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Understanding ChatGPT Adoption among Higher Education Students in Punjab, India: An Application of UTAUT2 Model

Comprender la adopción de ChatGPT entre estudiantes de educación superior en Punjab, India: una aplicación del modelo UTAUT2

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ABSTRACT

This study examines Indian Higher Education students' behavioural intention to use ChatGPT in their learning. Unified Theory of Acceptance, and Use of Technology 2 (UTAUT2) model is used to investigate the impact of the eight UTAUT2 factors on the students' behavioural intention towards using ChatGPT. A pilot study on 100 students was done to check the reliability and validity of the instrument based on the UTAUT2 model. Using a quantitative research approach, data was gathered from 362 students of Punjab (A North region State), India (313 students' data was included in final analysis) using purposive sampling technique. The study's findings revealed that PE (Performance Expectancy), SI (Social Influence), HM (Hedonic Motivation), Hb (Habit), FC (Facilitating Conditions) had significant positive influence on BI (Behavioural Intention) whereas EE (Effort Expectancy) had not significantly influenced BI. On ChatGPT use, H and BI had a positive influence, but FC did not significantly influence ChatGPT use. 67% of the respondents gave priority to learning AI tools in school. In terms of practical implications, this study adds to the current literature on ChatGPT or AI tools in higher education, being useful to education scholars. Also, this study highlights the validation of UTAUT2 model to use ChatGPT among HEI students in Punjab, India. The findings of this study could facilitate discussions among educators working for policies related to the use of AI tools, specifically ChatGPT in India.

KEYWORDS ChatGPT; Acceptance and Use; UTAUT2; PLS-SEM; Higher Education.

RESUMEN

Este estudio examina la intención conductual de los estudiantes indios de educación superior al utilizar ChatGPT en su aprendizaje. El modelo de Teoría Unificada de Aceptación y Uso de Tecnología 2 (UTAUT2) se utiliza para investigar el impacto de los ocho factores UTAUT2 en la intención de comportamiento de los estudiantes hacia el uso de ChatGPT. Se realizó un estudio piloto con 100 estudiantes para comprobar la confiabilidad y validez del instrumento basado en el modelo UTAUT2. Utilizando un enfoque de investigación cuantitativa, se recopilaron datos de 362 estudiantes de Punjab (un estado de la región norte), India (los datos de 313 estudiantes se incluyeron en el análisis final) utilizando una técnica de muestreo intencional. Los hallazgos del estudio revelaron que PE (expectativa de desempeño), SI (influencia social), HM (motivación hedónica), Hb (hábito), FC (condiciones facilitadoras) tuvieron una influencia positiva significativa en BI (intención conductual), mientras que EE (expectativa de esfuerzo) tuvo no influyó significativamente en el BI. En el uso de ChatGPT, H y BI tuvieron una influencia positiva, pero FC no influyó significativamente en el uso de ChatGPT. El 67% de los encuestados dio prioridad al aprendizaje de herramientas de IA en la escuela. En términos de implicaciones prácticas, este estudio se suma a la literatura actual sobre ChatGPT o herramientas de IA en la educación superior, siendo útil para los académicos de la educación. Además, este estudio destaca la validación del modelo UTAUT2 para utilizar ChatGPT entre estudiantes de IES en Punjab, India. Los hallazgos de este estudio podrían facilitar los debates entre los educadores que trabajan en políticas relacionadas con el uso de herramientas de inteligencia artificial, específicamente ChatGPT en India.

PALABRAS CLAVE ChatGPT; Aceptación y Uso; UTAUT2; PLS-SEM; Educación Superior.

1. INTRODUCTION

Artificial intelligence (AI) has entered almost each and every professional field in today's world and can be leveraged in the education field as well. It has opened a significant plethora of innovative opportunities for the teaching-learning processes and practices. From personalized learning experiences to predictive analytics, AI has had a profound impact on the way students learn and educators teach (Huang, 2023). With the advent of AI, and the increasing interest in the available technical AI chatbot applications, including Chat-GPT, Google Bard, Microsoft Bing, Jasper, and others, the students have been trying their hand at using these tools for finishing academic tasks at a faster pace. Everyone today needs quick fixes, and the students are always looking for ways to make their academic life easier and reduce related stress. Since ChatGPT's launch, generative artificial intelligence (gen-AI) systems have received a lot of attention because of its potential influence in a variety of domains (Dowling & Lucey, 2023; Eke, 2023; Lim et al., 2023; Soni et al., 2022; Vaishya et al., 2023), including higher education (Choi et al., 2023; Duong et al., 2023). ChatGPT has been downloaded more than a million times in just one week after its 2022 launch (Lund & Wang, 2023; Pavlik, 2023). ChatGPT has an enormous potential to enhance the effectiveness of learning activities, including creating customized content, assisting with assignments, and giving students feedback (Lund & Wang, 2023). But it also has a certain disadvantage as it could make the students totally dependent on it.

In the present era, students, Generation Z, "zoomers", or "digital natives" (Lim et al., 2022), are inclined towards integrating new technologies into their daily study routine. And this integration is not just limited to the higher education students. Students at all levels-primary, secondary, tertiary, and higher education, have begun using ChatGPT (Duong et al., 2023). ChatGPT has been used a lot in higher education (24.18%), K-12 education (22.09%), and practical skills learning (15.28%) as per Mogavi et al. (2024). This suggests that students are using ChatGPT to reduce cognitive load, further affecting their creativity and thinking skills negatively. A.I. tools in 21st century are not only marking their presence in classroom learning but also AlKursheh (2024) also highlighted the importance of Artificial intelligence in assesssment specifically in Higher education.

Following a review of the existing literature, the analysis pinpoints six crucial elements that many writers have suggested that encourage readers to use text generative AIs such as ChatGPT. The identified factors are: Time Saving and Task Management (TSTM), Ease of Access (EA), Aided Learning (AL), Inseparability of Content (IC), Technical Knowledge of the Program (TKP), Cognitive Miserliness of the User (CMU) (Niloy et al. 2024). These variables point towards the fact that if students continue to rely on ChatGPT, the goal of helping them build 21st century or life skills may appear very distant. It is recommended that students utilise ChatGPT as an additional tool to enhance their research and learning. It should not be used in place of crucial learning components, such as engaging with primary sources, gaining varied viewpoints, and developing critical thinking abilities. Preventing over-reliance on AI would give students the room they need to build the strong cognitive abilities required for independent learning (Mogavi et al. 2024). Aldosari (2020) concludes that experts anticipate an optimistic future scenario where AI enhances various academic facets including education quality, guidance, assessment, and student support. Experts advocate for faculty readiness through training programs to maximize AI benefits.

There is currently less peer-reviewed research that focuses only on how students in Higher Education use ChatGPT, as noted by Strzelecki and ElArabawy (2023). However, it has generated a great deal of interest from a variety of stakeholder groups, including college students who utilize this AI-powered application to help them finish their assignments (Strzelecki & ElArabawy, 2023). The UTAUT is a significant theory for examining people's intentions regarding the acceptance and use of technology (Venkatesh et al., 2003). Due to a lack of studies in the context of Indian higher education, the present study focused on understanding ChatGPT adoption among higher education students in Punjab, India, and applied the UTAUT2 model in the context of use of ChatGPT in the students.

2. LITERATURE REVIEW

2.1. Unified theory of acceptance and use of technology (UTAUT2 Model)

Four key components served as the primary predictors of information technology usage intention and acceptability in the previous UTAUT1, which was created by Venkatesh et al. in 2003 (Narayan & Naidu, 2024; Zacharis & Nikolopoulou, 2022). These consisted of social influence, enabling conditions, performance expectancy, and effort expectancy. The UTAUT2 model was further expanded upon by Venkatesh et al. (2012) by incorporating three more constructs: hedonic motivation, price value, and habit. As mentioned by Narayan and Naidu (2024), Researchers who have studied technology acceptance and use (such as e-learning) in higher education contexts include Al-Fraihat et al. (2020), Farooq et al. (2017), and Kumar and Bervell (2019). These researchers have used the UTAUT1 model.

The UTAUT2 model, which was created later, has also been investigated in other situations, such as online gaming, artificial intelligence, internet/mobile banking, online gaming, online gaming, artificial intelligence and VR technology (Gansser & Reich, 2021; Kwateng et al., 2018). The theory's creators urged researchers to investigate and validate their idea using a range of technologies, settings, and subjects (Narayan & Naidu, 2024; Zacharis & Nikolopoulou, 2022). By applying the UTAUT2 model in the context of higher education, educators and administrators can make informed decisions regarding the implementation of new technologies, design effective training programs, and create strategies to promote technology acceptance and use among both teachers and students (Chang et al., 2023). Talan et al. (2024) investigated the use and adoption of mobile learning tools among university students by using UTAUT2 model in higher education and highlighted the new ways and tools of learning among 21st century learners.

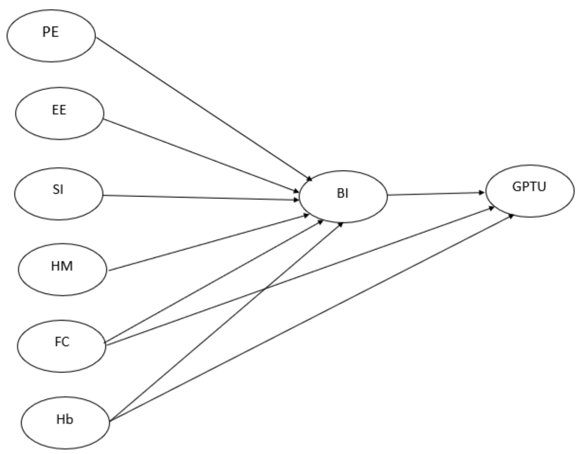
The UTAUT2 model was employed in a study on students at Indonesian higher education institutions to investigate the factors influencing the adoption and utilization of ChatGPT in the context of education. Facilitating situations were revealed to be the strongest predictor of behavioral intention to use ChatGPT in learning, according to the study. This implies that offering ChatGPT users the infrastructure, support, and resources they need can have a big impact on how ready students are to accept and use the technology. Additionally, the research revealed that the most significant factor influencing ChatGPT use was behavioral intention, suggesting that students' intentions to utilize the technology were critical to their actual utilization (Habibi et al., 2023).

2.2. Performance Expectancy (PE)

According to the UTAUT model, Performance Expectancy (PE) has a significant impact on an individual's inclination to use new technologies such as AI tools and ChatGPT for learning. According to Venkatesh et al. (2012), PE determines the user's ideas about their ability/capacity to use a specific technology (in this case, ChatGPT) to its full potential. Many studies in the context of education, specifically the use of AI technologies, indicated that PE was a strong predictor of BI (Andrews et al., 2021; Camilleri, 2024: Chatterjee & Bhattacharjee, 2020; Habibi et al., 2023; Lin et al., 2022). As Narayan and Naidu (2024) pointed out, some studies (Abbas, 2018; Ali et al., 2018; Althunibat, 2015; Dečman, 2015; Raza et al., 2021) found a positive association between PE and students' BI when adopting LMS, while other studies (Habibi et al., 2023; Zwain, 2019) found no positive impact.

H1: The significant role of PE in predicting BI to use CHATGPT among Higher Education Students of Punjab, India.

FIGURE 1. **A Proposed Model Investigating Indian Hei Students' Chatgpt acceptance and use by UTAUT2 model**



(Performance Expectancy [**PE**], Effort Expectancy [**EE**], Social Influence [**SI**], Facilitating Conditions [**FC**], Hedonic Motivation [**HM**], Habit [**Hb**], Behavioral Intention [**BI**], ChatGPT Use [**GPTU**])

In figure 1, list of hypotheses is : H1 – PE to BI, H2 – EE to BI, H3- SI to BI, H4- HM to BI, H5- FC to BI, H6- FC to GPTU, H7- Hb to BI, H8 – H to GPTU, H9- BI to GPTU.

2.3. Effort Expectancy (EE)

According to Venkatesh et al. (2012), the first UTAUT version defined EE as a variable that assesses how user-friendly technology-based tools and systems are. Positive relationships between EE and BI to apply AI have been observed in previous studies on a variety of technical systems, including digital libraries (Habibi et al., 2022), e-commerce (Bozorgkhou, 2015), banking systems (Abu-Taieh et al., 2022), and mobile payment (Al-Saedi et al., 2020). Education and artificial intelligence studies (Alhwaiti, 2023; Andrews et al., 2021; Chatterjee & Bhattacharjee, 2020; Guggemos et al., 2020; Lin et al., 2022; Raffaghelli et al., 2022) have looked into how EE affects BI. According to Guggemos et al. (2020) and Chatterjee & Bhattacharjee (2020), EE persuaded BI to use humanoid robots for academic writing and AI in Indian higher education, respectively. This PLS-SEM analysis demonstrates this influence.

H2: The significant role of EE in predicting BI to use CHATGPT among Higher Education Students of Punjab, India.

2.4. Social Influence (SI)

Social Influence (SI) refers to the extent to which influential individuals influence a person's decision to adopt technology (Venkatesh et al., 2003, 2012). Several research have indicated a favourable association between SI and students' intentions to utilize LMS (Im et al., 2011; Raza et al., 2021; Venkatesh et al., 2003) and video-based learning media assistance (Wijaya et al., 2022). As mentioned by Habibi et al. (2023), within the context of AI applications, including robotics (Guggemos et al., 2020), AI-based early warning systems (Raffaghelli et al., 2022), language learning with AI (Lin et al., 2022), augmented reality (Marto et al., 2019), post-COVID AI technology (Alhwaiti, 2023), and chatbots (Ragheb et al., 2022), researchers have reported that SI had a significant impact on BI.

H3: The significant role of SI in predicting BI to use CHATGPT among Higher Education Students of Punjab.

2.5. Hedonic Motivation (HM)

In the context of the UTAUT2 model, hedonic motivation is proposed as one of the constructs that influences behavioural intention and technology use. The UTAUT2 model extends the original UTAUT model by incorporating hedonic motivation, along with price value and habit, as additional constructs (Narayan & Naidu, 2024; Thongsri et al., 2018). Hedonic motivation refers to the pleasure or enjoyment that individuals derive from using a particular technology (Tamilmani et al., 2019). For example, as mentioned by Narayan & Naidu (2024), research like Raza et al. (2021) showed an insignificant impact of HM on BI in circumstances where in technology aids learning, Zwain (2019) and Hoi (2020) observed HM impacting both BI and Actual use. But Raza et al. (2020b) recommended that HM continue to be evaluated and examined for its impact on students' performance in further research. Study conducted by Habibi et al. (2023) concluded that Hm has a significant influence on BI. The integration of hedonic motivation into the UTAUT2 model provides a comprehensive understanding of the factors that influence technology adoption and use in education, especially in the case of ChatGPT.

H4: The significant role of SI in predicting BI to use CHATGPT among Higher Education Students of Punjab, India.

2.6. Facilitating Conditions (FC)

Facilitating conditions (FC) is defined as the existence of suitable organizational infrastructure and resources to facilitate the deployment of technology (Narayan & Naidu, 2024; Zacharis & Nikolopoulou, 2022). FC in an educational setting involves students' access to technology gadgets such as Wi-Fi, high-speed internet broadband service, personal computers, smartphones, technical support, laboratories with the necessary equipment. Consequently, FC in this way, raises the BI and Use of e-learning technologies, improving student performance and e-learning system acceptance. An obvious argument which comes out of this situation that without such prompt resource support, educators and students will get demotivated. (Yeop et al., 2016). As noted by Habibi et al. (2023) and Narayan and Naidu (2024), the literature reveals considerable discrepancies between earlier research on the effect of FC on BI, just like it does for PE and EE. This could be a result of the technological, economic, and developing states of many nations and academic institutions.

According to Habibi et al. (2023), FC has a considerable impact on BI and GPTU among Indonesian higher education students. According to Binyamin and Zafar's (2021) systematic review, FC and BI are strongly linked in the context of Mobile Health Services. On the contrary, Raza et al. (2021) and Venkatesh et al. (2003) discovered that FC is insignificant.

H5: The significant role of FC in predicting BI to use CHATGPT among Higher Education Students of Punjab, India.

H6: The significant role of FC in predicting GPTU use CHATGPT among Higher Education Students of Punjab, India.

2.7. Habit (Hb)

Habit is one significant variable that was included in the UTAUT2 model (Gansser & Reich, 2021). As rightly mentioned by Habibi et al. (2023), the sustainable use of a technology-based system is habitual, meaning it is done without conscious thought or purpose. The automatic, recurring behavioural patterns that people acquire over time are referred to as habits. When it comes to AI tools like ChatGPT and other technologies, user adoption and use are greatly influenced by habit. Studies have indicated that the presence of a habit can have a substantial impact on a person's inclination to utilize technology (Habibi et al.,2023; Moorthy et al., 2018; Shivdas et al., 2020; Tseng et al., 2019; Venkatesh et al., 2012). Due to their accustomed ways of engaging with technology, people often rely on habits when utilizing AI technologies (Venkatesh et al., 2002).

Two hypotheses in relation to habit as also checked by Habibi et al. (2023).

H7: The significant role of Hb in predicting BI to use CHATGPT among Higher Education Students of Punjab, India.

H8: The significant role of Hb in predicting GPTU (Use of ChatGPT) among Higher Education Students of Punjab, India.

2.8. Behavioural Intention (BI)

Behavioural intention refers to an individual's preparedness to use a specific technology for various tasks (Venkatesh et al., 2003). Behaviour Intention is a measure of attitudes, beliefs, and behaviours (Salifu et al., 2024). Furthermore, beliefs about an innovation before to adoption can act as the most reliable predictor of intent to succeed or fail (Vishwanath & Goldhaber, 2003).

As highlighted by Salifu et al. (2024), based on previous literature, Attitudes and beliefs are commonly recognized as the driving forces behind a user's behavioral intention to do a specific activity, which may eventually lead to the use of a specific technology. On the other hand, Actual use behavior refers to the physical evidence of technology integration into an individual's everyday life, and it serves as a measure of the effectiveness of intentions in the real application of the technology (Habibi et al., 2023; Narayan & Naidu, 2023; Salifu et al., 2024). Based on the previous literature (Ajzen, 1991; Mustafa et al., 2022; Venkatesh et al., 2012), an individual's actual use of a new technology is frequently reflective of their behavioural intentions. Therefore, behavioural intention is the most important aspect in real usage. Also, previous literature (Motaghian et al., 2013; Habibi et al., 2023; Raza et al., 2020a, 2022; Wang & Wang, 2009) highlights the strong relationship between BI and actual use in technology-assisted learning.

H9: The significant role of BI in predicting GPTU (use of CHATGPT) among Higher Education Students of Punjab, India.

3. METHOD

3.1. Instrument used

The current study took into account the 31 items utilized by Habibi et al. (2023) on a 5-point Likert scale. Four items for PE, EE, SI, FC, and BI (Habibi et al., 2023; Venkatesh et al., 2012). Meanwhile, HM and GPTU comprise three items, while H contains five items (Habibi et al., 2023). Ten specialists in educational technology were invited to analyse the items for the content validity process. Finally, 31 items presented in Appendix 1 were used for both the pilot research and the full data collection.

3.2. Data Collection

Data collection for this study was done by non-probability sampling using a Google Form Survey. The questionnaire included sections of demographic information and the main survey questions. No personal information was recorded so that respondents could freely express their options without any fear of issues with confidentiality. In a pilot study to check the reliability of the adapted questionnaire, 100 responses were taken. The Cronbach alpha value of reliability of each variable came out to be > 0.7 (Ramu et al., 2023). These responses were not included in the final analysis. For final data collection, out of 600 google forms reached to respondents via contacting concerned Faculty members of the institutions in Punjab State, India. 362 responses were received for further analysis. Out of 362, 49 responses were discarded due to lack of heterogeneity in the responses. The standard deviation for these responses came out to be 0, so for the final analysis, 313 responses were considered. No personal details were recorded beyond gender and educational level (graduate or postgraduate) of the students to make responses authentic and to ensure the confidentiality of respondents. Among 313 respondents, in terms of Gender, 194 were female. (62%) and 119 males (38%) and, in terms of education level, 103 graduate students (33%) and 210 postgraduate students (67%).

3.3. Data analysis

To do the data analysis, PLS-SEM by using Smart PLS 4 was employed due to its robustness of handling sample sizes and non – normal data assumptions (Hair et al., 2021). Measurement and Structural Model were assessed along with IPMA (Importance-performance map analysis technique) to support the Structural Model. Moreover, IPMA is helpful to understand results of PLS-SEM by taking the performance of each construct into account (Ringle et al., 2018).

3.4. Data preparation

Table 1 shows the descriptive level information of items under variables i.e. PE, EE, SI, FC, HM, Hb, BI, GPTU which shows skewness and kurtosis values. Expect items Hb3 and Hb4 under the variable of Habit, all items have VIF less than 4 (Ramayah et al., 2018).

TABLE 1. Mean, Standard Deviation, Kurtosis, Skewness and VIF (Item wise)

Variable	Item	Mean	SD	Kurtosis	Skewness	VIF
PE	PE1	4.026	0.719	-0.297	-0.297	1.978
	PE2	3.965	0.751	0.383	-0.488	2.181
	PE3	3.933	0.771	0.766	-0.602	2.223
	PE4	3.923	0.784	0.626	-0.585	2.107
EE	EE1	4.042	0.734	0.586	-0.553	1.689
	EE2	3.802	0.766	0.662	-0.545	1.716
	EE3	4.051	0.701	1.344	-0.689	1.929
	EE4	3.706	0.863	0.642	-0.623	1.483
SI	SI1	3.706	0.821	0.063	-0.383	2.428
	SI2	3.581	0.854	0.031	-0.225	2.413
	SI3	3.396	0.906	0.106	-0.245	1.856
	SI4	3.307	0.952	-0.125	-0.266	1.887
FC	FC1	4.105	0.794	1.679	-0.998	1.713
	FC2	3.843	0.845	0.343	-0.559	1.591
	FC3	4.019	0.741	0.287	-0.457	1.728
	FC4	3.623	0.867	0.044	-0.368	1.315
HM	HM1	3.552	0.911	0.193	-0.416	2.704
	HM2	3.613	0.876	0.618	-0.565	3.567
	HM3	3.461	0.886	0.347	-0.349	2.814

Variable	Item	Mean	SD	Kurtosis	Skewness	VIF
Hb	Hb1	2.895	1.107	-0.695	0.125	3.041
	Hb2	3.083	1.075	-0.599	0.066	3.729
	Hb3	3.096	1.047	-0.477	-0.042	*5.394*
	Hb4	3.019	1.057	-0.565	0.027	*4.933*
	Hb5	3.278	1.051	-0.412	-0.309	2.105
BI	BI1	3.381	0.918	0.078	-0.278	1.856
	BI2	3.521	0.865	0.357	-0.392	2.665
	BI3	3.559	0.825	0.194	-0.224	3.168
	BI4	3.612	0.804	0.355	-0.214	2.817
GPTU	GPTU1	3.153	1.018	-0.563	-0.074	1.809
	GPTU2	2.728	1.099	-0.567	0.235	2.194
	GPTU3	2.99	1.047	-0.477	0.086	1.965

After deleting Hb3 and Hb4, new VIF for Hb1, Hb2 and Hb5 was 2.542, 2.576 and 1.857, respectively.

4. FINDINGS

4.1. Measurement Model

The measurement model was employed to assess the reliability and validity of the proposed model (Figure 1). As mentioned by Hair et al. (2019), Loadings above 0.708 are recommended. Table 2 shows that loadings are above this threshold. Values of Cronbach's alpha, rho_A and Composite Reliability for variables in the model are within threshold limits (higher than 0.700). In table 2, the measure of convergent validity i.e. AVE (Average Variance Explained) is higher than >50% of the variance which indicates that each construct in the model explains 50% or more of the variance of the items that make up the construct (Hair et al., 2019). HM has highest AVE with 83% of the variance explained with FC has lowest value with 60% variance explained.

TABLE 2. Loadings, Cronbach alpha, rho_A, CR, AVE of Variables

Variable	Item	Loadings	Alpha	rho_A	CR	AVE
BI	BI1	0.811	0.892	0.894	0.926	0.757
	BI2	0.886				
	BI3	0.903				
	BI4	0.878				
EE	EE1	0.742	0.808	0.828	0.872	0.631
	EE2	0.788				
	EE3	0.85				
	EE4	0.794				
FC	FC1	0.802	0.783	0.782	0.86	0.607
	FC2	0.79				
	FC3	0.801				
	FC4	0.719				

Variable	Item	Loadings	Alpha	rho_A	CR	AVE
GPTU	GPTU1	0.869	0.836	0.844	0.901	0.752
	GPTU2	0.874				
	GPTU3	0.859				
Hb	Hb1	0.901	0.862	0.862	0.916	0.784
	Hb2	0.902				
	Hb5	0.853				
HM	HM1	0.898	0.904	0.908	0.94	0.839
	HM2	0.936				
	HM3	0.914				
PE	PE1	0.817	0.867	0.871	0.909	0.715
	PE2	0.858				
	PE3	0.857				
	PE4	0.852				
SI	SI1	0.825	0.829	0.835	0.886	0.661
	SI2	0.829				
	SI3	0.781				
	SI4	0.815				

For Discriminant Validity, as mentioned by Hair et al. (2019), according to Henseler et al. (2014), HTMT values for each construct need to be less than .90 to prove the constructs to be conceptually different. Table 3 shows that HTMT Values of all variables are within limits. Loadings in Table 5 for each variable are greater than their cross loadings on other variables. Loadings are highlighted in bold in Table 4. As per Fornell – Larcker criteria (Fornell & Larcker, 1981), the shared variance for all constructs under the model need to have smaller value than their AVEs (mentioned in Table 5).

TABLE 3. HTMT

	BI	EE	FC	GPTU	Hb	HM	PE
BI							
EE	0.618						
FC	0.69	0.735					
GPTU	0.812	0.52	0.502				
Hb	0.84	0.471	0.518	0.81			
HM	0.653	0.526	0.554	0.538	0.558		
PE	0.746	0.741	0.663	0.624	0.625	0.605	
SI	0.747	0.667	0.588	0.73	0.737	0.542	0.723

TABLE 4. Cross Loadings

	BI	EE	FC	GPTU	Hb	HM	PE	SI
BI1	**0.811**	0.391	0.462	0.601	0.698	0.478	0.512	0.606
BI2	**0.886**	0.48	0.484	0.588	0.639	0.554	0.617	0.533
BI3	**0.903**	0.541	0.557	0.665	0.64	0.503	0.592	0.575
BI4	**0.878**	0.474	0.504	0.629	0.582	0.508	0.569	0.542
EE1	0.312	**0.742**	0.419	0.174	0.217	0.248	0.403	0.313
EE2	0.378	**0.788**	0.43	0.348	0.284	0.397	0.506	0.409
EE3	0.474	**0.85**	0.545	0.372	0.346	0.411	0.527	0.46
EE4	0.513	**0.794**	0.473	0.479	0.404	0.377	0.543	0.57
FC1	0.478	0.437	**0.802**	0.272	0.297	0.333	0.442	0.301
FC2	0.433	0.468	**0.79**	0.35	0.371	0.293	0.373	0.366
FC3	0.462	0.455	**0.801**	0.276	0.279	0.345	0.438	0.355
FC4	0.424	0.483	**0.719**	0.38	0.376	0.474	0.45	0.465
GPTU1	0.705	0.403	0.382	**0.869**	0.721	0.435	0.527	0.549
GPTU2	0.535	0.317	0.26	**0.874**	0.636	0.352	0.388	0.476
GPTU3	0.599	0.453	0.42	**0.859**	0.604	0.437	0.471	0.567
Hb1	0.625	0.368	0.379	0.715	**0.901**	0.508	0.483	0.591
Hb2	0.654	0.359	0.391	0.668	**0.902**	0.43	0.475	0.536
Hb5	0.675	0.357	0.363	0.629	**0.853**	0.373	0.479	0.536
HM1	0.498	0.402	0.456	0.377	0.413	**0.898**	0.486	0.387
HM2	0.552	0.462	0.441	0.434	0.449	**0.936**	0.512	0.447
HM3	0.56	0.398	0.387	0.485	0.492	**0.914**	0.481	0.471
PE1	0.499	0.523	0.455	0.427	0.435	0.39	**0.817**	0.479
PE2	0.579	0.524	0.424	0.476	0.463	0.475	**0.858**	0.554
PE3	0.557	0.514	0.445	0.449	0.455	0.476	**0.857**	0.499
PE4	0.587	0.573	0.527	0.467	0.476	0.47	**0.85**	0.561
SI1	0.496	0.523	0.419	0.441	0.437	0.354	0.462	**0.825**
SI2	0.544	0.508	0.41	0.501	0.509	0.333	0.515	**0.829**
SI3	0.455	0.345	0.302	0.48	0.505	0.351	0.45	**0.78**
SI4	0.593	0.463	0.414	0.563	0.574	0.493	0.573	**0.815**

TABLE 5. Fornell – Larcker criteria

	BI	EE	FC	GPTU	H	HM	PE	SI
BI	0.871							
EE	0.543	0.795						
FC	0.577	0.593	0.779					
GPTU	0.714	0.454	0.412	0.867				
Hb	0.735	0.408	0.427	0.758	0.885			
HM	0.587	0.459	0.466	0.474	0.494	0.916		
PE	0.659	0.631	0.547	0.539	0.541	0.538	0.846	
SI	0.648	0.569	0.479	0.615	0.627	0.476	0.621	0.813

So, under the light of above calculation of Reliability measures of Cronbach Alpha, rho_A, Composite reliability and AVE and Validity measures of HTMT, Fornell- Larker criteria and cross loadings criteria proved the use of measurement model for further Hypotheses testing by using Structural model findings.

4.2. Structural Model

To assess the structural model of the current investigation, Standardized Root Mean Square Residual (SRMR) was calculated before determining the significance of the hypotheses under discussion (Habibi et al., 2023; Kono & Sato, 2022). The SRMR is a fit measurement used to prevent model misspecification in PLS-SEM (Magno et al., 2024). The ideal range for SRMR is 0.08 to 0.10, and the model can be educated to ensure a good fit. As shown in Table 6. The current model's SRMR value of 0.065 has proven to be a good fit. In addition, the squared Euclidean distance (d_ULS) and the geodesic distance (d_G) are provided, supporting the SRMR analysis (Table 6), in which both criteria have no specific measurement values; the values of d_ULS and d_G are 1.362 and 0.518, respectively (Hair et al., 2019).

The structural model used a boot-strapping procedure with 10,000 subsamples (Becker et al., 2022; Cheah et al., 2023). Path coefficient values (β, t, and p-values) were computed. Out of nine hypotheses, two are rejected (EE -> BI and FC -> GPTU), while the remaining seven are confirmed/supported.

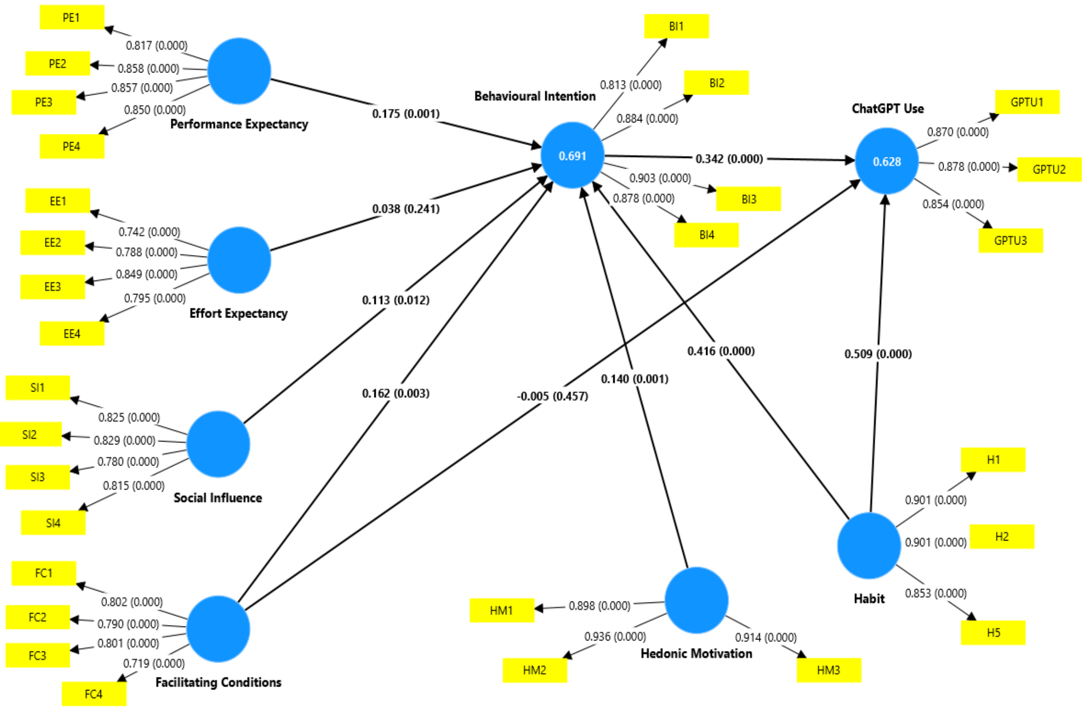
Four variables have a substantial impact on BI's use of ChatGPT in learning. In detail, FC is a significant predictor of BI followed by PE. The table 6 includes three values (β, t, and p), as well as the coefficient of determination (R2) and effect sizes (f2). R2 is the correlation of squares between dependent variables, which is used to assess how effectively an endogenous variable predicts external variables (Habibi et al.,2023). Figure 2 shows that all of the components (PE, EE, SI, HM, FC, and Hb) account for 69% of the variance within BI (R2 =0.691). Further variables (Hb, FC, and BI) explain 62.8% of the variation in the use of ChatGPT in learning among HEI students in Punjab, India.

R2 values are characterized as moderate (Cheah et al., 2023; Habibi et al., 2023; Hair et al., 2019; Kono & Sato, 2023). Along with this, effect sizes (f2) are calculated. Table 6 displays all f2 values for each relation in the model. The highest effect size emerges between H and GPTU (f2 =0.318), followed by the impact size between Hb and BI 0.3, while the smallest is seen in the association between EE and BI (f2 =0.002), followed by the effect between FC and BI (0.048). There is no effect size between FC and GPTU (f2 = 0.000).

TABLE 6. **Structural model of factors affecting Indian HEI students' ChatGPT acceptance and use**

Hypotheses	Relationship	Beta value	mean (M)	SD	T statistics	P values	Supported?	f2	Model fit
H1	PE -> BI	0.175	0.176	0.054	3.261	0.001	Supported	0.044	SRMR (0.065),
H2	EE -> BI	0.038	0.046	0.053	0.717	0.241	Not Supported	0.002	
H3	SI -> BI	0.113	0.115	0.05	2.247	0.012	Supported	0.018	
H4	HM -> BI	0.140	0.139	0.047	3.023	0.001	Supported	0.04	d_ULS(1.845),
H5	FC -> GPTU	-0.005	-0.004	0.042	0.043	0.457	Not Supported	0	
H6	FC -> BI	0.162	0.155	0.059	2.733	0.003	Supported	0.048	d_G(0.719)
H7	Hb -> BI	0.416	0.413	0.041	10.033	0	Supported	0.3	
H8	Hb -> GPTU	0.509	0.510	0.051	9.982	0	Supported	0.318	
H9	BI -> GPTU	0.342	0.341	0.056	6.166	0	Supported	0.118	

FIGURE 2. Final model investigating Indian HEI students' ChatGPT acceptance & use



(Performance Expectancy [**PE**], Effort Expectancy [**EE**], Social Influence [**SI**], Facilitating Conditions [**FC**], Hedonic Motivation [**HM**], Habit [**Hb**], Behavioral Intention [**BI**], ChatGPT Use [**GPTU**])

4.3. IPMA

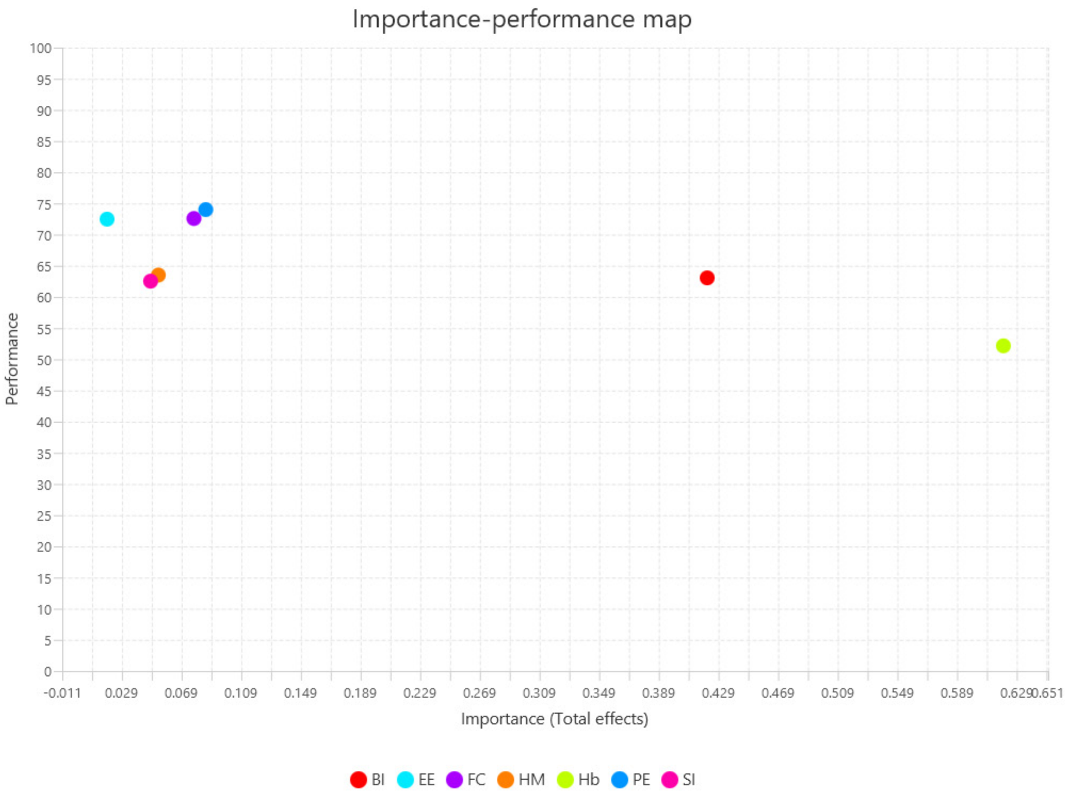
The importance-performance map analysis (IPMA) expands on the findings of PLS-SEM by taking into consideration the performance of each component. As a result, conclusions may be reached on two dimensions (importance and performance), which is very useful for prioritizing managerial initiatives (Hair et al., 2021). Table 7 presents the needed results for the current investigation. The results demonstrate that H has a high impact on both BI (0.416) and GPTU (0.507). Following that, PE on BI had a beta value of 0.176. Higher values, ranging from 1 to 100, indicate higher performance. Table 7 reveals that EE has the highest performance (72.487), while GPTU has the lowest at 49.449.

TABLE 7. IPMA results: Factors affecting ChatGPT BI and use

Performance		Importance	
		BI	**GPTU**
BI	63.066		0.422
EE	72.487	0.046	
FC	72.592	0.191	0.078
GPTU	49.449		
Hb	52.169	0.323	0.621
HM	63.513	0.128	
PE	74.018	0.203	
SI	62.538	0.115	

In Figure 3, IPMA (Importance-performance map), the x-axis reflects how important each factor is for the overall model. The Y-axis reflects the performance, showing how well each factor is rated by users in the context of ChatGPT usage among university students. From the map it can be deduced that PE (Performance Expectancy) and EE (Effort expectancy) were rated high which suggested that University students find ChatGPT useful and easy to use. BI (Behaviour Intention) was crucial but did not perform as strongly as it could have, so it indicated that University curriculum can be planned so that it can improve and promote use of such tools in their learnings. In terms of SI (Social Influence) and Hb (Habit), these two constructs played a weaker role in affecting ChatGPT use among university students.

FIGURE 3. IPMA (Importance- Performance Map)



Aside from the responses to the questionnaire adopted from Habibi et al. (2023). Researchers also asked the students, "According to you, in which class/grade do students need training/guidance related to ChatGPT & Artificial Intelligence?" with four options: "6-8th Grade," "9-10 Garde," "11-12 Grade," and "Graduation." The percentage of the given options are as follows:

TABLE 8. Responses of HEIs students on "According to you, in which class/grade, students need the training/guidance related to ChatGPT & Artificial Intelligence"

Options	Frequency	%age
6-8th Grade	51	16%
9-10 Grade	86	27%
11-12 Grade	74	24%
Graduation	102	33%
Total	**313**	

The table 8 demonstrates that HEI students recognized the necessity to learn AI tools in schools. 67% of respondents prioritized learning these techniques while in school. In the Indian setting, as indicated by NEP (2020) under point no. 4.23, 4.24 at page no. 15, the addition of coding and artificial intelligence-related subjects at all levels, is a positive step. NEP 2020 also highlighted the same concern under point no. 23 i.e. "Technology Use and Integration", to establish an autonomous body, the National Educational Technology Forum (NETF) for the free exchange of ideas on the use of technology to enhance learning at both school and higher education level.

5. DISCUSSION

The structural model and IPMA analysis revealed that PE, SI, Hb, FC, and HM had substantial relationships with BI; Hb had a significant relationship with GPTU, and BI had a significant link with GPTU as well. However, there is no relevant link between EE and BI, nor between FC and GPTU. The findings revealed that Hb is the most important variable influencing BI to utilize ChatGPT while learning, as perceived by Punjab (India) higher education students.

Previous research has revealed the significance of Hb toward BI and Hb towards actual usage of ChatGPT (Cabrera-Sánchez et al., 2021; Chatterjee & Bhattacharjee, 2020; Fadzil, 2018; Foroughi et al., 2023; Gansser & Reich, 2021; Venkatesh, 2021). So, both of the significant outcomes (Hb -> BI and Hb -> GPTU) indicate that Indian Higher Education Students' habit of using ChatGPT influences their intention and use of ChatGPT in learning.

For the significance of SI in BI, the current results suggest that Social Influence (SI) plays an essential role in predicting BI when using ChatGPT. Furthermore, the data show that important others among Indian Higher Education Students have an impact on the BI of utilizing ChatGPT. Many prior studies have found similar results, including Alhwaiti (2023), Fadzil (2018), Guggemos et al. (2021), Habibi et al. (2023), Lin et al. (2022), and Mohd Rahim et al. (2022).

The significance of PE toward BI in the Indian Higher Education Context could be attributed to ChatGPT's function in enhancing learning tasks as well as the views given by ChatGPT on learning themes. Previous investigations have supported this conclusion (Alhwaiti, 2023; Andrews et al., 2021; Chatterjee & Bhattacharjee, 2020; Fadzil, 2018; Guggemos et al., 2020; Habibi et al., 2023; Lin et al., 2022; Mohd Rahim et al., 2022; Raffaghelli et al., 2022).

Vankatesh (2021) emphasized the relevance of FC in relation to BI and the actual application of ChatGPT, citing resource availability and technological system support. In the current study, FC was found to be a significant predictor of BI but not of ChatGPT use. As a result, it raises the worry that, while FC is an essential predictor for Indian students' behavioural intentions while utilizing ChatGPT, they have expressed concern about a lack of resources and support systems in higher education. Mohd Rahim et al. (2022) found similar results supporting FC to BI in the application of AI chatbots in Higher Education. This finding is consistent with the findings of Cabrera-Sanchez et al. (2021), who found that FC has a considerable influence on the actual use of AI but not on BI. As a result, the current findings highlight the support provided by technological systems to Indian higher education students.

In terms of the importance of HM in BI, the current findings are consistent with many earlier studies, including Azizi et al. (2020) (in a medical context), Arain et al. (2019) (mobile learning in higher education), and Habibi et al. (2023) (ChatGPT use in higher education). As a result, the findings reveal a particular inclination/motivation among Higher Education Students to use ChatGPT in their learning. So, students in Indian higher education like using ChatGPT.

In the instance when the relationship between EE and BI is not significant in the current data, Habibi et al. (2023) found similar results with EE. Some prior investigations found comparable results in the UTAUT environment (Andrews et al., 2021; Shivdas et al., 2020; Mohd Rahim et al., 2022). According to Habibi et al. (2023), the reason for this outcome could be that ChatGPT is an extension of other services such as Google and other technologies, and students in Higher Education perceive this as a normal modification in the list of already used technologies. In addition, BI demonstrated to be a strong predictor of actual ChatGPT use among Higher Education students. It supports the UTAUT2 model's claim that the more people intend to use new technology, the more and better they perform. So, it applies to ChatGPT and its application in learning (Habibi et al., 2023).

Practical implications

In terms of practical implications of this study, the results provide significant insights for universities, educators and policy makers to design the current and upcoming policy level, university level and classroom level changes in curriculum overall by considering use of ChatGPt and AI tools in higher education. This study highlights the insignificant influence of Facilitation Conditions on actual use of ChatGPT. It opens up the discussion for HEIs in India on what type of preparation is taking place at the policy and institutional levels in terms of training courses or technology support for students in relation to AI technologies. This study intended to spark a discussion about the intention and use of ChatGPT among Indian higher education students, notably those in Punjab. As NEP 2020 (recent education policy) highlighted the use and importance of AI in the educational experiences of students by introducing coding at grade 6; this study also made similar inputs that most of the students wanted the use of ChatGPT and AI tools at the school level to explore these new knowledge tools. As suggested by NEP 2020, the National Educational Technological Forum (NETF) will be an autonomous body for the leadership of education institutions, State and Central governments, and other stakeholders to decide the induction, deployment, and use of technology, by providing, the latest knowledge and research as well as the opportunity to consult and share best practices.

So, this study highlighted the importance of incorporating courses or modules in the higher education curriculum. With this, university students can understand the role and importance of ChatGPT and AI tools in the context of learning. Moreover, the facilitating conditions need to be taken care of, if universities want to improve the adoption and use of AI in higher education. Along with this, ethical considerations and professionalism need to be practiced with AI use and adoption among university students. Also, the results can also add to a better understanding of the impact and utility of future AI systems by focusing on the relevance of user intentions in aiming to maximize the potential of such technologies for learning.

HEIs need to review their policies related to academic honesty and integrity in relation to ChatGPT and other AI tools. It is imperative that some mentoring and support is provided to help staff and students enhance their research technological expertise. Also, it is important that one helps students use ChatGPT as an adjunct to spontaneous human creativity and critical thinking.

Theoretical Implications

In terms of theoretical implications, this study provided the validation of the UTAUT2 model among university students in the context of Punjab, India. With 62.8% variance explained, this study gave compelling evidence in favour of the UTAUT2 model in the context of ChatGPT adoption and use among university students. In the context of a developing country, India can tackle the emergence of AI; the study's findings can be helpful in the adoption of AI technology. The results can be generalized to other developing countries considering the low level of awareness about AI tools.

6. LIMITATIONS AND FUTURE WORK

The current study on the use of ChatGPT in higher education, specifically among students in Punjab, India, highlights important insights but also faces some limitations. The research focuses on a single region-Punjab, limiting the generalizability of the findings across India's diverse socio-economic and educational contexts. Also, with a relatively small sample size and a focus only on students, the study does not account for teachers' perspectives, which are crucial in understanding the overall readiness for AI integration. Furthermore, concerns about academic integrity related to AI tools like ChatGPT were acknowledged but not explored in depth. The present study employed only quantitative methods for data analysis. For a more holistic perspective, research in the future could also use a combination of qualitative and quantitative methods; for eg., interviews of students could also be conducted to get a deeper understanding of their viewpoints regarding ChatGPT use.

Future research may focus on including other regions in the country, offering comparative studies to identify both common and unique factors affecting AI adoption. The inclusion of teachers' perspectives is essential, as they play a major role in implementing AI tools in the classroom. Additionally, multigroup analyses considering factors like age, gender, and cultural diversity could help provide more comprehensive insights. Researchers should also examine institutional readiness, policies, and support systems that facilitate AI integration, along with more focus on academic integrity and ethical use of AI. Expanding the scope of the UTAUT2 model and exploring technological infrastructure and readiness will further contribute to a more holistic understanding of AI's role in higher education.

7. CONCLUSION

The Horizon report (2023) in its Teaching and Learning Edition expressed concern for Higher Education Institutions about the need to plan for how to harness AI and its impending tools and services, such as ChatGPT, to improve efficiency and learning. However, this survey raises several issues about academic integrity, correctness, and cheating among higher education students. As a result, it encourages higher education educators to be mindful of the introduction of AI tools such as ChatGPT into the lives of their students. So that curriculum and assessments may be created accordingly to incorporate AI tools such as ChatGPT into the learning process. Şimşek and Ateş (2022) concluded in their study that it is important to understand teachers' intentions to use Web 2.0 technologies in their respective courses which ultimately empowers students' efforts to use such tools in their own learning.

Moreover, present study results also highlight the insignificant influence of Facilitation Conditions on actual use of ChatGPT. It opens up the discussion for HEIs in India on what type of preparation is taking place at the policy and institutional levels in terms of training courses or technology support for students in relation to AI technologies. This study intended to spark a discussion about the intention and use of ChatGPT among Indian higher education students, notably those in Punjab.

8. REFERENCES

Abbas, J. (2018). Exploring the relationships among system quality, knowledge quality, and user satisfaction in the success of knowledge management systems: An empirical study. *Journal of Information & Knowledge Management, 17*(1), 1–21. https://doi.org/10.1142/S0219649218500079

Abu-Taieh, E. M., AlHadid, I., Abu-Tayeh, S., Masa'deh, R., Alkhawaldeh, R. S., Khwaldeh, S., & Alrowwad, A. (2022). Continued intention to use of M-banking in Jordan by integrating UTAUT, TPB, TAM, and service quality with ML. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), Article 120. https://doi.org/10.3390/joitmc8030120

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-t

Aldosari, S. A. (2020). The future of higher education in light of artificial intelligence transformations. *International Journal of Higher Education*, *9*(3), 145. https://doi.org/10.5430/ijhe.v9n3p145

Al-Fraihat, D., Joy, M., Masa'deh, R., & Sinclair, J. (2020). Evaluating E-learning systems success: An empirical study. *Computers in Human Behavior*, *102*, 67-86. https://doi.org/10.1016/j.chb.2019.08.004

Alhwaiti, M. (2023). Acceptance of artificial intelligence application in the post-covid era and its impact on faculty members' occupational well-being and teaching self efficacy: A path analysis using the UTAUT 2 model. *Applied Artificial Intelligence*, *37*(1), Article 2175110 https://doi.org/10.1080/08839514.2023.2175110

Ali, M., Raza, S. A., Qazi, W., & Puah, C. (2018). Assessing E-learning system in higher education institutes. *Interactive Technology and Smart Education*, *15*(1), 59-78. https://doi.org/10.1108/itse-02-2017-0012

AlKursheh, T. (2024). Higher tertiary education perspectives: Evaluating the electronic assessment techniques of the blackboard platform for fairness and reliability. *Innoeduca. International Journal of Technology and Educational Innovation*, *10*(1), 144-165. https://doi.org/10.24310/ijtei.101.2024.17813

Al-Saedi, K., Al-Emran, M., Ramayah, T., & Abusham, E. (2020). Developing a general extended UTAUT model for M-payment adoption. *Technology in Society*, *62*, Article 101293. https://doi.org/10.1016/j.techsoc.2020.101293

Althunibat, A. (2015). Determining the factors influencing students' intention to use M-learning in Jordan higher education. *Computers in Human Behavior*, *52*, 65-71. https://doi.org/10.1016/j.chb.2015.05.046

Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. *The Journal of Academic Librarianship*, *47*(6), 102437. https://doi.org/10.1016/j.acalib.2021.102437

Arain, A. A., Hussain, Z., Rizvi, W. H., & Vighio, M. S. (2019). Extending UTAUT2 toward acceptance of mobile learning in the context of higher education. *Universal Access in the Information Society*, *18*(3), 659-673. https://doi.org/10.1007/s10209-019-00685-8

Azizi, S. M., Roozbahani, N., & Khatony, A. (2020). Factors affecting the acceptance of blended learning in medical education: Application of UTAUT2 model. *BMC Medical Education*, *20*(1). https://doi.org/10.1186/s12909-020-02302-2

Becker, J., Cheah, J., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2022). PLS-SEM's most wanted guidance. *International Journal of Contemporary Hospitality Management*, *35*(1), 321-346. https://doi.org/10.1108/ijchm-04-2022-0474

Binyamin, S. S., & Zafar, B. A. (2021). Proposing a mobile apps acceptance model for users in the health area: A systematic literature review and meta-analysis. *Health Informatics Journal, 27*(1), Article 1460458220976737. https://doi.org/10.1177/1460458220976737

Bozorgkhou, N. (2015). An internet shopping user adoption model using an integrated TTF and UTAUT: Evidence from Iranian consumers. *Management Science Letters*, *5*(2), 199-204. https://doi.org/10.5267/j.msl.2014.12.017

Cabrera-Sánchez, J., Villarejo-Ramos, Á. F., Liébana-Cabanillas, F., & Shaikh, A. A. (2021). Identifying relevant segments of AI applications adopters – Expanding the UTAUT2's variables. *Telematics and Informatics*, *58*, Article 101529. https://doi.org/10.1016/j.tele.2020.101529

Camilleri, M. A. (2024). Evaluating service quality and performance of higher education institutions: A systematic review and a post-COVID-19 outlook. *Journal of Marketing for Higher Education, 34*(1), 1–24. https://doi.org/10.1080/08841241.2023.2165965

Chang, L., Wang, Y., Liu, J., Feng, Y., & Zhang, X. (2023). Study on factors influencing college students' digital academic reading behavior. *Frontiers in Psychology, 13*. https://doi.org/10.3389/fpsyg.2022.1007247

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

Cheah, J., Amaro, S., & Roldán, J. L. (2023). Multigroup analysis of more than two groups in PLS-SEM: A review, illustration, and recommendations. *Journal of Business Research*, *156*, Article 113539. https://doi.org/10.1016/j.jbusres.2022.113539

Choi, J. H., Hickman, K. E., Monahan, A., & Schwarcz, D. (2023). ChatGPT goes to law school. *71 Journal of Legal Education, 387*. https://doi.org/10.2139/ssrn.4335905

Dečman, M. (2015). Modeling the acceptance of E-learning in mandatory environments of higher education: The influence of previous education and gender. *Computers in Human Behavior*, *49*, 272-281. https://doi.org/10.1016/j.chb.2015.03.022

Dowling, M., & Lucey, B. (2023). ChatGPT for (finance) research: The banality of evil or the best of both worlds? *Finance Research Letters, 51*, 103362. https://doi.org/10.1016/j.frl.2023.103362

Duong, D., Nguyen, T., & Nguyen, A. (2023). The impact of ChatGPT on education: A study on the use of AI tools in academic settings. *Journal of Educational Technology Development and Exchange, 16*(2), 1-15. https://doi.org/10.18785/jetde.1602.01

Eke, D. O. (2023). ChatGPT and the rise of AI in creative writing: Implications for authors and publishers. *Publishing Research Quarterly, 39*(2), 203-217. https://doi.org/10.1007/s12109-023-09912-3

Fadzil, F. (2018). A study on factors affecting the behavioral intention to use mobile apps in Malaysia. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3090753

Farooq, M. S., Salam, M., Jaafar, N., Fayolle, A., Ayupp, K., Radovic-Markovic, M., & Sajid, A. (2017). Acceptance and use of lecture capture system (LCS) in executive business studies. *Interactive Technology and Smart Education*, *14*(4), 329-348. https://doi.org/10.1108/itse-06-2016-0015

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., Annamalai, 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*, *40*(17), 4501–4520. https://doi.org/10.1080/10447318.2023.2226495

Gansser, O. A., & Reich, C. S. (2021). A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society*, *65*, Article 101535. https://doi.org/10.1016/j.techsoc.2021.101535

Guggemos, J., & Seufert, S. (2021). Teaching with and teaching about technology- Evidence for professional development of in-service teachers. *Computers in Human Behavior*, *115*, Article 106613. https://doi.org/10.1016/j.chb.2020.106613

Guggemos, J., Seufert, S., & Sonderegger, S. (2020). Humanoid robots in higher education: Evaluating the acceptance of Pepper in the context of an academic writing course using the UTAUT. *British Journal of Educational Technology*, *51*(5), 1864-1883. https://doi.org/10.1111/bjet.13006

Habibi, A., Muhaimin, M., Danibao, B. K., Wibowo, Y. G., Wahyuni, S., & Octavia, A. (2023). ChatGPT in higher education learning: Acceptance and use. *Computers and Education: Artificial Intelligence*, *5*, Article 100190. https://doi.org/10.1016/j.caeai.2023.100190

Habibi, A., Yaakob, M. F., & Sofwan, M. (2022). Student use of digital libraries during COVID-19: Structural equation modelling in Indonesian and Malaysian contexts. *The Electronic Library*, *40*(4), 472-485. https://doi.org/10.1108/el-12-2021-0212

Hair, J. F., Hult, G. T., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). An introduction to structural equation modeling. In *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R. Classroom Companion: Business* (pp. 1-29). Springer. https://doi.org/10.1007/978-3-030-80519-7_1

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. https://doi.org/10.1108/ebr-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2014). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115-135. https://doi.org/10.1007/s11747-014-0403-8

Hoi, V. N. (2020). Understanding higher education learners' acceptance and use of mobile devices for language learning: A Rasch-based path modeling approach. *Computers & Education*, *146*, 103761. https://doi.org/10.1016/j.compedu.2019.103761

Huang, K. (2023). Artificial intelligence in education: A review of current developments and future prospects. *Educational Technology & Society, 26*(1), 105-117. https://doi.org/10.1007/s11423-023-10012-8

Im, I., Hong, S., & Kang, M. S. (2011). An international comparison of technology adoption: Testing the UTAUT model. *Information & Management, 48*(1), 1–8. https://doi.org/10.1016/j.im.2010.09.001

Kono, S., & Sato, M. (2022). The potentials of partial least squares structural equation modeling (PLS-SEM) in leisure research. *Journal of Leisure Research*, *54*(3), 309-329. https://doi.org/10.1080/00222216.2022.2066492

Kumar, J. A., & Bervell, B. (2019). Google Classroom for mobile learning in higher education: Modelling the initial perceptions of students. *Education and Information Technologies*, *24*(2), 1793-1817. https://doi.org/10.1007/s10639-018-09858-z

Kwateng, K. O., Atiemo, K. A., & Appiah, C. (2018). Acceptance and use of mobile banking: An application of UTAUT2. *Journal of Enterprise Information Management, 32*(1), 118–151. https://doi.org/10.1108/JEIM-03-2018-005

Lim, W. M., Kumar, S., & Ali, F. (2022). Understanding Generation Z: A review and future research agenda. *Journal of Business Research, 142*, 1-16. https://doi.org/10.1016/j.jbusres.2021.12.038

Lim, W. M., Kumar, S., & Ali, F. (2023). Exploring the potential of ChatGPT in higher education: A preliminary study. *Education and Information Technologies, 28*(3), 2501-2520. https://doi.org/10.1007/s10639-023-11021-2

Lin, H. C., Ho, C. F., & Yang, H. (2022). Understanding adoption of artificial intelligence-enabled language e-learning system: An empirical study of UTAUT model. *International Journal of Mobile Learning and Organisation*, *16*(1), 74. https://doi.org/10.1504/ijmlo.2022.119966

Lund, B. D., & Wang, T. (2023). ChatGPT in academia: Opportunities and challenges. *Journal of Academic Librarianship, 49*(1), Article 102123. https://doi.org/10.1016/j.acalib.2022.102123

Magno, F., Cassia, F., & Ringle, C. M. (2024). A brief review of partial least squares structural equation modeling (PLS-SEM) use in quality management studies. *The TQM Journal*, *36*(5), 1242-1251. https://doi.org/10.1108/tqm-06-2022-0197

Marto, A., Gonçalves, A., Martins, J., & Bessa, M. (2019). Applying UTAUT model for an acceptance study alluding the use of augmented reality in archaeological sites. In A. Tremeau, G. M. Farinella, & J. Braz (Eds.). *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications* (pp. 111-120). https://doi.org/10.5220/0007364101110120

Mogavi, O., Smith, J., & Lee, A. (2024). Balancing AI assistance and cognitive development in education. *Computers & Education, 182*, Article 104484. https://doi.org/10.1016/j.compedu.2022.104484

Mohd 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), Article 12726. https://doi.org/10.3390/su141912726

Moorthy, K., Chun T'ing, L., Ming, K. S., Ping, C. C., Ping, L. Y., Joe, L. Q., & Jie, W. Y. (2018). Behavioral intention to adopt digital library by the undergraduates. *International Information & Library Review*, *51*(2), 128-144. https://doi.org/10.1080/10572317.2018.1463049

Motaghian, H., Hassanzadeh, A., & Moghadam, D. K. (2013). Factors affecting university instructors' adoption of web-based learning systems: Case study of Iran. *Computers & Education*, *61*, 158-167. https://doi.org/10.1016/j.compedu.2012.09.016

Mustafa, S., Zhang, W., Shehzad, M. U., Anwar, A., & Rubakula, G. (2022). Does Health Consciousness Matter to Adopt New Technology? An integrated model of UTAUT2 with SEM-fsQCA approach. *Frontiers in Psychology*, *13*, Article 836194. https://doi.org/10.3389/fpsyg.2022.836194

Narayan, J., & Naidu, S. (2024). A new contextual and comprehensive application of the UTAUT2 model post-COVID-19 pandemic in higher education. *Higher Education Quarterly, 78*(1), 47–77. https://doi.org/10.1111/hequ.12441

Niloy, M. I., Rahman, M. M., & Islam, M. S. (2024). Factors influencing students' adoption of AI-based educational tools: A structural equation modeling approach. *Computers & Education, 182*, Article 104484. https://doi.org/10.1016/j.compedu.2022.104484

Pavlik, J. V. (2023). Collaborating with ChatGPT: Considering the implications of generative artificial intelligence for journalism and media education. *Journalism & Mass Communication Educator, 78*(1), 84-93. https://doi.org/10.1177/10776958221149577

Raffaghelli, J. E., Rodríguez, M. E., Guerrero-Roldán, A., & Bañeres, D. (2022). Applying the UTAUT model to explain the students' acceptance of an early warning system in higher education. *Computers & Education*, *182*, Article 104468. https://doi.org/10.1016/j.compedu.2022.104468

Ragheb, M. A., Tantawi, P., Farouk, N., & Hatata, A. (2022). Investigating the acceptance of applying chat-bot (Artificial intelligence) technology among higher education students in Egypt. *International Journal of Higher Education Management*, *8*(2), 1-13. https://doi.org/10.24052/ijhem/v08n02/art-1

Ramayah, T. J. F. H., Cheah, J., Chuah, F., Ting, H., & Memon, M. A. (2018). *Partial least squares structural equation modeling (PLS-SEM) using smart PLS 3.0: An updated guide and practical guide to statistical analysis* (2nd edition). Pearson

Ramu, P., Osman, M., Abdul Mutalib, N. A., Aljaberi, M. A., Lee, K., Lin, C., & Hamat, R. A. (2023). Validity and reliability of a questionnaire on the knowledge, attitudes, perceptions, and practices toward food poisoning among Malaysian secondary school students: A pilot study. *Healthcare*, *11*(6), Article 853. https://doi.org/10.3390/healthcare11060853

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2020a). Social isolation and acceptance of the learning management system (LMS) in the time of COVID-19 pandemic: An expansion of the UTAUT model. *Journal of Educational Computing Research*, *59*(2), 183-208. https://doi.org/10.1177/0735633120960421

Raza, S. A., Qazi, W., Umer, B., & Khan, K. A. (2020b). Influence of social networking sites on life satisfaction among university students: A mediating role of social benefit and social overload. *Health Education*, *120*(2), 141-164. https://doi.org/10.1108/he-07-2019-0034

Raza, S. A., Qazi, Z., Qazi, W., & Ahmed, M. (2021). E-learning in higher education during COVID-19: Evidence from blackboard learning system. *Journal of Applied Research in Higher Education*, *14*(4), 1603-1622. https://doi.org/10.1108/jarhe-02-2021-0054

Ringle, C. M., Sarstedt, M., Mitchell, R., & Gudergan, S. P. (2018). Partial least squares structural equation modeling in HRM research. *The International Journal of Human Resource Management*, *31*(12), 1617-1643. https://doi.org/10.1080/09585192.2017.1416655

Salifu, I., Arthur, F., Arkorful, V., Abam Nortey, S., & Solomon Osei-Yaw, R. (2024). Economics students' behavioural intention and usage of ChatGPT in higher education: A hybrid structural equation modelling-artificial neural network approach. *Cogent Social Sciences*, *10*(1), Article 2300177. https://doi.org/10.1080/23311886.2023.2300177

Shivdas, A., Menon, D. G., & Nair, C. S. (2020). Antecedents of acceptance and use of a digital library system. *The Electronic Library*, *38*(1), 170-185. https://doi.org/10.1108/el-03-2019-0074

Şimşek, A. S., & Ateş, H. (2022). The extended technology acceptance model for Web 2.0 technologies in teaching. *Innoeduca. International Journal of Technology and Educational Innovation*, *8*(2), 165-183. https://doi.org/10.24310/innoeduca.2022.v8i2.15413

Soni, N., Kumar, S., & Singh, P. (2022). Generative AI: Transforming industries and society. *AI & Society, 37*(4), 1231-1245. https://doi.org/10.1007/s00146-021-01234-5

Strzelecki, A., & ElArabawy, S. (2024). Investigation of the moderation effect of gender and study level on the acceptance and use of generative AI by higher education students: Comparative evidence from Poland and Egypt. *British Journal of Educational Technology, 55*(3), 1209-1230. https://doi.org/10.1111/bjet.13425

Talan, T., Doğan, Y., & Kalinkara, Y. (2024). Digital natives' mobile learning adoption in terms of UTAUT-2 model: A structural equation model. *Innoeduca. International Journal of Technology and Educational Innovation*, *10*(1), 100-123. https://doi.org/10.24310/ijtei.101.2024.17440

Tamilmani, K., Rana, N. P., Prakasam, N., & Dwivedi, Y. K. (2019, June 1). The battle of Brain vs. Heart: A literature review and meta-analysis of "hedonic motivation" use in UTAUT2. *International Journal of Information Management, 46*, 222-235. https://doi.org/10.1016/j.ijinfomgt.2019.01.008

Thongsri, N., Shen, L., Bao, Y., & Alharbi, I. M. (2018). Integrating UTAUT and UGT to explain behavioural intention to use M-learning. *Journal of Systems and Information Technology, 20*(3), 278-297. https://doi.org/10.1108/jsit-11-2017-0107

Tseng, T. H., Lin, S., Wang, Y., & Liu, H. (2019). Investigating teachers' adoption of MOOCs: The perspective of UTAUT2. *Interactive Learning Environments*, *30*(4), 635-650. https://doi.org/10.1080/10494820.2019.1674888

Vaishya, R., Javaid, M., Khan, I. H., & Haleem, A. (2023). Artificial intelligence (AI) applications for COVID-19 pandemic. *Diabetes & Metabolic Syndrome: Clinical Research & Reviews, 14*(4), 337-339. https://doi.org/10.1016/j.dsx.2020.04.012

Venkatesh, V., Morris, M. G., Davis, G. B. & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. & 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

Venkatesh, V. (2021). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1-2), 641-652. https://doi.org/10.1007/s10479-020-03918-9

Vishwanath, A., & Goldhaber, G. M. (2003). An examination of the factors contributing to adoption decisions among late-diffused technology products. *New Media & Society*, *5*(4), 547-572. https://doi.org/10.1177/146144480354005

Wang, W., & Wang, C. (2009). An empirical study of instructor adoption of web-based learning systems. *Computers & Education*, *53*(3), 761-774. https://doi.org/10.1016/j.compedu.2009.02.021

Wijaya, T., Cao, Y., Weinhandl, R., Yusron, E., & Lavicza, Z. (2022). Applying the UTAUT model to understand factors affecting micro-lecture usage by mathematics teachers in China. *Mathematics*, *10*(7), Article 1008. https://doi.org/10.3390/math10071008

Yeop, M. A., Wong, K. T., & Noh, N. M. (2016). Blended learning in selected journals: A content analysis using the complex adaptive blended learning systems. *International Journal of Instructional Technology and Distance Learning, 13*(10), 47–58.

Zacharis, 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

Zwain, A. A. (2019). Technological innovativeness and information quality as neoteric predictors of users' acceptance of learning management system. *Interactive Technology and Smart Education*, *16*(3), 239-254. https://doi.org/10.1108/itse-09-2018-006

9. APPENDIX

Instrument (Habibi et al., 2023- English Version)

ENGLISH

This survey looks at your perspective on the use of ChatGPT in learning

- Gender [Male/female]
- Age
- Do you use ChatGPT

If yes, please continue ☐

UTAUT

Performance Expectancy [PE], PE1-PE4

1. ChatGPT is useful to carry out my tasks.
2. Using ChatGPT would increase the efficiency of my work.
3. Using ChatGPT would improve the quality of my tasks.
4. Using ChatGPT would allow me to have more convenient at work.

Effort Expectancy [EE], EE1-EE4

1. It is easy to enter in the ChatGPT page.
2. My interactions with my mobile phone and transaction terminals when using ChatGPT are clear and understandable.
3. I find it easy to use ChatGPT.
4. It is easy for me to become skilful at using ChatGPT.

Social Influence [SI], SI1-SI3

1. My friends think that I should use ChatGPT.
2. My family think that I should use ChatGPT.
3. People who influence my behaviour use ChatGPT.
4. The use of ChatGPT gives me professional status.

Facilitating Conditions [FC], FC1-FC4

1. I have the necessary resources (laptop, internet connection, mobile, desktop, etc.) to use ChatGPT.
2. I have the necessary knowledge to use ChatGPT.
3. The ChatGPT is compatible with the existing technology (like windows/mac for laptop, android/iOS for mobile, etc.) that I use.
4. I can get help from others when I have difficulty in using the ChatGPT.

Hedonic Motivation [HM], HM1-HM3

1. Using ChatGPT system is fun.
2. Using ChatGPT system is enjoyable.
3. Using ChatGPT system is very entertaining.

Habit [Hb], H1-H5

1. The use of ChatGPT has become a habit for me.
2. I don't even think twice before using the ChatGPT.
3. Using the ChatGPT has become natural to me.
4. Using the ChatGPT has become automatic for me.
5. When faced with research or assignments, using the ChatGPT is an obvious choice.

Behavioral Intention [BI], BI1-BI4

1. I intend to use the ChatGPT.
2. I like using the ChatGPT.
3. I plan to continue to use the ChatGPT.
4. I will recommend my friends to use the ChatGPT.

ChatGPT Use, GPTU1-GPTU3

1. I use frequently use ChatGPT.
2. I depend on ChatGPT for learning.
3. I use all functions in ChatGPT.

According to you, in which class/grade, students need the training/guidance related to ChatGPT & Artificial Intelligence

1. 6-8th Grade.
2. 9-10th Grade.
3. 11-12th Grade.
4. Graduation.