Factors Driving ChatGPT Adoption in Higher Education: A UTAUT-Based Analysis of Student Behavioural Intentions

Tehreem Mansoor Siddiqui[1], Arifmiboy[2], Norshahida Shaadan[3], Shuhaida Mohamed Shuhidan[4], Anitawati Mohd Lokman[5*]

[1 3 5] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA, 40450 Shah Alam, Malaysia
[2] Universitas Islam Negeri Sjech M. Djamil Djambek Bukittinggi, Indonesia
[4] Centre for Research in Data Science, Computer and Information Sciences Department, Faculty of Science, Management & Computing, Universiti Teknologi Petronas, Malaysia
[1] tehreem.edu@gmail.com
[2]arifmiboy@uinbukittinggi.ac.id
[3] norshahida588@uitm.edu.my
[4] shuhaida.shuhidan@utp.edu.my
[5*] anitawati@uitm.edu.my
[*]Corresponding Author

https://doi.org/10.24191/ajue.v21i1.42

Received: 29 September 2024
Accepted: 17 June 2025
Date Published Online: 25 July 2025
Published: 25 July 2025

Abstract: The transformative potential of open-source AI platforms like ChatGPT in education highlights the importance of understanding user motivations and perceptions. This research investigates key factors influencing the behavioural intention to use ChatGPT in higher education. Employing a positivist paradigm, the study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) model as a theoretical foundation to develop a survey questionnaire. Descriptive analysis, Partial Least Squares Structural Equation Modelling (PLS-SEM), and Multi-Group Analysis (PLS-MGA) were used to analyse survey responses from 353 university students. Key findings reveal that performance expectancy and learning value are critical factors in students' intention to use ChatGPT. Interestingly, social influence has minimal impact on adoption intentions. The results also indicate that demographic factors such as age, gender, and education level generally do not significantly influence the relationships between independent variables and the intention to adopt ChatGPT. A slight exception was found in the field of study, which impacts the relationship between Social Influence and Behavioural Intention. This research contributes to the growing body of knowledge on AI adoption in education, offering a nuanced understanding of student attitudes towards ChatGPT. By identifying key drivers of adoption, the study paves the way for more effective integration of AI tools in academic settings, potentially enhancing the quality and personalization of education. These insights can inform pedagogical practices, guide academic policymakers, and assist AI application developers in understanding the potential implications and effective strategies for integrating advanced language models in education.

Keywords: AI Adoption in Education, Behavioural Intention, ChatGPT, Higher Education, UTAUT

1. Introduction

In an era of rapid technological advancement, the adoption of innovative tools has become pivotal for enhancing learning experiences and engagement. This study explores the technical, educational, and sociological drivers influencing the uptake of ChatGPT among higher education students. Open-source AI derivative platforms like ChatGPT represent a novel development in language processing technology, sparking a transformative revolution in academics, research, and professional practices.

ChatGPT's ability to simulate natural conversations makes it a promising tool in educational settings (Perera, 2023; Montenegro-Rueda, 2023) for supplementing learning materials (Kirmani, 2023). Fu et al. (2024) supports Redzuan et al. (2013) assertion that positive user experience is linked to positive emotion, which are crucial for engaging students in online learning. Additionally, students' readiness to embrace technological innovations profoundly impacts the evolution of educational and academic practices (Shoufan, 2023; Zacharias & Nikolopoulou, 2022; Mhlanga, 2023). Moreover, an effective internet-based learning could benefit not only at-risk students but also other learners as a means of enhancing their learning capabilities (Bajaj, 2024; Isa et al., 2015; Redzuan et al., 2011). Educators also benefit from the automation of teaching activities (Tajik & Tajik, 2023). However, integrating ChatGPT in higher education introduces intricate challenges regarding technical and ethical considerations, such as information bias, transparency, and academic dishonesty. These issues raise concerns for responsible integration and informed policymaking. The insights from this study can aid educators, students, and administrators in improving their practices and guide policymakers towards effective adaptation of ChatGPT and similar technologies within the academic environment. As of July 2024, research on ChatGPT's implications in academia remains limited. The body of knowledge on this topic only began to emerge in June 2022, as the technology was introduced for public use in March 2022. Being a relatively recent innovation, its implications and impacts are still under observation, with significant gaps in studies due to limited research on user acceptance and use (Yifan, Mengmeng & Omar, 2023). This study has implications for curriculum design, resource allocation, and institutional planning. Educators can adapt their teaching strategies to align with the identified factors, fostering an engaging and effective learning environment with pedagogically sound practices. Developers can gain insights into specific key drivers, informing the design improvement of educational technologies that better align with student needs. Furthermore, this research addresses interdisciplinary fields such as Educational Technology, Technology Adoption, and Human-Computer Interaction. Adapting academic and pedagogical practices in accordance with emerging technologies will contribute to their successful integration in higher education.

This research aims to identify key motivational factors and analyse their influence on higher education students' behavioural intention to use ChatGPT. Specifically, it examines the impact of performance expectancy, effort expectancy, social influence, and learning value. The study explores correlations between these factors and the behavioural intention (BI) to use ChatGPT through four targeted research questions (RQ), which are:

RQ1: What is the correlation between Performance Expectancy and BI to use ChatGPT?
RQ2: What is the correlation between Effort Expectancy and BI to use ChatGPT?
RQ3: What is the correlation between Social Influence and BI to use ChatGPT?
RQ4: What is the correlation between Learning Value and BI to use ChatGPT?

2. Theoretical Background

ChatGPT (referring to ChatGPT, GPT-3, or ChatGPT 3.5) is a "Large Language Model" (LLM) recently developed by OpenAI. It's a text-generative tool within the field of Natural Language Processing (NLP), (Khalkar et al., 2021). GPT, which stands for "Generative Pre-trained Transformer," is based on the Transformer model originally developed by Google. Launched on November 30, 2022, ChatGPT is available as a freemium service. ChatGPT falls under the category of Generative AI, capable of creating new content (Fui-Hoon, 2023). Its performance is continually refined through deep learning, utilising data collected from user prompts (Koubaa, 2023). This process is part of its "Transformer architecture," which is pre-trained on vast datasets. The current versions of ChatGPT offer various applications, including translation, analysis, and summarisation. It can comprehend and produce human-like text, as well as generate creative content such as charts, tables, and images (Kirmani, 2023; Hassani, 2020). Programmers frequently use it to generate basic to mid-level code for numerous applications (Biswas, 2023; Nigar, Surameery, & Shakor, 2023). ChatGPT can function as a conversational agent with an assigned persona (De Winter, Driessen, & Dodou, 2023), achieved through prompt engineering (Shoufan, 2023). While it excels at problem-solving tasks, its mathematical capabilities are limited (Frieder et al., 2023).

The evolution of technology necessitates changes in traditional academic practices as AI penetrates more roles, tasks, and industries (Hassani et al., 2020). Emerging challenges include algorithmic bias and auto-generated text being passed off as original authoring (Medina-Romero, 2023). Montenegro-Rueda (2023) observed that ChatGPT's general impact on students' learning and educators' teaching practices is largely positive, further enabling global learning (Biswas, 2023). Perera et al. (2023) assessed it as a beneficial tool for content creation, creative writing, grammar correction, and vocabulary enhancement (Dempere, 2023; Oranga, 2023). ChatGPT excels as a virtual tutor and assists in optimising code snippets (Biswas, 2023; Nigar, Surameery, & Shakor, 2023). It facilitates idea generation in an engaging manner (Mhlanga, 2023; Dementieva et al., 2023). The interactive chat can be used for brainstorming sessions, allowing users to explore various perspectives and refine their ideas (Oranga, 2023; Mhlanga, 2023; Biswas, 2023). Its free availability democratises access to valuable educational resources, potentially reducing educational inequities (Shalva, 2023). To encourage the adoption of GPT technology, it's crucial to provide teacher training on ethical and optimised usage (Montenegro-Rueda, 2023; Medina-Romero, 2023). The potential benefits are considered particularly significant for developing nations (Mhlanga, 2023). ChatGPT can simplify complex queries and offer explanations suitable for all educational levels. Its 24-hour availability provides assistance at any time (Dementieva et al., 2023), and it can promptly assess assignments, offer feedback, and identify areas for improvement (Bozic, 2023). However, challenges, limitations, and biases within the technology can hinder its adoption or usage. Algorithmic bias and prompt manipulation can lead to the generation of biased or false information (Geoffrey, 2023). There are concerns that it may limit users' innovative thinking and undermine crucial skills such as critical thinking and information analysis (Yeo, 2023). Shkliarevsky (2023) argues that ChatGPT's perceived impact in most applications is overestimated. Ariyaratne (2023) raises concerns about legal liability, particularly regarding its use in medical research (Kim et al., 2023) or clinical practice.

The Technology Acceptance Model (TAM), developed by Fred Davis in 1989, explains how users accept and use new technologies. The model establishes two primary contributing factors: "perceived usefulness" and "perceived ease of use." In higher education, educators' and students' perceptions of ChatGPT's ease of use and usefulness significantly impact its acceptance and use (Shaengchart, 2023). An extension of TAM is the Unified Theory of Acceptance and Use of Technology (UTAUT) and UTAUT2, which incorporate additional factors (Venkatesh et al., 2012). The original publication demonstrates that UTAUT can explain 70% of the variance in "Behavioural Intention," making it a reliable predictive tool (Williams, 2015). It identifies four key constructs—Performance Expectancy (Chatterjee & Bhattacharjee, 2020), Effort Expectancy, Social Influence (Leow et al., 2021; Sing et al., 2022) and Facilitating Conditions—that contribute to users' intentions and behaviours regarding technology adoption and usage (Hasselqvist, 2023; Foroughi, 2023). Recent studies have modified the UTAUT2 model by eliminating certain factors (Strzelecki, 2023; Hasselqvist, 2023; Foroughi, 2023) and analysed data using Partial Least Square-Structural Equation Modelling (PLS-SEM). Most of these studies employed a modified version of a validated questionnaire by Sallam et al. (2023).

3. Research Methodology

This research adopted the UTAUT model to identify key factors influencing ChatGPT technology adoption in higher education. Employing a quantitative research design, the study aims to quantify variables and establish relationships through statistical inference. This method is chosen for its replicability, generalisability, and objectivity (Park, 2020), aligning with the positivist framework. The target population comprises 590,254 higher education students in West Malaysia as of 2022 (UNESCO World Higher Education Conference, 2022). The respondents for this study were students from the Malaysian demographic, as the research focuses on the influence of GPT tools on academic behaviour among higher education groups. These groups were classified based on various demographics, including age, gender, field of study, and level of education. Employing an adequate sample size is critical for ensuring statistical validity, as larger samples tend to provide greater statistical power and enable more accurate generalisations about the population (Lokman et al., 2009). Accordingly, non-probability convenience sampling is used in this study, with a minimum sample size of 119 university students, calculated using Raosoft (9% margin of error, 95% confidence level). Data collection utilises a questionnaire with closed-ended questions based on a 5-point Likert scale (Croasmun & Ostrom, 2011). The survey instrument used in this study is a previously validated and reliable questionnaire that has undergone rigorous testing. It has been employed in multiple published papers (Foroughi et al., 2023), demonstrating that the items of the questionnaire are effective measures for data collection. The questionnaire is divided into two sections: demographic information and ordinal data on variables. Ethical principles for anonymity, confidentiality, and consensual response are observed throughout the process (Oldendick, 2012; MRS Guidelines for Questionnaire Design, 2014). Data analysis was performed using Jamovi, SmartPLS4, and Excel. Fig. 1 shows the method for data collection and analysis used in this research.

The analysis methods include descriptive statistics, Partial Least Squares Structural Equation Modelling (PLS-SEM) for regression analysis, and PLS Multi-Group Analysis (PLS-MGA) for comparing data among different respondent groups. PLS-SEM aims to maximize covariance between predictors and the response variable, while PLS-MGA allows for comparison of structural models across different subgroups within the dataset.

The research model was derived from a modified version of the well-established (Unified Theory of Acceptance and Use of Technology) UTAUT & UTAUT2 frameworks as presented in past research papers (Strzelecki, 2023; Hasselqvist, 2023; Foroughi et al., 2023; Venkatesh et al., 2012) to identify the strength and direction of correlations. Fig. 2 helps to visualize the theoretical structure and guide the data analysis and interpretation process. It reflects the specific correlation of constructs, the effect of influencing factors. This method presents constructs as latent variables, which are measured by multiple observed indicators.

Figure 1

The Research Methods

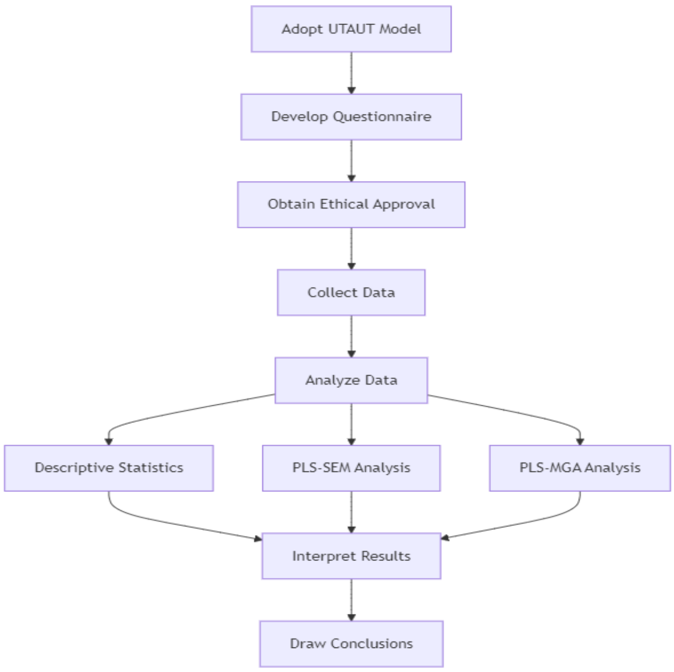
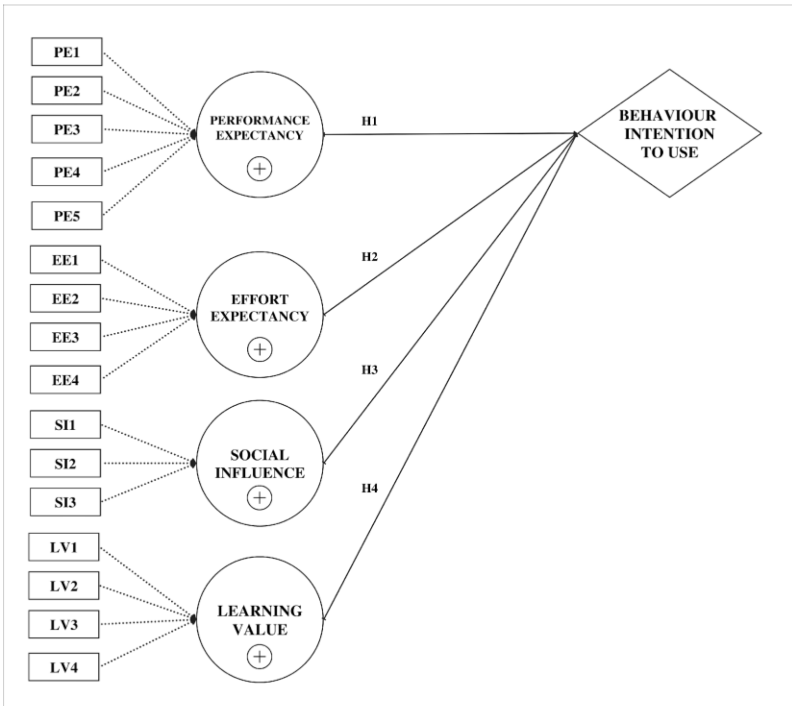


Figure 2

The Research Model



The research model consists of two main components: the inner (structural) model and the outer (measurement) model. The inner model defines relationships between latent variables, including the endogenous variable Behavioural Intention (BI) and exogenous variables Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Learning Value (LV). The outer model comprises indicator variables measuring these latent constructs. This study modifies the UTAUT model by excluding moderating variables and facilitating conditions due to their irrelevance or lack of correlation with BI in the context of ChatGPT usage (Foroughi et al., 2023; Hasselqvist, 2023; Strzelecki, 2023). The Learning Value variable is introduced based on its significance in previous studies (SitarTaut & Mican, 2021; Foroughi et al., 2023). Additionally, the Behaviour Use construct is excluded as it is directly associated with facilitating conditions (Foroughi et al., 2023). These modifications aim to create a more focused and relevant model for examining ChatGPT adoption among higher education students.

PE is defined as the user's belief in how well a particular technology will help them perform a specific task or achieve a particular goal efficiently (Venkatesh et al., 2012). Studies have demonstrated a positive correlation between students' use of chatbots for learning purposes and PE. Several researchers have found that PE has a major influence on learners' behavioural intention to use novel educational technologies (Al-Emran et al., 2023). EE refers to the user's perception of the ease associated with using a particular technology. Any new technology requires additional effort to use (Davis, 1989), which significantly impacts its acceptance (Chatterjee & Bhattacharjee, 2020; Venkatesh & Davis, 2003). SI is the degree to which an individual believes that people in their life influence their perceptions and usage of a new technology (Leow et al., 2021). Social impact is particularly important in the initial phases of technology adoption. LV assesses student's perceptions of ChatGPT's usefulness as a learning tool for time savings and learning improvement (Hong et al., 2022; Yin et al., 2021; Zacharias & Nikolopoulou, 2022). BI refers to an individual's subjective probability or intention to use a specific technology in the future (Shen et al., 2019; Venkatesh et al., 2012). The research hypotheses are:

Ho1: There is no correlation between PE and BI to use Chat-GPT
Ha1: There is a positive correlation between PE and BI to use ChatGPT

Ho2: There is no correlation between EE and BI to use Chat-GPT
Ha2: There is a positive correlation between EE and BI to use ChatGPT
Ho3: There is no correlation between SI and BI to use Chat-GPT
Ha3: There is a positive correlation between SI and BI to use ChatGPT
Ho4: There is no correlation between LV and BI to use Chat-GPT
Ha4: There is a positive correlation between LV and BI to use ChatGPT

4. Results and Discussions

A total of 353 individuals completed the questionnaire. Male respondents numbered 138 (39.1%), and female respondents 215 (60.9%). Regarding education level, 80.2% were undergraduate students, 12.4% Masters, and 7.3% PhD. In terms of field of study, 96.4% were from IT/CS, 24.6% from natural sciences, and 19% from social sciences. Age-wise, the 18–25 group comprised 79.6% of respondents, the 25–35 age group 15%, and the 35+ age group 5.4%. The following sub-sections elaborate and discuss further analysis results.

4.1 Construct Reliability and Validity

Table 1

Construct Reliability and Validity Calculations

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
EE	0.842	0.849	0.893	0.677
LV	0.865	0.875	0.909	0.714
PE	0.883	0.886	0.914	0.682
SI	0.883	0.886	0.928	0.811

The reliability and validity of the measurements have been rigorously tested using multiple tests for construct reliability, discriminant validity, variance inflation and Model fit assessment. Table 1 presents the Construct Reliability and Validity Calculations for the research model, showcasing four key metrics (Cronbach's alpha, Composite reliability, and Average Variance Extracted) for each construct (EE, LV, PE, and SI). The results strongly support the reliability and validity of the constructs used in the study. All constructs demonstrate high Cronbach's alpha values (0.842-0.883) and composite reliability measures (0.849-0.928), indicating excellent internal consistency and reliability. Additionally, AVE values for all constructs exceed 0.5 (range: 0.677-0.811), demonstrating good convergent validity. These findings provide robust evidence for the measurement model's validity, lending credibility to the study's conclusions on ChatGPT adoption in higher education. The Heterotrait-Monotrait Ratio (HTMT) values below the 0.85 threshold indicate strong discriminant validity. The resulting values for PE ↔ EE (HTMT = 0.86) and PE ↔ LV (HTMT = 0.88) suggest a high degree of similarity, likely due to a shared conceptual relationship between these constructs. Furthermore, the highest cross-loading value for each item was associated with its respective construct, reinforcing the discriminant validity of all constructs. Additionally, a Low Variance Inflation Factor (VIF < 3) indicates minimal collinearity among the predictor variables within the regression model, which contributes to more reliable and interpretable results. The Standardised Root Mean Square Residual (SRMR), which measures the average discrepancy between the observed correlations and the model-predicted correlations, had a value of 0.06. This suggests that the model fits the data well.

4.2 Descriptive Statistics

Measure of Central Tendency results showed high mean for PE (4.0-4.3), EE (4.0-4.4), which indicates user satisfaction with the tool's performance and learning value. For SI (3.4-3.5), is comparatively low than the other factors, which suggests it is a less significant factor. Value for BI (4.1) indicates a generally positive intention to continue using the system. Most PE and EE items showed low standard deviations, <1.0, indicating that respondents generally have consistent opinions about these items. The kurtosis analysis (Table 2) of the latent variables reveals that most variables exhibit mild deviations from a normal distribution. EE and PE show slightly leptokurtic distributions with heavier tails, while LV is nearly mesokurtic, closely resembling a normal distribution. BI and SI display slightly platykurtic distributions with lighter tails. These kurtosis values indicate data for most variables are reasonably close to a normal distribution, with only minor deviations in the tails. This suggests that the responses are generally well-distributed without extreme outliers, which is advantageous for many statistical analyses. Measure of Skewness (Table 3) describes the asymmetry of the distribution of values, showing strong negative skewness in PE, EE and LV indicating users generally perceived the system very positively. Also, the near-zero skewness for SI factors indicates a balanced perception.

Table 2

Excess kurtosis of Latent Variables

	Kurtosis	
BI	-0.239	
EE	0.467	leptokurtic
LV	0.004	mesokurtic
PE	0.365	leptokurtic
SI	-0.074	Platykurtic

Table 3

Latent Variable Skewness

	Skewness
BI	-0.693
EE	-0.832
LV	-0.631
PE	-0.707
SI	-0.038

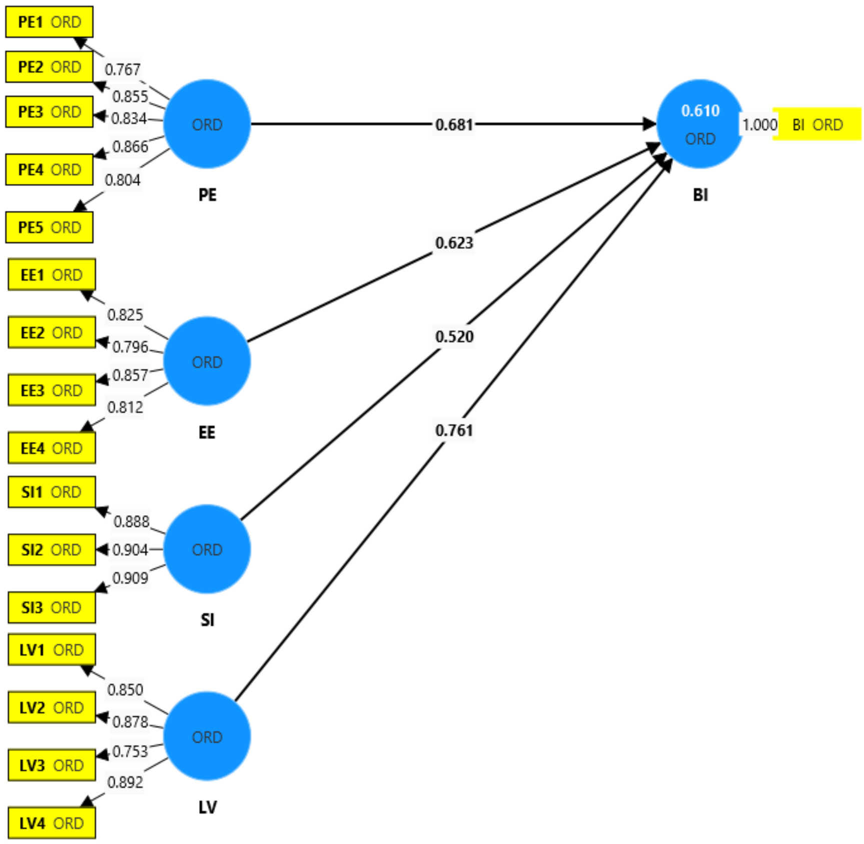
4.3 Multivariate Analysis Using PLS-SEM

Fig.3 shows the result from PLS-SEM, named Modified UTAUT Model for ChatGPT Adoption in Higher Education. The model demonstrates a strong positive relationship between PE and BI, with a path coefficient of 0.681. This suggests that students' belief in ChatGPT's ability to enhance their academic performance significantly influences their intention to adopt the technology. This finding aligns with previous research showing that PE has a major influence on learners' behavioural intention to use novel educational technologies (Al-Emran et al., 2023).

With a path coefficient of 0.623, EE shows a moderate to strong positive relationship with BI. This implies that the perceived ease of using ChatGPT plays a crucial role in students' adoption intentions, consistent with the findings of Venkatesh et al. (2012) on the importance of EE in technology adoption. The path coefficient of 0.520 between SI and BI indicates a moderate positive relationship. This suggests that opinions of peers, teachers, and other influential individuals have a notable impact on students' intention to use ChatGPT, supporting previous findings on the role of social influence in technology adoption in educational settings (Leow et al., 2021). LV shows the strongest relationship with BI, with a path coefficient of 0.761. This indicates that the perceived educational benefits of using ChatGPT have the most significant influence on students' adoption intentions. This finding supports the inclusion of LV as a construct in the modified UTAUT model, aligning with previous studies that have highlighted the importance of learning value in educational technology adoption (Sitar-Taut & Mican, 2021; Foroughi et al., 2023). To align the model with the research objective, and narrow the theoretical relevancy, the moderating factors have been removed. Past studies conclude little or no correlation of ‘Behavioural intention’ with facilitating conditions. The hypothesis has been proven irrelevant and eliminated in past studies too (Strzelecki, 2023; Foroughi et al., 2023). The variable is irrelevant to the model because the Chat GPT platform is an open-source, online and free tool. The ‘Behaviour Use’ construct of UTAUT is directly associated with ‘Facilitating conditions’, since our model has excluded the predictor arable, the BU variable is also eliminated from the model. The principle of parsimony suggests that all else being equal, simpler explanations or models are generally preferred over more complex ones.

Figure 3

Modified UTAUT Model for ChatGPT Adoption in Higher Education



The R^2 value of 0.610 for Behavioural Intention indicates that the model explains 61% of the variance in the intention to use ChatGPT. This suggests a moderately strong explanatory power, consistent with previous applications of modified UTAUT models in educational technology contexts (Strzelecki, 2023; Hasselqvist, 2023; Foroughi, 2023).

These findings have significant implications for the integration of ChatGPT in higher education settings. The strong influence of Learning Value suggests that educators and institutions should focus on demonstrating the educational benefits of ChatGPT to encourage adoption. Additionally, the moderate impact of Effort Expectancy highlights the importance of ensuring that ChatGPT is user-friendly and easily integrated into existing learning environments. Future research could explore potential moderating variables, such as age, gender, or prior experience with AI technologies, which were excluded from this modified model. Furthermore, longitudinal studies could provide insights into how these relationships evolve over time as ChatGPT becomes more prevalent in educational settings. This modified UTAUT model provides valuable insights into the factors influencing ChatGPT adoption among higher education students. By understanding these factors, educators and institutions can develop more effective strategies for integrating ChatGPT into the learning environment, potentially enhancing student engagement and learning outcomes.

4.4 Hypothesis Result

Table 4 presents the results of hypothesis testing for the modified UTAUT model examining ChatGPT adoption in higher education. The table includes four independent variables: Performance Expectancy (PE), Effort Expectancy (EE), Learning Value (LV), and Social Influence (SI), and their relationships with the dependent variable Behavioural Intention (BI).

Table 4

Result of the Hypothesis

		BI	Direction	Strength	Alternate Hypothesis	Result	Null Hypothesis	Result
PE	β	0.143	Positive	Moderate				
	r	0.681	Positive	Strong	Ha1	TRUE	Ho1	FALSE
	$f2$	0.016		Small				
EE	β	0.122	Positive	Moderate				
	r	0.623	Positive	Strong	Ha2	TRUE	Ho2	FALSE
	$f2$	0.015)		Small				
LV	β	0.523	Positive	Strong				
	r	0.761	Positive	Strong	Ha3	TRUE	Ho3	FALSE
	$f2$	0.237		Moderate				
SI	β	0.072	Positive	Weak				
	r	0.52	Positive	Weak	Ha4	TRUE	Ho4	FALSE
	$f2$	0.008		Very Small				

The result shows that all four hypotheses are supported, indicating that PE, EE, LV, and SI all have positive relationships with BI. However, Learning Value (LV) stands out as the strongest predictor of Behavioural Intention to use ChatGPT among higher education students, followed by Performance Expectancy and Effort Expectancy. Social Influence, while still significant, has the weakest effect on Behavioural Intention.

Data analysis was performed using Jamovi, SmartPLS4, and Excel. The analysis methods include descriptive statistics, Partial Least Squares Structural Equation Modelling (PLS-SEM) for Multivariate Analysis, and PLS Multi-Group Analysis (PLS-MGA) for comparing data among different respondent groups. PLS-SEM aims to maximize covariance between predictors and the response variable, while PLS-MGA allows for comparison of structural models across different subgroups within the dataset.

4.5 Comparison of Structural Models Across Different Subgroups Using PLS-MGA

Table 5

Categorisation of the Demographic Groups

Age		Gender		Level of Ed		Field	
18-25	G1	Male	M	Undergraduate	U	Natural sci	NS
25-35	G2	Female	F	Masters	PM	Social Sci	SS
35+	G3			PhD	PP	IT/CS	IT

Table 5 categorises the demographic groups used in the study, including age (18-25, 25-35, 35+), gender (Male, Female), level of education (Undergraduate, Masters, PhD), and field of study (Natural Sciences, Social Sciences, IT/CS).

Table 6

Path Coefficients, Age Group Comparison

	Difference (G1 - G2)	Difference (G1 - G3)	1-tailed (G1 vs G2) p value	1-tailed (G1 vs G3) p value	2-tailed (G1 vs G2) p value	2-tailed (G1 vs G3) p value
EE -> BI	-0.085	-0.27	0.687	0.874	0.313	0.126
LV -> BI	0.241	0.13	0.235	0.242	0.235	0.242
PE -> BI	-0.161	-0.131	0.785	0.697	0.215	0.303
SI -> BI	-0.106	0.093	0.77	0.297	0.23	0.297

Table 6 compares path coefficients across age groups. The results show no statistically significant differences between age groups for any of the paths (EE -> BI, LV -> BI, PE -> BI, SI -> BI), as all p-values are greater than 0.05.

Table 7

Path Coefficients, Gender Comparison

	Difference (F - M)	1-tailed (F vs M) p value	2-tailed (F vs M) p value
EE -> BI	0.136	0.123	0.123
LV -> BI	-0.078	0.692	0.308
PE -> BI	-0.017	0.544	0.456
SI -> BI	0.046	0.3	0.3

Table 7 presents a gender comparison of path coefficients. Similar to the age group comparison, no statistically significant differences are observed between males and females for any of the paths, with all p-values exceeding 0.05.

Table 8

Path Coefficients, 'Level of Education' Group Comparison

	Difference (U - PM)	Difference (U - PP)	1-tailed (U vs PM) p value	1-tailed (U vs PP) p value	2-tailed (U vs PM) p value	2-tailed (U vs PP) p value
EE -> BI	0.073	-0.092	0.401	0.716	0.401	0.284
LV -> BI	-0.059	0.23	0.584	0.162	0.416	0.162
PE -> BI	-0.102	-0.333	0.649	0.944	0.351	0.056
SI -> BI	0.056	0.008	0.286	0.483	0.286	0.483

Table 8 compares path coefficients across education levels. Again, no statistically significant differences are found between undergraduate, masters, and PhD students for any of the paths, with all p-values above 0.05.

Table 9

Path Coefficients, 'Field of Education' Group Comparison

	Difference (NS - IT)	Difference (NS - SS)	1-tailed (NS vs IT) p value	1-tailed (NS vs SS) p value	2-tailed (NS vs IT) p value	2-tailed (NS vs SS) p value
EE -> BI	-0.091	0.147	0.738	0.188	0.262	0.188
LV -> BI	-0.032	-0.287	0.57	0.922	0.43	0.078
PE -> BI	0.233	0.213	0.074	0.165	0.074	0.165
SI -> BI	-0.206	-0.12	0.964	0.837	0.036	0.163

Table 9 compares path coefficients across fields of education. Most comparisons show no significant differences, except for the SI -> BI path between Natural Sciences and IT/CS students, which shows a statistically significant difference ($p = 0.036$ for the two-tailed test).

The above findings reveal that demographic factors such as age, gender, and education level generally do not significantly influence the relationships between the independent variables (EE, LV, PE, SI) and the behavioural intention to adopt ChatGPT among higher education students. However, a slight impact of field of study on the relationship between Social Influence (SI) and Behavioural Intention (BI) was observed, particularly when comparing Natural Sciences and IT/CS students. This suggests that while the factors influencing ChatGPT adoption are relatively consistent across diverse student populations, the influence of peers and authority figures may vary depending on the academic discipline. These results indicate that strategies to promote or manage ChatGPT use in higher education could be broadly applicable, with minor adjustments for different fields of study. Further research is recommended to explore the reasons behind the difference in Social Influence between Natural Sciences and IT/CS students and to investigate whether this finding is replicated in other studies or contexts.

5. Conclusion

This study investigated the factors influencing ChatGPT adoption among university students using the UTAUT model. The findings reveal that LV is the strongest predictor of BI, followed by PE and EE. SI, while significant, has the weakest effect. Demographic factors generally do not significantly influence these relationships, except for a slight impact of field of study on the SI-BI relationship. The results align with previous research on technology adoption in educational settings. The importance of Learning Value corroborates the findings of Perera (2023) and Montenegro-Rueda (2023), who highlighted ChatGPT's potential in enhancing learning experiences. The significance of Performance Expectancy and Effort Expectancy aligns with Kirmani's (2023) observations on ChatGPT's role in supplementing learning materials. Our study extends beyond previous research by providing a comprehensive analysis of demographic factors, suggesting that ChatGPT's appeal transcends traditional demographic boundaries.

The research confirms that performance expectancy, learning value, and effort expectancy strongly influence the intention to use ChatGPT. Students perceive it as a valuable tool enhancing their learning experience and efficiency, as demonstrated by Hasselqvist (2023) and Foroughi (2023). However, certain technological limitations may reduce these factors' total effect (Kasneci, 2023). Social influence has a weaker impact, consistent with findings by Strzelecki (2023) and Hasselqvist (2023).

These findings have implications for academia and industry, highlighting the importance of design focus in developing interactive systems. Developers should prioritise enhancing ease of use and perceived learning value to drive user engagement and satisfaction. Universities should integrate ChatGPT into curricula, focusing on its learning value and ease of use. Additionally, EdTech companies can develop AI-powered educational tools emphasising learning value and performance enhancement. Policymakers could use these insights to develop guidelines supporting beneficial AI adoption in education while addressing potential challenges. Understanding adoption factors can also aid in developing public awareness campaigns about AI in education.

The study identified that 39.5% variance remains unexplained, and survey responses might contain self-reporting bias. While multigroup analysis differences are not statistically significant, natural science students seem less affected by social influence, highlighting their objective approach to technology (Tsang, 2017). Further research can be conducted to validate this research findings. Future research directions include exploring the reasons behind differences in Social Influence between Natural Sciences and IT/CS students, conducting longitudinal studies on adoption factors, and investigating ethical considerations of widespread ChatGPT adoption in education. Furthermore, this study's limitations include its use of non-probability convenience sampling with 353 respondents, which restricts the generalisability of the findings. As such, the results should be interpreted as a case study specific to the sample population rather than representative of the entire student population in the country. To enhance the generalisability of these findings, future research should employ random sampling techniques (Stratton, 2021). This approach would provide a more robust foundation for drawing broader conclusions about ChatGPT adoption among university students.

6. Co-Author Contribution

The authors affirmed that there is no conflict of interest in this article. Author 1 was responsible for designing the study framework and methodology, conducting primary data analysis, and drafting the initial manuscript. Author 2, provided feedback on the statistical analyses, ensured data reliability, and contributed to the writing of the results section. Author 3, reviewed the research design and survey instrument, and provided feedback on manuscript drafts. Author 4, oversaw review of existing literature to inform the study. Author 5 oversaw the project timeline, coordinated communication among co-authors, and assisted in editing and formatting the final manuscript, ensuring a cohesive and well-organized presentation of the research findings.

7. Acknowledgements

The authors wish to express sincere gratitude to the Malaysia Association of Kansei Engineering (MAKE), and RIG Kansei and Design Engineering (RIG EKDE), UiTM for the support to the research activities and the preparation of this paper.

8. References

Al-Emran, M., Al-Qudah, A. A., Abbasi, G. A., Al-Sharafi, M. A., & Iranmanesh, M. (2023). Determinants of using AI-based chatbots for knowledge sharing: Evidence from PLS-SEM and fuzzy sets (fsQCA). *IEEE Transactions on Engineering Management*, 1–15. https://doi.org/10.1109/TEM.2023.3237789

Ariyaratne, & Hasala. (2023, May 16). ChatGPT and intermediary liability: Why Section 230 does not and should not protect generative algorithms. *SSRN*. http://dx.doi.org/10.2139/ssrn.4422583

Bajaj, M. (2024). The role of digital learning platforms in enhancing student engagement. *Unified Visions*, *1*.

Biswas, S. (2023). Role of ChatGPT in computer programming. *Mesopotamian Journal of Computer Science*, *2023*, 8–16. https://doi.org/10.58496/MJCSC/2023/002

Božić, V., & Poola, I. (2023). Chat GPT and education. https://doi.org/10.13140/RG.2.2.18837.40168

Burns, K. M., Burns, N. R., & Ward, L. (2016). Confidence—More a personality or ability trait? It depends on how it is measured: A comparison of young and older adults. *Frontiers in Psychology*, *7*, Article 518. https://doi.org/10.3389/fpsyg.2016.00518

Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Croasmun, J. T., & Ostrom, L. (2011). Using Likert-type scales in the social sciences. *Journal of Adult Education*, *40*(1). https://eric.ed.gov/?id=EJ961998

Dale, R. (2021). GPT-3: What's it good for? *Natural Language Engineering*, *27*(1), 113–118. https://doi.org/10.1017/S1351324920000601

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

De Winter, J., Driessen, T., & Dodou, D. (2023). The use of ChatGPT for personality research: Administering questionnaires using generated personas. *Department of Cognitive Robotics*.

Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, Article 102274. https://doi.org/10.1016/j.lindif.2023.102274

Dempere, J., Modugu, K., Hesham, A., & Ramasamy, L. K. (2023). The impact of ChatGPT on higher education. *Frontiers in Education*, *8*, Article 1206936. https://doi.org/10.3389/feduc.2023.1206936

Foroughi, B., Gunaratnege, S. M., Iranmanesh, M., Khanfar, A., Ghobakhloo, M., Annamalai, N., & Abbaspour, B. N. (2023). Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. *International Journal of Human-Computer Interaction*, *1*–21. https://doi.org/10.1080/10447318.2023.2226495

Frieder, S., Pinchetti, L., Chevalier, A., Griffiths, R.-R., Salvatori, T., Lukasiewicz, T., Petersen, P. C., & Berner, J. (2023). Mathematical capabilities of ChatGPT. *arXiv:2301.13867*. https://doi.org/10.48550/arXiv.2301.13867

Fu, P., Gao, C., Chen, X., Zhang, Z., Chen, J., & Yang, D. (2024). Proactive personality and its impact on online learning engagement through positive emotions and learning motivation. *Scientific Reports*, *14*(1), 28144.

Fui-Hoon, N. F., Zheng, R., Cai, J., Siau, K., & Chen, L. (2023). Generative AI and ChatGPT: Applications, challenges, and AI-human collaboration. *Journal of Information Technology Case and Application Research*, *25*(3), 277–304. https://doi.org/10.1080/15228053.2023.2233814

Geoffrey, M. C. (2023). Academic integrity and artificial intelligence: Is ChatGPT hype, hero, or heresy? *Seminars in Nuclear Medicine*, *53*(5), 719–730. https://doi.org/10.1053/j.semnuclmed.2023.04.008

Goodman, P., Robert, R. C., & Johnson, J. E. (2020). Rigor in PhD dissertation research. *Nursing Forum*, *55*(4), 611–620. https://doi.org/10.1111/nuf.12477

Hassani, H., Silva, E. S., Unger, S., TajMazinani, M., & Mac Feely, S. (2020). Artificial intelligence (AI) or intelligence augmentation (IA): What is the future? *AI*, *1*(2), 143–155. https://doi.org/10.3390/ai1020008

Hasselqvist, H. J. (2023). Students' acceptance and use of ChatGPT in academic settings (Dissertation). Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-505766

Hong, J., Tai, K., Luo, W., Sher, Y., & Kao, Y. (2022). Comparing the Taiwanese learning effects of Shaking-On and Kahoot. *Journal of Computer Assisted Learning*, *38*(3), 892–905. https://doi.org/10.1111/jcal.12655

Isa, W. A. R. W. M., Lokman, A. M., Mustapa, M. N., Sah, I. N. M., Hamdan, A. R., & Luaran, J. E. (2015). Exploring the adoption of blended learning: Case of mobile learning. In *2015 3rd International Conference on Artificial Intelligence, Modelling and Simulation (AIMS)* (pp. 359-364). IEEE.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Elsevier Educational Research*.

Khalkar, R., Dikhit, A., & Goel, A. (2021). Handwritten text recognition using deep learning (CNN & RNN). *IARJSET*, *8*, 870–881. https://doi.org/10.17148/IARJSET.2021.86148

Kim, J. K., Chua, M., Rickard, M., & Lorenzo, A. (2023). ChatGPT and large language model (LLM) chatbots: The current state of acceptability and a proposal for guidelines on utilization in academic medicine. *Journal of Pediatric Urology*, *19*(5), 598–604. https://doi.org/10.1016/j.jpurol.2023.05.018

Kirmani, A. R. (2023). Artificial intelligence-enabled science poetry. *ACS Energy Letters*, *8*(1), 574–576. https://doi.org/10.1021/acsenergylett.2c02758

Koubaa, A. (2023). GPT-4 vs. GPT-3.5: A concise showdown. *Preprints*. https://doi.org/10.20944/preprints202303.0422.v1

Leow, L. P., Phua, L. K., & Teh, S. Y. (2021). Extending the social influence factor: Behavioral intention to increase the usage of information and communication technology-enhanced student-centered teaching methods. *Educational Technology Research and Development*, *69*(3), 1853–1879. https://doi.org/10.1007/s11423-021-10017-4

Lokman, A. M., Harun, A. F., Md. Noor, N. L., & Nagamachi, M. (2009). Website affective evaluation: Analysis of differences in evaluations result by data population. In *Human Centered Design: First International Conference, HCD 2009, Held as Part of HCI International 2009, San Diego, CA, USA, July 19-24, 2009 Proceedings 1* (pp. 643-652). Springer Berlin Heidelberg.

Medina-Romero, M. Á., Huallpa, J., Flores-Arocutipa, J., Panduro, W., Chauca Huete, L., Flores Limo, F. A., ... & Hernández, F. (2023). Exploring the ethical considerations of using ChatGPT in university education. *Periodicals of Engineering and Natural Sciences (PEN)*, *11*, 105–115. https://doi.org/10.21533/pen.v11i4.3770

Mhlanga, D. (2023). Digital transformation in education: Opportunities and challenges of the application of ChatGPT to emerging economies. *Education Research International*, *2023*, 1–13. https://doi.org/10.1155/2023/7605075

Montenegro-Rueda, M., Fernández-Cerero, J., Fernández-Batanero, J. M., & López-Meneses, E. (2023). Impact of the implementation of ChatGPT in education: A systematic review. *Computers*, *12*(8), 153. https://doi.org/10.3390/computers12080153

Nigar, M., Surameery, S., & Shakor, M. Y. (2023). Use Chat GPT to solve programming bugs. *International Journal of Information Technology & Computer Engineering (IJITC)*, *3*(1), 17–22. https://doi.org/10.55529/ijitc.31.17.22

Oldendick, R. W. (2012). Survey research ethics. In L. Gideon (Ed.), *Handbook of survey methodology for the social sciences* (pp. 37–52). Springer. https://doi.org/10.1007/978-1-4614-3876-2_3

Oranga, J. (2023). Benefits of artificial intelligence (ChatGPT) in education and learning: Is ChatGPT helpful? *International Review of Practical Innovation, Technology and Green Energy (IRPITAGE)*, *3*(3), 46–50. https://doi.org/10.54443/irpitage.v3i3.1250

Perera, P., & Lankathilaka, M. (2023). AI in higher education: A literature review of ChatGPT and guidelines for responsible implementation. *International Journal of Research and Innovation in Social Science*, *VII*(VI), 306–314. https://doi.org/10.47772/ijriss.2023.7623

Redzuan, F., Mohd. Lokman, A., Ali Othman, Z., & Abdullah, S. (2011). Kansei design model for engagement in online learning: A proposed model. In *Informatics Engineering and Information Science: International Conference, ICIEIS 2011, Kuala Lumpur, Malaysia, November 12-14, 2011. Proceedings, Part I* (pp. 64-78). Springer Berlin Heidelberg.

Sallam, M., Salim, N. A., Barakat, M., Al-Mahzoum, K., Al-Tammemi, A. B., Malaeb, D., Hallit, R., & Hallit, S. (2023). Assessing health students' attitudes and usage of ChatGPT in Jordan: Validation study. *JMIR Medical Education*, *9*, e48254. https://doi.org/10.2196/48254

Shaengchart, Y. (2023). A conceptual review of TAM and ChatGPT usage intentions among higher education students. *Advance Knowledge for Executives*, *2*(3), 1–7. https://doi.org/10.2139/ssrn.4581231

Shen, C. W., Ho, J. T., Ly, P. T. M., et al. (2019). Behavioral intentions of using virtual reality in learning: Perspectives of acceptance of information technology and learning style. *Virtual Reality*, *23*, 313–324. https://doi.org/10.1007/s10055-018-0348-1

Shkliarevsky, G. (2023). The emperor with no clothes: Chomsky against ChatGPT. *SSRN*. https://ssrn.com/abstract=4439662

Shoufan, A. (2023). Exploring students' perceptions of ChatGPT: Thematic analysis and follow-up survey. *IEEE Access*, *11*, 38805–38818. https://doi.org/10.1109/ACCESS.2023.3268224

Sing, C. C., Teo, T., Huang, F., Chiu, T. K. F., & Xing Wei, W. (2022). Secondary school students' intentions to learn AI: Testing moderation effects of readiness, social good, and optimism. *Educational Technology Research and Development*, *70*(3), 765–782. https://doi.org/10.1007/s11423-022-10111-1

Sitar-Taut, D.-A., & Mican, D. (2021). Mobile learning acceptance and use in higher education during social distancing circumstances: An expansion and customization of UTAUT2. *Online Information Review*, *45*(5), 1000–1019. https://doi.org/10.1108/OIR-01-2021-0017

Stratton, S. (2021). Population research: Convenience sampling strategies. *Prehospital and Disaster Medicine*, *36*(4), 373–374. https://doi.org/10.1017/S1049023X21000649

Strzelecki, A. (2023). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *1*–23. https://doi.org/10.1007/s10755-023-09686-1

Taharim, N. F., Lokman, A. M., Isa, W. A. R. W. M., & Noor, N. L. M. (2013). A relationship model of playful interaction, interaction design, kansei engineering and mobile usability in mobile learning. In *2013 IEEE conference on open systems (ICOS)* (pp. 22-26). IEEE.

Tajik, E., & Tajik, F. (2023). A comprehensive examination of the potential application of Chat GPT in higher education institutions. https://doi.org/10.36227/techrxiv.22589497

Tsang, T. L. (2017). A quantitative analysis examining differences between US humanities and STEM students' propensity toward innovation. *Journal of Further and Higher Education*, *43*(2), 149–165. https://doi.org/10.1080/0309877X.2017.1357069

UiTM. (2023). University transformation division, facts & figures data 2023. https://online.fliphtml5.com/nwfpy/zmcc/p=16

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Williams, M. D., Dwivedi, Y. K., & Rana, N. P. (2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. *Journal of Enterprise Information Management*, *28*(4), 443–488. https://doi.org/10.1108/JEIM-09-2014-0088

Wong, K. (2013). Partial least square structural equation modeling (PLS-SEM) techniques using SmartPLS. *Marketing Bulletin*, *24*, 1–32.

Yaslıoglu, M., & Toplu Yaslıoglu, D. (2020). How and when to use which fit indices? A practical and critical review of the methodology. *Istanbul Management Journal*, *88*, 1–20. https://doi.org/10.26650/imj.2020.88.0001

Yeo, M. A. (2023). Academic integrity in the age of artificial intelligence (AI) authoring apps. *TESOL Journal*, *14*, e716. https://doi.org/10.1002/tesj.716

Yifan, W., Mengmeng, Y., & Omar, M. K. (2023). "A friend or a foe?" Determining factors contributing to the use of ChatGPT among university students. *International Journal of*

Academic Research in Progressive Education and Development, *12*(2), 2184–2201. https://doi.org/10.6007/ijarped/v12-i2/17400

Yin, J., Goh, T.-T., Yang, B., & Xiaobin, Y. (2021). Conversation technology with micro-learning: The impact of chatbot-based learning on students' learning motivation and performance. *Journal of Educational Computing Research*, *59*(1), 154–177. https://doi.org/10.1177/0735633120952067

Zacharias, G., & Nikolopoulou, K. (2022). Factors predicting university students' behavioral intention to use eLearning platforms in the post-pandemic normal: An UTAUT2 approach with 'learning value'. *Education and Information Technologies*, *27*(9), 12065–12082. https://doi.org/10.1007/s10639-022-11116-2