROACH TO SERIAL MULTIPLE MEDIATION THAT MODIFIES KNOWLEDGE SHARING

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ABSTRACT

The emergence of productive artificial intelligence, exemplified by ChatGPT, has catalyzed a paradigm shift within the educational domain. Specifically, scholarly and practical discourse has been sparked regarding the potential ramifications of ChatGPT on student learning, particularly concerning its capacity to generate contextually relevant responses that closely mimic human language. Empirical studies on ChatGPT's adoption among college students have not focused substantially on its impact, despite the rising interest and concerns in the academic and professional areas. This research utilizes an adapted version of the Technology Acceptance Model (TAM) and involves a cohort of 129 higher education students selected from a Department of Social Policy in Greece, employing a convenience sampling methodology. The results of the analysis showed that for these students through performance expectancy, effort expectation not only influences their actual ChatGPT usage but also tangentially improves their behavioral intention to use ChatGPT. Moreover, the results showed that university students' progression from the point of intention to the actual use of ChatGPT was significantly influenced by knowledge exchange produced by the use of Chat GPT. As the consequences of this use are unprecedented this article will try to clarify the intentions of the users and detect their expectations.

INTRODUCTION

The modern world is changing rapidly and the relationship between education and new technology is becoming more and more clear, interrelated and supportive. Due to the technological advances that have intruded into school life either in the form of equipment, teaching programs or information, significant changes are occurring in the ways that education is provided, accessed, and experienced by the students or the teachers which constitute the living form of education. As Papaioannou et al. (2023) describe contemporary higher education utilizes diverse learning spaces such as traditional classrooms, online platforms, and virtual reality settings. These spaces enable various teaching and learning approaches, including collaboration, projects, and experiential learning. Physical spaces such as flexible classrooms, technology-rich environments, and outdoor areas, along with virtual spaces including online forums and video conferencing platforms, support different learning styles (Papaioannou, et al, 2023). The integration of cutting-edge technologies and platforms in smart education systems is revolutionizing the way students engage with and gain knowledge from course material (Almogren et al, 2024). Digital classrooms and learning management systems (LMS), augmented reality (AR) and virtual reality (VR), gamification, massive open online courses (MOOCs), virtual universities, mobile learning (m-Learning), ubiquitous learning as the concept of learning anytime, artificial intelligence (AI) and machine learning, Internet of Things (IoT) devices and sensor networks, wearable technology offer unprecedented opportunities for innovation, accessibility, and personalization in the area of education. On November 30, 2022 ChatGPT (Generative Pretrained Transformer), as it was called, an experimental artificial intelligence software developed by Open AI with interactive capabilities, a natural language processing (NLP) model, user-friendly chatbot, became globally available for free, and forever overturned the image we have of computers' abilities to manage human language. This conversational big language model became the fastest adopted digital platform and fastest growing application in the history of human technology (Gavriilidou, 2023). According to analysts per Forbes, ChatGPT, has become a very popular artificial intelligence chatbot as it reached 100 million users just two months after launching (Milmo, 2023). Sallam et al., (2023) pointed out that knowledge acquisition as it is conceived until now may be transformed by ChatGPT. The influence of ChatGPT on academic standards remains undetermined due to the inherent risks and uncertainties associated with its implementation. Evaluating the uptake and application of this promising tool is crucial (Sallam et al., 2023). Mohammed et al (2023) in their research among Arab postgraduate students in India indicate that ChatGPT enables real-time interaction between students and educational information by using machine learning and natural language comprehension, such as content production, cooperative problem solving, information search, and tutoring. Additionally to the above Mohammed (2023) found that lecturers viewed the efficacy of ChatGPT in teaching English to foreign language students. Farrokhnia et al. (2023) in their literature review recognize both strengths and weaknesses in the ChatGPT. The key strengths of ChatGPT mentioned in their article are: a)generating plausible responses, b)self-improving capability, c)providing personalized responses, d) providing real-time responses, e)opportunities for education, f)increasing accessibility of information, h)facilitating personalized learning, i)facilitating complex learning, j)decreasing teaching workload. On the other hand a list of weaknesses are recognized: a)lack of deep understanding, b)difficulty in evaluating the quality of responses, c)the risk of biases and discrimination, d)lack of higher-order thinking skills, e)threats to education, f)lack of understanding of the context, g)threatening academic integrity, h)perpetuating discrimination in education, i)democratization of plagiarism in education/research, j)declining in high-order cognitive skills. Adding to the weaknesses of ChatGPT is Strzelecki's (2024) mention in his article, about Altman's (2023) comment on Twitter, that ChatGPT has limitations such as difficulty answering questions which have a specific wording and a lack of quality control, which can lead to erroneous responses. As ChatGPT is a new technology, the Technology Acceptance Model (TAM) framework is used to examine the ChatGPT use for learning, as well as, the moderating influence of knowledge sharing on the behaviors and the users' willingness to utilize it. In order to gain a deeper understanding how effort and performance expectations impact higher education students' intentions and actions regarding our study will employ a modified version of the of the Technology Acceptance Model (TAM).

The following research questions (RQs) will be answered in this research:

RQ1.This study question looks into how much effort expectancy and performance expect-ancy, two key components of the modified TAM, predict higher education students' intentions and actual use of ChatGPT for learning.

RQ2. This study question aims to determine whether knowledge sharing can aid in closing the gap between intention and behavior when it comes to using ChatGPT for education.

RQ3. The purpose of this research question is to investigate how behavioral intentions and performance expectancy combine to serially mediate the relationship between effort expectancy and the actual behaviors associated with using ChatGPT for learning.

The research questions aim to shed light on the factors that influence higher education students' intentions and behaviors when using ChatGPT for learning. More specifically the practical application will be clarified and illuminated by creating efficient interventions and systems that motivate students to use ChatGPT for learning, educators and tech developers can benefit from the findings. Also the findings of the research may contribute to policy implications as the study's findings may influence laws pertaining to the use of AI-based tools in classrooms and provide guidance to organizations on how best to use cutting-edge technology to enhance students' education This paper is organized as follows: to enable a comprehensive analysis of the suggested model and to tackle the research inquiries the investigation is segmented into five principal segments. The impact on pedagogical strategies of ChatGPT in the first section is followed by the research questions. The second section introduces the theoretical background and modified TAM research framework and hypotheses. The procedure for gathering data, including the scales employed, analytical techniques, and pertinent data, is described in the third section. In the fourth section the findings are discussed and the validity and reliability of the scales and common method variance are evaluated. Finally, the fifth section extensively addresses the main findings and conclusions of the research

THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

a. Research Framework

TAM was developed by Davis (1989) to explain the user's acceptance of information systems and the computer-usage behavior. TAM (Davis, 1989) is based on the theory of reasoned action (TRA) (Ajzen and Fishbein, 1980) and has become an influential socio-technical model that seeks to identify and explain the end-users' acceptance of technology (Cheng, 2019). The goal of TAM is to provide an explanation of the determinants of computer acceptance that in general being capable of explaining user behavior across a broad range of end-user computing technologies and user populations while at the same time being both parsimonious and theoretically justified (Davis et al, 1989). The acceptance and usage are finally decided by the user's perception about technology and the knowledge and skills of computers (Al-Gahtani, 2014; Tarhini, Hone, & Liu, 2015; Wong, Teo, & Goh, 2015). Various studies have explained the TAM framework for general usage (Venkatesh & Bala, 2008). The model has been adopted and expanded in many studies in various types of technologies including e-mail, word processor, World Wide Web, enterprise resources planning (ERP) systems and proved high validity (Cakır and Solak, 2015). As per the theory of reasoned action, the behavioral intention to use technology depends upon the individual perceived usefulness and perceived ease of use (Venkatesh and Davies, 2000). TAM specifies causal linkages between two key sets of constructs: (1) perceived usefulness (PU) and perceived ease of use (PEOU), and (2) user's attitude (AT), behavioral intentions (BI), and actual computer usage behavior (ACU) (Malhotra and Galetta, 1999). In the Theory of Reasoned Action it was demonstrated that the Technology Acceptance Model postulates that the use of an information system is determined by the behavioral intention; but on the other hand, it asserts that the behavioral intention is determined by the person's attitude towards the use of the system and also by his perception of its utility. The perceived ease-of-use and perceived usefulness are core aspects of the relationship between humans- humanoids. Studies either showed perceived usefulness as a stronger determinant on behavioral intention than perceived ease of use or showed that perceived ease of use was not a significant determinant (Sharp, 2007). Accordingly, both social believes and the external environment, impact the perception of such technologies (Del Giudice et al., 2023). In Duong's et al. (2023) article we read that Sepasgozar (2022) further proposed that certain notions must be used in the educational setting. As such, in many contemporary studies conducted in the context of education, perceived ease of use and perceived usefulness have been replaced by the terms effort expectancy and performance expectancy. They are used to explain students' adoption of technology, such as the use of mobile devices for language learning (Hoi, 2020), the use of mobile learning (Al-Azawei & Alowayr, 2020), and the use of mobile internet (Nikolopoulou et al., 2021). Additionally in Foroughi's et al. (2023) we are informed that positive association between performance expectancy and students' intention of use of Chatbots for learning purposes has been validated (Almahri et al., 2022;Rahim et al., 2022).

b. Effort expectancy (Perceived ease of use)

Another important factor is effort expectancy (perceived ease of use), which is the degree to which a person believes that using a particular system would be free from effort (Davis, 1989; Umrani and Ghadially, 2003). Performance expectancy will be the measure of the tool's perceived value and results. As per Gong et al. (2004), effort expectancy (perceived ease of use) has a direct relation to students' attitudes and performance expectancy (perceived usefulness). In the same way, students are more likely to use ChatGPT as a useful tool to help them understand ways of studying, manage how to retrieve knowledge and learning, enrich their writing of assignments with ideas. Teachers could accept ChatGPT as a valuable tool for creating and designing their course presentations if the tool proves to be easy to use.

H1. Effort expectancy is positively correlated with performance expectancy.

H2. Effort expectancy is positively correlated with behavioral intention to use ChatGPT.

H3. Effort expectancy is positively correlated with the actual use of ChatGPT.

c. Performance expectancy (Perceived usefulness)

Performance expectancy-(Perceived usefulness) refers to a person's belief that the use of the computer will result in the achievement of personally relevant goals. It is defined as being the degree up to which a person believes that the use of a system will improve his performance (Davis, 1989). Performance expectancy, referring to the extent of the benefits perceived by users from the use of a particular technology (Al-Azawei & Alowayr, 2020), will be the measure of ChatGPT's usability.

H4. Performance expectancy is positively correlated with behavioral intention to use ChatGPT.

H5. Performance expectancy is positively correlated with actual use of ChatGPT.

d. Behavioral intention to use ChatGPT

Behavioral intention can be used as a direct predictor of actual behavior, according to the Theory of Planned Behavior (TPB). According to Ajzen and Fishbein (1980), an individual's intentions alone should be a reliable predictor of their behavior when they have complete control over the behavior and it is totally voluntary. In certain situations, the intention to act now can be a reliable predictor of behavior in the future. As a long-standing mediator between behavior and a number of variables, including attitude, satisfaction, subjective norms, and perceived behavioral control, it is the intention to use technology (Ajzen, 1991; Ajzen and Fishbein, 1980).

H6. Behavioral intention is positively correlated with the actual use of ChatGPT.

e. Knowledge sharing as a moderator

Knowledge sharing is an activity through which knowledge (namely, information, skills, or expertise) is exchanged among people, friends, peers, families, communities (for example, Wikipedia), or within or between organizations (Serban and Luan, 2002). Alavi & Leidner (2001) stated that knowledge sharing is a key process of knowledge management including knowledge generation, knowledge acquisition, knowledge storage, and knowledge application. Knowledge sharing can be defined not only as a process of knowledge transfer, but also an interaction and reconstruction of knowledge system between the knowledge senders and the knowledge receivers (Yao et al, 2021). Social media has become a useful tool for learning and teaching due to its functions for knowledge sharing, such as documents exchange, virtual communication, and knowledge formation. Higher education institution that recognise the value of social media and the importance of individual motivation have sought to encourage its use to bolster learning performance (Hosen et al., 2021). The perception of knowledge sharing and learning performance rely on a learning community, active participation, social interaction, understanding, negotiation, and observation (Eid & Al-Jabri, 2016). In Duong et al (2023) we are informed that the primary factors influencing students' knowledge-sharing behaviors are their collectivist motivations, which are driven by pro-social reasons such as a desire to see their peers succeed (Bouton et al., 2021). By offering a helpful environment for learning and exchanging experiences with ChatGPT, knowledge sharing may assist in transforming students' intentions into real behavior.

H7. Knowledge sharing positively moderates the intention-behavior link regarding the use of ChatGPT.

f. Performance expectancy and behavioral intention as serial mediators

Venkatesh and Davies (2000), raised the issue in the scientific debate, that the behavioral intention to use technology depends upon the individual performance expectancy (perceived usefulness) and effort expectancy (perceived ease of use). The TAM suggested that users' perceived ease of use (effort expectancy) and perceived usefulness (performance expectancy) are key determinants of their behavioral intentions and subsequent actual use of technology (Fishbein & Ajzen, 2011). Performance expectancy and effort expectancy were found to be positive and significant mediator variables among website design, customer service and customer's intention to adopt internet banking (Rahi & Ghani, 2019). Performance expectancy and effort expectancy were found to significantly influence the behavioral intentions to adopt mobile commerce with significant effect of mediator and the results for this study could be fruitful for telecommunication, mobile commerce companies and marketers in formulating strategies to attract potential consumers effectively and efficiently (Sair & Danish, 2018). Even for travelers it was found from Oh et. al, (2009) their intentions to use mobile devices primarily depended on performance expectancy rather than effort expectancy. Basically, if we reduce the issue to ChatGPT as a new AI technology tool, it can be said very simply according to previous researches, that if users think that ChatGPT is easy in its use then they will be more likely to use it and consequently consider it useful for their learning.

H8. Performance expectancy positively mediates the effect of effort expectancy on behavioral intention to use ChatGPT.

H9. Behavioral intention to use ChatGPT positively mediates the effect of performance expectancy on the actual use of ChatGPT.

H10. Performance expectancy and behavioral intention to use ChatGPT serially mediate the effect of effort expectancy on the actual use of ChatGPT.

Taken together, and in line with the existing literature on TAM, a conceptual model is formulated in the present study (see Figure 1).

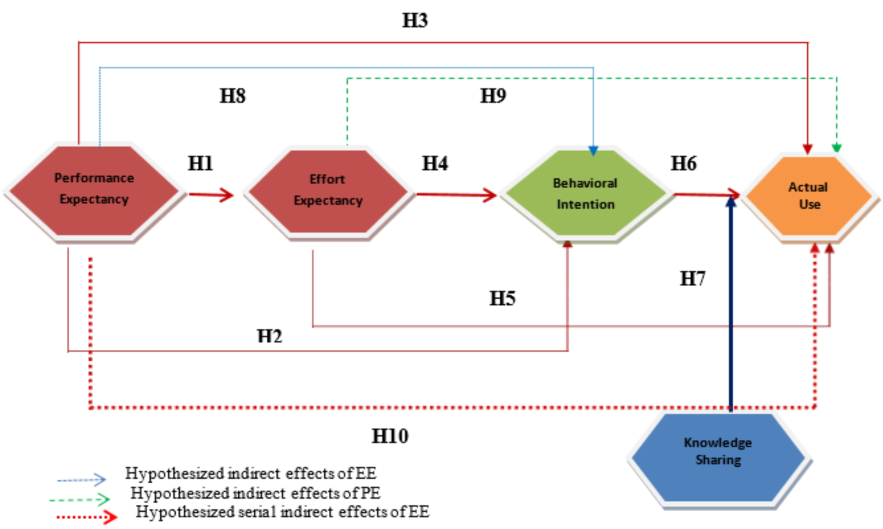

Fig. 1. Hypothesized Model

RESEARCH METHODOLOGY

a. Data collection

The present study employed a convenience sampling approach to collect the research data. Two assistants were asked if they would be willing to distribute the questionnaires and provide guidance to ensure that the students responded comprehensively to all the questions. When they agreed to distribute questionnaires for the research, printed questionnaires were delivered to them. A total number of 164 undergraduate students participated in the study through convenience sampling in the department of social policy sciences in a regional university in Greece. Students were approached out of the university's auditorium, at the end of their exams to fill the questionnaire. In accordance with the recommendations proposed by Podsakoff, et al. (2003), in order to mitigate the risk of common method bias, the study's participants were guaranteed complete anonymity, confidentiality and were made fully aware that their involvement was entirely voluntary without incentives for participation and they could withdraw the research at any time. It was also underlined that all information gathered would be kept private and utilized only for scholarly research. They were also informed that there was only evaluation of the questions on a 5-point Likert-scale and that they should reflect their true opinions as objectively as possible on each item. However, because 35 of the questionnaires filled had partial replies, they were not included in the additional analyses. Finally, a total of 129 questionnaires (101 questionnaires filled by females and 28 questionnaires filled by males) were found complete and valid for the purpose of further analysis, this yield a response rate of 78%. The students, ranged from 18 to 44 in age, were enrolled in the two compulsory elective courses entitled "Gender and ICTs" and "Teaching Social Science through ICTs" both taught by the author. The participants were from theoretical studies background, such as humanitarian and social science, socioeconomics and education. Most of them as they declared were computer users, a 30% of them more than 10 years computer users and 51% of them considering themselves from good to excellent computer users. The demographic profile of the participants can be viewed in Table 1.

b. Scales

This study employed an instrument adapted from previous research of Duong et al. (2023) and Al-Azawei & Alowayr (2020) that found the measures to be valid and reliable for the constructs they were measuring. Our research used latent variables, as illustrated in Fig. 1, which were gauged through reflective latent constructs adapted with minor adjustments from the previous researches. Specifically, two primary constructs within the Technology Acceptance Model (TAM), namely effort expectancy (consisting of 5 items) and performance expectancy (comprising 5 items), were sourced from Duong et al.'s (2023) study, which was built upon the work of Al-Azawei & Alowayr (2020). Additionally, the scales assessing behavioral intentions (with 3 items), actual usage of ChatGPT (consisting of 2 items), and knowledge sharing (comprising 6 items) were also drawn from Duong et al.'s (2023) investigation, with slight modifications to align with the objectives of this study. The research was divided into two sections and was administered in clear, easy to understand Greek, thus to eliminate any possibility of misinterpretation. The first section included demographics of the participants such as gender, age, academic level and year of their studies (Table 1) and the second section included a closed-ended section examining students about their intent to use ChatGPT for academic purposes. The complete phrasing of the included items is highlighted as follows in Table 2. Each item was evaluated on a 5-point Likert-scale with the following responses: strongly agree scored as 5, agree scored as 4, neutral/no opinion scored as 3, and disagree scored as 2, and strongly disagree scored as 1. Codes were assigned to each survey item, a unique number was assigned to each survey, and each survey was coded. SPSS was used to enter the data. Every variable's range and frequency were assessed. The first questionnaire was reviewed in order to rectify any outliers that emerged during data entry. There were no instances of missing values found.

c. Analytic approach-Data analysis

Confirmatory factor analysis (CFA) analysis was performed using Jamovi (v2.3.26) and the reliability and validity of the constructs used in the study were assessed using the Cronbach's alpha (α) index. Reliability is usually evaluated by "Cronbach's alpha" and "composite reliability (CR)" The values of Cronbach's alpha and composite reliability should be 0.70 and above in order to be accepted (Al-Emran, 2020). The model's fit was assessed by the estimation of the indices Comparative Fit Index (CFI) and Tucker Lewis Index (TLI), as well as the Root Mean Square Error of Approximation (RMSEA) and the Standardized Root Mean Square Residual (SRMR) index. The Confirmatory factor analysis CFA indicated high standardized loadings and in all cases statistically significant with p values<0.001 and the constructs' reliability and validity was also examined using the Average Variance Extracted (AVE) and Composite Reliability (CR) indices (reliability refers to the degree to which a scale yields consistent and stable measures over time). The Harman's single-factor method with an unrotated factor solution was adopted to test the Common Method Bias (CMB). After checking assumptions of multicollinearity and autocorrelation, hierarchical regression models were applied to determine independent prognostic factors and the R2 was used to compare the models examined. Mediation analysis was used to examine the indirect effects that emerged on a theoretical basis. Statistical significance was set at 0.05 in all cases. Furthermore, multiple linear regression analysis was conducted to investigate the predicted relationships in the research model, while also controlling demographic variables like gender, age, and fields of study.

Table 1: Demographics

Socio-demographic characteristics		**Frequency**	**Percentage**
Gender	Male	28	21,4
	Female	101	77,1
Age	<21	84	64,1
	From 21 to 34	29	22,1
	From 35 to 44	18	13,7
Year of study	First year	41	31,3
	Second year	38	29
	Third year	33	25,2
	Fourth year	13	9,9
	Fifth year+	6	4,6

Note N=130

RESULTS

a. Reliability, validity, and common method variance

We read in Hair et al. (2017) that the construct reliability method ("Cronbach's alpha (CA), and composite reliability (CR)") and validity ("discriminant and convergent validity") can be used to estimate the measurement model.

Accordinlgy, the reliability of the constructs employed in the study was evaluated through the application of Cronbach's alpha (α) and confirmatory factor analysis (CFA). In Table 2 it can be seen that Cronbach's alpha (α) for Effort expectancy is α = 0.906, for Performance expectancy is α = 0.846, for Behavioral intention to use ChatGPT is α = 0.856, for Actual use of ChatGPT is α = 0.862 and for Knowledge sharing is α = 0.931. The internal consistency of all the constructs was deemed to be acceptable when their α values were greater than the cut-off value of 0.63 (Fornell & Larcker, 1981 as in Duong et al , 2023). All constructs had composite reliability scores above 0.8 and had average variance extracted scores exceeding 0.5 and Cronbach's Alpha exceeding 0.6, this suggests that all constructs had adequate reliability. The reliability of items can be assessed by examining the standardised factor loadings. Table 2 presents the factor loadings for the scale items. The threshold for sufficient loadings depends on the sample size, with a value of 0.65 deemed sufficient for the population (N = 129) of this study. All items exhibited loadings above the threshold, ranging from 0.654 to 0.956. Consequently, the outcomes of the factor loadings demonstrate that each construct is distinct and that all items employed to assess a specific construct are highly correlated and load into a single construct. Three criteria of measures as Fornell & Larcker (1981) describe are used to assess the convergent validity of the model: Standardized factor loadings of the items, Composite Reliability (CR), and Average Variance Extracted (AVE) values of each construct.

Table 3 demonstrates that the composite reliability (CR) of the constructs exceeded the threshold values of 0.7 and the average variance extracted (AVE) exceeds the threshold value of 0.5 in most cases with slightly smaller values observed for BI and PE with scores equal to 0.478 and 0.466 respectively. Since these deviations are rather small while the composite reliability (CR) scores are significantly higher than 0.7, these results are considered to confirm the reliability and validity of the constructs in the hypothetical model (Idiana et al., 2022; Lam, L. W. et al (2012 as in Duong et al , 2023). The validity of the constructs employed in the study were evaluated through the application of confirmatory factor analysis (CFA). The result of Confirmatory Factor Analysis CFA reported great indices of fitness: x2 = 130, df = 124, x2/df = 1.05; p=0.344, Comparative Fit Index (CFI) = 0.997, Tucker Lewis Index (TLI) = 0.996, Root Mean Square Error of Approximation (RMSEA) = 0.0188 and Standardized Root Mean Square Residual (SRMR) = 0.0535 while Table 3 revealed that the Standardized Regression Weights of all the items were higher than the cut-off value of 0.5 (Hair et al., 2020 as in Duong et al , 2023).

Table 2: Measures of Reliability

Constructs	Indicators	Standardized loadings
EE	**Effort expectancy (α = 0.906)**	
EE1	Learning how to use ChatGPT is easy to me.	0.841
EE2	My interaction with ChatGPT is clear and easy to understand.	0.897
EE3	I find ChatGPT easy to use to manage knowledge.	0.750
EE4	ChatGPT is convenient and user-friendly.	0.889
EE6	ChatGPT is easy to access.	0.736
PE	**Performance expectancy (α = 0.846)**	
PE1	I find ChatGPT useful in my daily study.	0.738
PE2	ChatGPT increases my chances of achieving tasks that are important to me in my study.	0.736
PE3	Using ChatGPT helps me to accomplish tasks more quickly.	0.885
PE4	Using ChatGPT increases my productivity in my study.	0.856
PE5	Using ChatGPT can save my time.	0.654
BI	**Behavioral intention to use ChatGPT (α = 0.856)**	
BI1	I intend to use increase my use of ChatGPT.	0.807
BI2	It is worth recommending ChatGPT to other students.	0.809
BI3	I'm interested in using ChatGPT more frequently in the future.	0.786
AU	**Actual use of ChatGPT (α = 0.862)**	
AU1	I use ChatGPT on a daily basis.	0.798
AU2	I use ChatGPT frequently.	0.956
KS	**Knowledge sharing (α = 0.931)**	
KS1	ChatGPT allows me to share knowledge with my instructor and classmates.	
KS2	ChatGPT supports discussions with my instructor and classmates.	0.904
KS3	ChatGPT facilitates the process of knowledge sharing anytime anywhere.	0.937
KS4	ChatGPT enables me to share different types of resources with my class instructor and classmates.	0.788
KS5	ChatGPT through AI-learning application strengthens the relationships with my instructor and classmates.	0.778

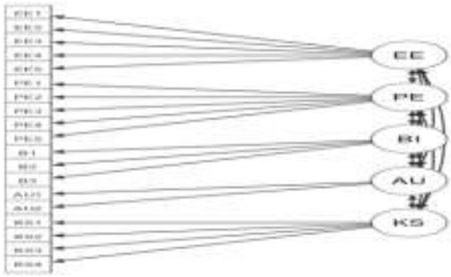

Figure 2: Measurement model

Table 3: Descriptive statistics and correlation matrix

	Mean	AVE	CR	Gender	Age	Computer Knowledge	EE	KS	BI	AU
Gender	1.80			-						
age	1.50			-0.075						
Computer Knowledge	2.65			-0.059	0.111					
EE	3.85	0.680	0.914	-0.041	-0.159	-0.001				
KS	3.28	0.723	0.912	-0.049	-0.029	0.041	0.511***			
BI	3.29	0.478	0.731	-0.013	-0.065	0.068	0.414***	0.580***		
AU	2.32	0.626	0.770	0.039	0.097	-0.078	0.327***	0.489***	0.559***	
PE	3.35	0.466	0.806	-0.016	0.023	-0.012	0.447***	0.540***	0.651***	0.525***

Note N=130 **: Significance at 0.01 level (two-tailed); ***: Significance at 0.001 level (two-tailed); α: Cronbach's' alpha; SD: Standard Deviation; AVE: Average Variance Extracted; CR: Composite Reliability; The square roots of the AVE of each construct are shown in parentheses.

In order to address a possible common method bias (CMB) as data came from students from one department of social policy of one university, both procedural and statistical methods were employed. Firstly, the questionnaire, used for this survey was the same used by Duong et al. (2023) and as the authors of the previous article said it underwent thorough testing and revision by experts. The common method bias (CMB) was tested using the Harman's single factor approach with an unrotated factor solution. When all the items of the scales were constrained to be loaded on one common factor, the explained variance was 39.640, far less than Harman's cut-off value of 50. A single-factor for Confirmatory Factor Analysis (CFA) was performed, in which all the items of the five constructs were constrained to a one-factor measurement model. The results revealed poor fit indices: $x2 = 1021$, $df = 152$, $x2/df = 6.72$; $p<0.001$, CFI=0.527, TLI=0.466, RMSEA=0.209 and SRMR=0.134 suggesting that Common method bias CMB was not a significant threat to this study.

b. Hypothesis Testing

Hierarchical regression models are presented in Table 4. It is possible that the results of the study were influenced by multicollinearity, as indicated by the high correlation coefficients observed among several variables in Table 4. To assess the extent of multicollinearity, the variance inflation factor (VIF) was computed for all the independent variables. The results showed that all VIF values were lower than 2.1, which is below the threshold indicating multicollinearity (Usefi, 2022). Therefore, it can be concluded that the model estimations were not biased by multicollinearity.

In terms of the direct effects of effort expectancy, our study reported that effort expectancy was positively and significantly correlated with performance expectancy ($\beta=0.494$; p-value<0.001), supporting H1 but not H2 and not H3. Our study also revealed that performance expectancy was strongly related to behavioral intentions to use ChatGPT ($\beta = 0.631$; p-value<0.001), supporting H4 but not H5. Moreover, behavioral intentions to use ChatGPT were found to be positively and significantly correlated with actual use of ChatGPT ($\beta=0.407$; p-value<0.001) supporting H6 while knowledge sharing was also found to correlate and significantly and positive with actual use of ChatGPT ($\beta=0.242$; p-value<0.01), thus supporting H7.

Table 4: Regression models

Variables	PE		BI		AU		VIF
	Model 1 β	Model 2 β	Model 1 β	Model 2 β	Model 1 β	Model 2 β	
Constant	3.388*** (0.460)	1.277* (0.552)	3.290*** (0.488)	0.463 (0.502)	2.120** (0.627)	-1.187 (0.683)	
Gender	-0.032 (0.188)	0.020 (0.168)	-0.032 (0.199)	0.005 (0.150)	0.123 (0.256)	0.183 (0.201)	1.008
Age	0.029 (0.113)	0.126 (0.103)	-0.100 (0.120)	-0.088 (0.092)	0.192 (0.153)	0.263* (0.124)	1.017
Computer knowledge	0.015 (0.088)	-0.022 (0.079)	0.079 (0.093)	0.087 (0.070)	-0.116 (0.130)	-0.158 (0.093)	1.018
EE		0.494 *** (0.088)		0.159 (0.096)		0.125 (0.117)	1.336
PE				0.631*** (0.079)		0.254 (0.137)	2.029
BI						0.407** (0.128)	2.072
KS						0.242* (0.108)	1.624
R^2	0.001	0.209	0.004	0.455	0.019	0.417	
R^2 Adjusted	0.0001	0.184	0.0001	0.431	0.0001	0.384	

Notes: N = 129, results are based on trimmed scales. The figures in parentheses are standard errors. *p < 0.05. **p < 0.01. ***p < 0.001.

The results from the mediation analysis appear in Table 5. Mediation effects showed that effort expectancy was significantly correlated with behavioral intentions to use ChatGPT through performance expectancy (βEE-PE-BI = 0.297; 95% CI [0.168, 0.464]). Performance expectancy was also found to be indirectly associated with the actual use of ChatGPT via behavioral intentions to use ChatGPT (βPE-BI-AU = 0.292; 95% CI [0.173, 0.446]). Effort expectancy therefore serially and indirectly affected the actual use of ChatGPT through performance expectancy and behavioral intentions to use ChatGPT (βEE-PE-BI-AU = 0.139; 95% CI [0.074, 0.251]). Consequently, H8, H9, and H10 were supported.

DISCUSSIONS, IMPLICATIONS, AND CONCLUSIONS

By using the modified TAM to evaluate the direct and indirect impacts of effort expectation and performance expectancy on the behavioral intentions of higher education students, this study adds information on the use of ChatGPT by university students in particular and the AI use in education in general. The findings of the study may leverage the advantages and reduce any problems that may arise from the use of ChatGPT by seeking solutions from the outset.

Table 5: Mediation analyses

Description	Estimate	SE	95% Confidence Intervals Lower	Upper	p
EE ⇒ BI ⇒ AU	0.082	0.055	0.012	0.210	0.136
PE ⇒ BI ⇒ AU	0.292	0.067	0.173	0.446	< .001
EE ⇒ PE ⇒ BI	0.297	0.077	0.168	0.464	< .001
EE ⇒ PE ⇒ AU	0.172	0.074	0.052	0.343	0.021
EE ⇒ PE ⇒ BI ⇒ AU	0.139	0.043	0.074	0.251	0.001

A synopsis of the principal findings of this study is presented in Fig. 3.

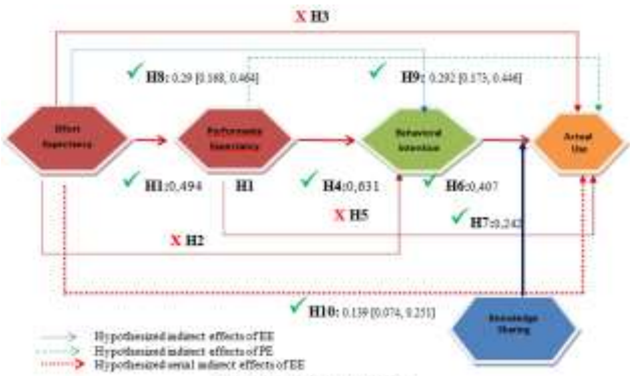

Fig. 3. *Results of hypothesized model*

a. Summary of key findings

The results of this study provide both theoretical and practical perspectives on the factors influencing the adoption and usage of ChatGPT in tertiary education environments, which are significant insights for academics and educators alike.

The results showed that effort expectancy (perceived ease of use) was positively correlated with performance expectancy (perceived usefulness) but did not directly increase higher education students' behavioral intentions and actual use of ChatGPT for learning. On the other hand performance expectancy (perceived usefulness) directly increased behavioral intentions but did not directly increase higher education students' actual use of ChatGPT for learning. The above findings mean that students in higher education are more likely to perceive ChatGPT as a beneficial tool for their learning if they find it straightforward to use for their studies and their educational needs. This, in turn, leads to an increased intention to use ChatGPT, which subsequently results in a greater number of individuals utilizing it for educational purposes. On the other hand the students of the research did not take in consideration the effort needed for the use of ChatGPT. That means if something is useful for their studies they do not consider their endeavors to be in vain.

These findings show a relative consistency with the findings of previous researches such as Duong's et al. (2023), in which both key constructs in the modified TAM, effort expectancy and performance expectancy, directly increased higher education students' behavioral intentions and actual use of ChatGPT for learning. In previous researches, which similarly utilized the Technology Acceptance Model (TAM), it was observed that a positive correlation exists among effort expectancy (perceived ease of use) and performance expectancy (perceived usefulness) with individuals' behavioral intentions towards adopting technology (Sair & Danish, 2018; Cheng, 2019; Ianole-Calin & Druica, 2022; Kao & Huang, 2023; Strzelecki, 2024; Abdaljaleel et al., 2024). Sair and Danish's (2018) results show that the performance expectancy and effort expectancy significantly influence the behavioral intentions to adopt mobile commerce with significant effect of mediator and the results for this study could be fruitful for telecommunication, mobile commerce companies and marketers in formulating strategies to attract potential consumers effectively and efficiently As Cheng (2019) explains, with regard to the relationships between learners' beliefs and their usage intention of m-learning, learners intend to use m-learning mainly because they perceive it to be easier to use to their learning and secondarily because it is useful and enjoyable. More additionally Ianole-Calin & Druica's (2022) findings are consistent with the literature in emphasizing perceived usefulness and perceived ease of use as key determinants for the use of a novel technology. The results in Kao and Huang's (2023) research reveal that as customers perceive a higher level of interaction quality with a service robot, they perceive the robotic to be easy to use and useful, resulting in an increase in their attitudes toward the robot. In turn, customers perceive a stronger rapport between the customers and the robot and have a greater intention to adopt robotic services. Strzelecki's (2024) study revealed that habit had the greatest impact on behavioral intention to adopt ChatGPT, followed by performance expectancy and hedonic motivation. For the behavior of use, the most significant factors were the behavioral intention, habit, and facilitating conditions. The results in Abdaljalee's et al. (2024) survey indicated that a positive attitude and usage of ChatGPT were determined by factors like ease of use, positive attitude towards technology, social influence, perceived usefulness, behavioral/cognitive influences, low perceived risks, and low anxiety.

The findings of the research, presented in this study, define a significant correlation between the behavioral intentions of higher education students to utilize ChatGPT with their subsequent use of the platform for educational purposes. The significant relationship between behavioral intentions and use behaviors has been affirmed in numerous previous research studies (Nikou & Economides, 2014; Cheng, 2019; Hooda et al., 2022). Nikou & Economides (2014) in their findings suggest that behavioral intention to use is attributed to attitudes towards use and perceived ease of use. Cheng (2019) has found in his research that learners' PEOU (perceived ease of use) has positive and strong effects on their intention to use m-learning, and their PU (perceived usefulness) has a more powerful effect on their intention to use m-learning than their PE (perceived enjoyment). Hooda et al., 2022) in their study integrated e-government trust into the UTAUT model to uncover its impact on intention to use and e-government use behaviors of users. This study found that trust plays a central role through direct and several mediating effects on users' intention to use e-government and e-government system use behavior.

Additionally to the above, there is an importance, in the findings of the research, that knowledge sharing was correlated significantly and positively with the actual use of ChatGPT. Knowledge sharing refers to students exchanging experiences and skills when interacting with each other at the university, during a project or writing an essay. ChatGPT as an AI- tool has all the characteristics to improve collaboration in knowledge-sharing of the students in order to facilitate the expansion of their collective knowledge, enhance their capacity for collaboration and facilitate constructive discourse between them. As a result the combination of knowledge sharing and ChatGPT is ideal for improving collaboration and creating environments friendly to supporting creativity for the students in the university. The utilization of ChatGPT may facilitate collaborative endeavors, whereby students may engage in the creation of shared papers or projects, while simultaneously receiving real-time recommendations, content expansions, and corrections. This may prove conducive to the development of effective teamwork, with each member of the group being able to make a meaningful contribution, thereby enhancing the sense of shared ownership. ChatGPT has the potential to facilitate connections between students with shared interests or complementary talents, thereby enhancing the sharing of information and teamwork. This has the potential to expand the collaborative learning environment beyond the conventional classroom. It also may bring a change in the way students in the university react to learning. At this juncture, the AI tool ChatGPT can facilitate the perception that the students are part of a community of knowledge, of ideas, of dialogue with which they can engage in communication and mutual support. Thus dialogue among students can be expanded, exchanging ideas can become easier and simultaneously it is possible for student performance to improve. ChatGPT is capable of analyzing each student's interactions and adapting the manner in which information is presented, thereby fostering a more personalized learning experience even in group activities. This can encourage students who might otherwise feel overshadowed in group settings to engage more actively, thereby enhancing their collaborative learning experience. The integration of multimodal resources (text, images, audio, and video) may enable ChatGPT to assist in the presentation of material in various forms that accommodate varying learning preferences, thus promoting a more thorough and captivating exchange of knowledge among students. Students are more inclined to adopt technology, like ChatGPT, to succeed academically as a group when they believe it may improve knowledge exchange. This sense of shared accomplishment may be a strong motivation as it appeals to their shared goals of academic success and support from one another. According to Al-Emran (2018) the remarkable difference in the results obtained in his research is the role of knowledge sharing as it has a positive influence on perceived ease of use, while it does not affect the perceived usefulness. Lee's (2001) study confirms the widely held belief that knowledge sharing is one of the major predictors for outsourcing success, organizational capability to learn or acquire the needed knowledge from other organizations is a key source of successful knowledge sharing, and partnership quality is a significant intervening factor between knowledge sharing and outsourcing success. El Said (2015), in his research, suggests that knowledge sharing intention was found to be positively and significantly affecting the Knowledge Management Systems' (KMS) usage and positively and significantly affecting impact on employees' performance in work place.

Mediation effects showed that effort expectancy was significantly correlated with behavioral intentions to use ChatGPT through performance expectancy which was indirectly associated with the actual use of ChatGPT via behavioral intentions to use ChatGPT. Effort expectancy (perceived ease of use) therefore serially and indirectly affected the actual use of ChatGPT through performance expectancy (perceived usefulness) and behavioral intentions to use ChatGPT. This sequential mediation process provides a robust framework for predicting and understanding technology adoption behavior in educational contexts. The above findings are in agreement with the findings of Duong et al (2023). The proposed mediation effect posits that performance expectation and behavioral intents play a secondary role in influencing actual usage, via the impact of effort expectancy on actual usage. This suggests a connection between simplicity of use and conviction in the tool's use, which in turn raises intention to use and, eventually, actual utilization. The intricate relationship between perceived utility, perceived ease of use, and real technology adoption behaviors is demonstrated by this serial mediation.

CONCLUSIONS

Finally, all the above findings indicate that enhancing both the perceived ease of use and the perceived usefulness can significantly enhance the adoption rates of such technologies among students. It is of paramount importance to comprehend the mediation effects if one is to successfully design and implement educational technologies such as ChatGPT. Consequently, developers and educators should prioritize the improvement of these aspects in order to facilitate a more seamless integration of AI tools in educational settings. In practical as well as clearly communicate the potential benefits and improvements in academic performance that these tools can bring. Training sessions, demonstrations, and user support terms, educational institutions should provide intuitive and user-friendly platforms, can be pivotal in shaping positive user perceptions and encouraging actual use. (Limna et al., 2023)

The value of this research lies in its attempt to understand how students in a particular area of higher education use technology in the classroom. Such knowledge may help to advance the field and ensure that technology is seamlessly incorporated into teaching methods. The most important of all is that students should be encouraged to utilize ChatGPT for preliminary research and to critically assess the data they have obtained for relevance and accuracy, should critically evaluate the replies from ChatGPT, separating important information from less pertinent material (Shaengchart et al., 2023). In addition to the above it is important to mention that when utilizing AI tools, the education on the ethical implications and responsible use of AI should be integrated into the curriculum.

Students should be taught about the ethical considerations, potential biases, and limitations of AI technologies through courses or modules that explore AI ethics, data privacy, and the socio-economic impacts of AI. This helps in cultivating a responsible approach to AI use and understanding its broader societal impacts.

REFERENCES

Abdaljaleel, M., Barakat, M., Alsanafi, M. et al. (2024). A multinational study on the factors influencing university students' attitudes and usage of ChatGPT. Sci Rep 14, 1983 . https://doi.org/10.1038/s41598-024-52549-8

Al-Azawei, A., & Alowayr, A. (2020). Predicting the intention to use and hedonic motivation for mobile learning: A comparative study in two middle eastern countries. Technology in Society, 62. https://doi.org/10.1016/j.techsoc.2020.101325

Alavi, M. and Leidner, D.E. (2001) Knowledge Management and Knowledge Management Systems: Conceptual Foundations and Research Issues. MIS Quarterly, 25, 107-136. http://dx.doi.org/10.2307/3250961

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology acceptance model in M-learning context: A systematic review. Computers & Education, 125, 389–412. https://doi.org/10.1016/j.compedu.2018.06.008

Al-Gahtani, S. S. (2014), "Empirical investigation of e-learning acceptance and assimilation: A structural equation model", Applied Computing and Informatics, 11(3), pp.158–169. https://www.researchgate.net/publication/265687777_Empirical_Investigation_of_E-Learning_Acceptance_and_Assimilation_A_Structural_Equation_Model

Almahri, F. A. J., Bell, D., & Merhi, M. (2020). Understanding student acceptance and use of chatbots in the United Kingdom universities: A structural equation modelling approach. In 2020 6th International Conference on Information Management (ICIM), 284–288. https://doi.org/10.1109/ICIM49319.2020.244712

Almogren, A., Al-Rahmi, W. M., Dahri, N. a. (2024). Exploring factors influencing the acceptance of ChatGPT in higher education: A smart education perspective, Heliyon,10(11), ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2024.e31887

Ajzen, I. (1991), "The theory of Planned Behaviour", Organizational Behavior and Human Decision Process, 50(2), pp. 179-211.

Ajzen, I. and Fishbein, M. (1980), "Understanding Attitudes and Predicting Social Behavior", Prentice-Hall, Englewood Cliffs, NJ.

Bouton, E., Tal, S. B., & Asterhan, C. S. C. (2021). Students, social network technology and learning in higher education: Visions of collaborative knowledge construction vs. the reality of knowledge sharing. The Internet and Higher Education, 49. https://doi.org/10.1016/j.iheduc.2020.100787

Cakır R. and Solak E. (2015). Attitude of Turkish EFL Learners towards e-Learning through Tam Model, Procedia - Social and Behavioral Sciences, 176, 596–601 https://www.sciencedirect.com/science/article/pii/S1877042815005522

Cheng, E. W. (2019). Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). Educ. Technol. Res. Dev. 67, pp.21–37. doi: 10.1007/s11423-018-9598-6

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340..

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social

Psychology, 22(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Del Giudice, M., Scuotto, V., Orlando, B., & Mustilli, M. (2023). Toward the human – centered approach. A revised model of individual acceptance of AI. Human Resource Management Review, 33(1). https://doi.org/10.1016/j.hrmr.2021.100856

Duong, C. D., Vu, T.N. & Ngo, T. V. N. (2023). Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator, The International Journal of Management Education, 21(3), https://www.sciencedirect.com/science/article/pii/S1472811723001210?via%3Dihub

Eid, M. & Al-Jabri, I. (2016). Social networking, knowledge sharing, and student learning: The case of university students. Computers & Education. 99. 14-27. 10.1016/j.compedu.2016.04.007.

El Said, G.R. (2015). Understanding knowledge management system antecedents of performance impact: extending the task-technology fit model with intention to share knowledge construct, Future Business Journal. 1(1).75–87 https://doi.org/ 10.1016/j.fbj.2015.11.003.

Farrokhnia, M., Banihashem, S.K., Noroozi, O., & Wals, A. (2024) A SWOT analysis of ChatGPT: Implications for educational practice and research, Innovations in Education and Teaching International, 61(3), 460-474 https://doi.org/10.1080/14703297.2023.2195846

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Reading, MA: Addison-Wesley

Fishbein, M., & Ajzen, I. (2011). Predicting and changing behavior: The reasoned action approach. Psychology press.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Foroughi, B. Senali, M.G., Iranmanesh, M. Khanfar, A., Ghobakhloo, M., Annamala, N. & Naghmeh-Abbaspour, B. (2023). Determinants of Intention to Use ChatGPT for Educational Purposes: Findings from PLS-SEM and fsQCA, International Journal of Human–Computer Interaction, https://doi.org/10.1080/10447318.2023.2226495

Gavriilidou, Z. (2024). Teaching and learning a language byusing the ChatGPT. Kritiki Editions, Athens

Gong, M., Yan, X. and Yuecheng. Y. (2004). An enhanced technology acceptancemodel for web-based Learning. Journal of Information Systems Education 15(4), 365-374.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). Handbook of Market Research (2nd ed.). Sage. doi:10.1007/978-3-319-05542-8_15-1.

Hoi, V. N. (2020). Understanding higher education learners' acceptance and use of mobile devices for language learning: A rash-based path modeling approach. Computers & Education, 146. https://doi.org/10.1016/j.compedu.2019.103761

Hosen, M., Ogbeibu, S., Giridharan, B., Cham, T.-H., Lim, W. M., & Paul, J. (2021). Individual motivation and social media influence on student knowledge sharing and learning performance: Evidence from an emerging economy. Computers & Education, 172. https://doi.org/10.1016/j.compedu.2021.104262

Hooda, A., Gupta, P., Jeyaraj, A., Giannakis, M., & Dwivedi, Y. K. (2022). The effects of trust on behavioral intention and use behavior within e-government contexts. International Journal of Information Management, 67. https://doi.org/10.1016/j.ijinfomgt.2022.102553

Ianole-Călin,R.&Druica,E. (2022). A risk integrated technology acceptance perspective on the intention to use smart grid technologies in residential electricity consumption. Journal of Cleaner Production. 370.133436.10.1016/j.jclepro.20222.133436.

Kao, W.-K., & Huang, Y.-S. (2023). Service robots in full- and limited-service restaurants: Extending technology acceptance model. Journal of Hospitality and Tourism Management, 54, 10–21. https://doi.org/10.1016/j.jhtm.2022.11.006

Lee, J.N. (2001). The impact of knowledge sharing, organizational capability and partnership quality on IS outsourcing success, Information & Management, 38(5), 323-335, ISSN 0378-7206, https://doi.org/10.1016/S0378-7206(00)00074-4.

Limna, P., Kraiwanit, T., Jangjarat, K., Klayklung, P., & Chocksathaporn, P. (2023). The Use of ChatGPT in the Digital Era: Perspectives on Chatbot Implementation. Journal of Applied Learning and Teaching, 6(1), 64-74. https://doi.org/10.37074/jalt.2023.6.1.32.

Malhotra , Y. and Galletta, D. F. (1999). "Extending the technology acceptance model to account for social influence: theoretical bases and empirical alidation," Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. HICSS-32. Abstracts and CD-ROM of Full Papers, Maui, HI, USA, pp. 14, doi: 10.1109/HICSS.1999.772658

Milmo, D. (2023). ChatGPT reaches 100 million users two months after launch. The Guardian. https://www.theguardian.com/technology/2023/feb/ 02/ chatgpt-100-million- users-open-ai- fastest-growing-app. Accessed 15 May 2024

Mohammed, A.; Al-ghazali, A. & Alqohfa, K. (2023). Exploring ChatGPT uses in higher studies: A case study of Arab postgraduates in India. Journal of English Studies in Arabia Felix, 2(2), 8–15. DOI: 10.56540/jesaf.v2i2.55

Mohamed, A. M. (2023). Exploring the potential of an AI-based Chatbot (ChatGPT) in enhancing English as a Foreign Language (EFL) teaching: Perceptions of EFL faculty members. Education and Information Technologies, 1-23. https://doi.org/10.1007/s10639-023-11917-z

Nikou, S. & Economides, A.(2015). The effects of Perceived Mobility and Satisfaction on the adoption of Mobile-based Assessment, 2015 International Conference on Interactive Mobile Communication Technologies and Learning (IMCL),167-171. https://doi.org/10.1109/ICALT.2014.136

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. Computers and Education Open, 2. https://doi.org/10.1016/j.caeo.2021.100041

Oh, S., Lehto, X. Y., & Park, J. (2009). Travelers' Intent to Use Mobile Technologies as a Function of Effort and Performance Expectancy. Journal of Hospitality Marketing & Management, 18(8), 765–781. https://doi.org/10.1080/19368620903235795

Papaioannou, G., Volakaki, M.-G., Kokolakis, S., Vouyioukas, D. (2023). Learning spaces in higher education: a state-of-the-art review, Trends High. Educ. 2(3), 526–545 https://doi.org/10.3390/higheredu2030032

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: a critical review of the *literature and recommended remedies. Journal of applied psychology, 88(5), 879.*

Rahim, N. I., A. Iahad, N., Yusof, A. F., & A. Al-Sharafi, M. (2022). AI-Based Chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach. Sustainability, 14(19), 12726. https://doi.org/10.3390/su141912726

Rahi, S. and Abd.Ghani, M. (2019). "Investigating the role of UTAUT and e-service quality in internet banking adoption setting", The TQM Journal, 31(3), 491-506. https://doi.org/10.1108/TQM-02-2018-0018

Sair, S. A., Danish, R. Q. (2018). Effect of performance expectancy and effort expectancy on the mobile commerce adoption intention through personal innovativeness among Pakistani consumers, Pakistan Journal of Commerce and Social Sciences (PJCSS), 12(2), 501-520. https://www.econstor.eu/bitstream/10419/188355/1/pjcss435.pdf

Sallam, M., Salim, N.,Barakat, M, Al Mahzum, K. Al-Tammemi, Al., Malaeb, D., Hallit,S. Hallit, R. (2023). Validation of a Technology Acceptance Model-Based Scale TAME-ChatGPT on Health Students Attitudes and Usage of ChatGPT in Jordan, JMIR Medical Education, DOI: 10.2196/preprints.48254

Sepasgozar, S. M. E. (2022). Immersive on-the-job training module development and modeling users' behavior using parametric multi-group analysis: A modified educational technology acceptance model. Technology in Society, 68. https://doi.org/10.1016/j.techsoc.2022.101921

Serban, A. M., Luan, J. (2002). "An Overview of Knowledge Management", University of Kentucky

Shaengchart, Y. & Bhumpenpein, N. & Kongnakorn, K. & Khwannu, P. & Tiwtakul, A. & Detmee, S. (2023). Factors Influencing the Acceptance of ChatGPT Usage Among Higher Education Students in Bangkok, Thailand. 2. 1-14.

Sharp (2007). Development, Extension, and Application: A Review of the Technology Acceptance Model. Information Systems Education Journal, 5 (9). http://isedj.org/5/9/. ISSN: 1545-679X. (Also appears in The Proceedings of ISECON 2006:§2522. ISSN: 1542-7382.)

Strzelecki, A. (2024). Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology, Innovative Higher Education 49:223–245 https://doi.org/10.1007/s10755-023-09686-1

Tarhini, A., Hone, K. and Liu, X.(2015), "A cross-cultural examination of the impact of social, organisational and individual factors on educational technology acceptance between British and Lebanese university students", British Journal of Educational Technology, 46(4), pp.739-755. https://doi.org/10.1111/bjet.12169

Usefi, H. (2022). Clustering, multicollinearity, and singular vectors. Computational Statistics & Data Analysis, 173. https://doi.org/10.1016/j.csda.2022.107523

Umrani, F. and Ghadially, R. (2003), " Empowering women through ICT education:Facilitating computer adoption', Gender, Technology and Development, 7(3), pp. 359-377.

Venkatesh, V. and Bala, H. (2008). "Technology Acceptance Model 3 and a Research Agenda on Interventions," Decision Sciences, 39(2), 273-15. https://doi.org/10.1111/j.1540-5915.2008.00192.x https://www.researchgate.net/publication/247644487_Technology_Acceptance_Model_3_and_a_Research_Agenda_on_Interventions#fullTextFileContent [accessed Apr 23 2024].

Venkatesh, V. and Davis, F. D. (2000), "A Theoretical Extension of the Technology Acceptance Model: Four

Longitudinal Field Studies", Management Science, 46(2), p. 186. https://doi.org/10.1287/mnsc.46.2.186.11926.

Wong, K.-T., Teo, T. & Goh, P.S. C. (2015). Understanding the intention to use interactive whiteboards: model development and testing, Interactive Learning Environments, 23(6),731-747, https://doi.org/10.1080/10494820.2013.806932 https://www.tandfonline.com/doi/full/10.1080/10494820.2013.806932

Yao, Q.,Yi Man Li, R., Song, L., Crabbe, J. (2021). Construction safety knowledge sharing on Twitter: A social network analysis, Safety Science, Volume 143, https://doi.org/10.1016/j.ssci.2021.105411.