Vol.7 No.2 (2024)

Journal of Applied Learning & Teaching

ISSN : 2591-801X

Content Available at : http://journals.sfu.ca/jalt/index.php/jalt/index

Examining Google Gemini's acceptance and usage in higher education

Ahmed Mohamed Hasanein[A]

A Assistant Professor, College of Administration Science, King Faisal University, Saudi Arabia; Faculty of Tourism and Hotel Management, Helwan University, Cairo, Egypt

Abu Elnasr Elsayed Sobaih[B]

B Professor, College of Administration Science, King Faisal University, Saudi Arabia; Faculty of Tourism and Hotel Management, Helwan University, Cairo, Egypt

Ibrahim Abdelhamid Elshaer[C]

C Professor, College of Administration Science, King Faisal University, Saudi Arabia; Faculty of Tourism and Hotel Management, Helwan University, Cairo, Egypt

Keywords

AI learning tools;
behavioral intention;
Google Gemini;
higher education;
Saudi Arabia;
study discipline;
technology use;
UTAUT.

Correspondence

aabdelrazek@kfu.edu.sa [A]

Article Info

Received 28 May 2024
Received in revised form 3 June 2024
Accepted 28 June 2024
Available online 4 July 2024

DOI: https://doi.org/10.37074/jalt.2024.7.2.5

Abstract

Due to the growing use of chatbots such as ChatGPT and Google Gemini in educational contexts, there is an increasing interest in exploring the perception of students accepting and using Gemini as a unique and effective platform in their educational activities. This research examines the perceptions of Saudi Arabian higher education students towards accepting and using Gemini for academic purposes. Drawing upon the Unified Theory of Acceptance and Use of Technology (UTAUT), a self-administered questionnaire was used; 400 forms were completed and validated for analysis from seven public universities in Saudi Arabia. Structural Equation Modeling (SEM) using SmartPLS was adopted to examine the research hypotheses. The major findings agree with UTAUT and prior studies to some extent in terms of the positive influence of performance expectancy (PE), effort expectancy (EE), and social influence (SI) on students' intention to utilize Gemini, as well as the influence only of PE on the actual use of Gemini. However, the findings differ from previous research regarding the influence of facilitating conditions (FC) on students' intention to utilize Gemini; the results were significant but negative. In addition, EE, SI, and FC did not directly affect the actual use of Gemini. These results were due to the lack of valid resources, assistance, and guidance from educational authorities and external sources about the ideal use of Gemini. Furthermore, the findings exposed that BI partially mediates the connection between PE and Gemini's actual usage and fully mediates between EE and SI and Gemini's actual usage.

Introduction

Under the National Vision 2030 project, which strongly emphasizes technological integration, Saudi Arabia's educational system is experiencing radical change (Asem et al., 2024; Ismail et al., 2024). According to Perera and Lankathilake (2023), Google Gemini, a large language model to personalize instruction and supply on-demand information, offers exciting opportunities for revolutionary learning tools. Nevertheless, student acceptance and usage decisions are critical to the effectiveness of these technologies in their learning (Lee et al., 2023; Popenici et al., 2023; Popenici, 2023). In the context of higher education, Google Gemini, a state-of-the-art large language model (LLM), is a revolutionary force that affects teaching and learning (Lee et al., 2023; Perera & Lankathilake, 2023; Hasanein & Sobaih, 2023; Mardiansyah & Surya, 2024; Rudolph et al., 2024; Sobaih et al., 2024). Artificial Intelligence platforms like Google Gemini are multi-faceted in different contexts (Popenici, 2023; Metwally et al., 2024; Rane et al., 2024a). These facets in terms of educational context comprised simplicity of usage, ease of access to the platform, and rising students' academic performance (Rane et al., 2024b). A recent study by Latif and Zhai (2024) added other benefits of using AI for educational purposes, such as guiding students with their assignments, helping them comprehend critical subjects, and enhancing their mindsets by creating innovative ideas about specific topics. Moreover, AI applications can motivate students to overcome their language obstacles in terms of proofreading, grammar checking, listening as well as speaking skills (Perera & Lankathilake, 2023; Rudolph et al., 2023; Rane et al., 2024a; Carlà et al., 2024; Sevnarayan & Potter, 2024).

However, several studies have argued that using AI platforms for educational purposes does not have a specific validated framework by educational institutions for its efficient usage (Lee et al., 2023; Yeadon & Hardy, 2024). Due to the numerous features of using AI platforms, e.g., Gemini and ChatGPT, some questions remain unanswered regarding using these tools while maintaining long-term impacts (Sobaih, 2024; Mardiansyah & Surya, 2024). Recent studies (Lee et al., 2023; Mardiansyah & Surya, 2024; Sobaih, 2024) reported several issues regarding the use of AI platforms for educational purposes. One of these issues is the biased information by AI platforms, which mislead students with unverified information (Lee et al., 2023). Moreover, the complete reliance on AI platforms negatively affects students' mindsets and decreases their mind-mapping skills (Mardiansyah & Surya, 2024). In addition, generating texts for assignments or essays in a few seconds solely by AI platforms may negatively affect the quality of work and academic integrity (Sobaih, 2024).

This research study examines the perceptions of Saudi Arabian students' regarding the use of AI tools in higher education, particularly Gemini, in their educational activities. The study's theoretical framework has adopted the UTAUT to comprehend the key aspects that affect Saudi Arabian students' acceptance and usage of AI platforms, particularly Gemini, for educational purposes. Additionally, this study seeks to comprehend the role of behavioral intention (BI) in the relationship between students' acceptance of using Gemini on their BI and its use in their education.

Literature review

Students' acceptance to use Google Gemini and BI

The UTAUT was utilized because it provides a comprehensive framework for the adoption and use of AI platforms in many contexts, particularly in education (Magsamen-Conrad et al., 2015; Venkatesh, 2022; Venkatesh et al., 2003). According to Venkatesh et al. (2003), there are four elements of the UTAUT framework: performance expectation (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). In terms of PE, it was adopted to explore students' perception of using AI platforms e.g., using Gemini to enhance their academic performance (Brachten et al., 2021). As mentioned by numerous studies (e.g., Fagan et al., 2012; Kasilingam, 2020; Brachten et al., 2021; Al-Emran et al., 2023; Sevnarayan & Potter, 2024), students mainly rely on using AI in their challenging educational activities because of their beliefs that it may assist them in the critical activities as well as enhance their performance. With regard to EE, it indicates students' observations of how simple or difficult it is to utilize the technology. Students perceive AI platforms like Gemini to be intuitive, user-friendly, and effortlessly incorporated into daily activities, which improves their BI (Menon & Shilpa, 2023). Elements such as user interface design, overall user experience, and ease of interaction all influence students' impressions (Strzelecki, 2023; Al-Emran et al., 2023; Ashrafimoghari et al., 2024). Considering the fact that using AI platforms such as Gemini requires minimal effort, it increases the likelihood that students will incorporate it into their regular learning routines (Hasanein & Sobaih, 2023; Wang & Zhao, 2023; Chaka, 2024; Tian et al., 2024).

SI addresses how teachers and colleagues affect students' attitudes toward AI platforms, such as Gemini (Venkatesh et al., 2003; García-Peñalvo, 2024). This influence may be reflected in how students perceive others' attitudes, beliefs, and actions toward the use of Gemini in the classroom (Venkatesh, 2022). Empirical research (e.g., Menon & Shilpa, 2023) has shown that when peers use Gemini for learning, it has the ability to improve other students' BI performance. FC assesses the availability of resources necessary for efficient usage (Venkatesh et al., 2003). The FC component comprises technical mobility, access to appropriate instruction and tools, and broad incentive programs for integration (Strzelecki, 2023; Menon & Shilpa, 2023; Oye et al., 2014). Students' BI refers to their intention to utilize AI learning platforms, e.g., ChatGPT is highly impacted by their view that the learning environment provides the resources and help required for its successful implementation (Hasanein & Sobaih, 2023; Sevnarayan & Potter, 2024). A recent study by Al-Emran et al. (2023) deepens the emphasis of FC over technological facilities and improves students' ability to interact with technology by highlighting the necessity for a favourable environment that supports students' navigation in the effective usage of ChatGPT. Thus, we are prompted to develop the following hypotheses:

H1: PE positively affect BI to use Google Gemini.

H2: EE positively affect BI to use Google Gemini.

H3: SI positively affect BI to use Google Gemini.

H4: FC positively affect BI to use Google Gemini.

Students' acceptance to use Google Gemini and actual usage

A growing body of research (e.g., Al-Emran et al., 2023; Cheong et al., 2023; Asrif & Fatmi, 2024; García-Peñalvo, 2024; Ashrafimoghari et al., 2024; Sobaih et al., 2024) has examined the significance of PE (e.g., the chatbot for educational purposes, accessibility) and EE (e.g., clarity, and its compatibility with the particular requirements of the students) in predicting students' acceptance and utilization of chatbots in education, e.g., Google Gemini. According to Venkatesh (2022) and Terblanche and Kidd (2022), SI enhances the significance of behavioral intention in adopting technology. According to Chang and Park's study (2024), adopting AI chatbots, such as Google Gemini, can be strongly influenced by favorable social cues from peers in their social network who actively utilize the technology or encourage it. Furthermore, as recent research by Tian et al. (2024) demonstrated, students' decisions to use technology in their daily educational activities, such as integrating Google Gemini into their learning tasks, can be greatly influenced by recommendations, inspiration, or positive shared experiences of others. The significant influence of FC on adoption and actual usage is highlighted by earlier studies (Menon & Shilpa, 2023; Al-Emran et al., 2023; Chan & Zhou, 2023; Duong et al., 2023) evaluating Gemini's adaptability in education. In terms of the FC aspect, it contained all the infrastructure needed and assistance towards the effective use of AI platforms in an educational context (Menon & Shilpa, 2023). Therefore, we can hypothesize that:

H5: PE positively affect Google Gemini Usage

H6: EE positively affect Google Gemini Usage

H7: SI positively affect Google Gemini Usage

H8: FC positively affect Google Gemini Usage

Students' BI and actual use of Google Gemini

One of the most vital roles in comprehending the beneficial characteristics of using AI tools is to explore the relationship between students' behavioral intention to use AI platforms in educational themes (Terblanche & Kidd, 2022). Users' behavioral intention reflects their alignment toward accepting and using new innovative technology, e.g., AI platforms (Venkatesh et al., 2003). The positive behavioral intention towards students' usage of AI applications for educational purposes is considered a crucial motive for their actual usage in their daily educational tasks (Menon & Shilpa, 2023; Al-Emran et al., 2023; Duong et al., 2023; Anayat et al., 2023; Chaka, 2024). Recent studies argued that a strong positive correlation exists between students' BI and the actual use of AI in an educational context due to the critical help needed to complete their educational activities (Chan & Zhou, 2023). Thus, drawing upon these insights, we are driven to construct this hypothesis:

H9: BI positively affect Google Gemini Usage

The role of BI in the link between accepting and using Google Gemini

Despite the numerous studies (Yeadon & Hardy, 2024; García-Peñalvo, 2024; Sobaih et al., 2024; Tian et al., 2024; Carlà et al., 2024) that explored the crucial relationship between BI, students' accepting as well as using AI platforms e.g., Gemini in educational purposes, there is still limited research interest regarding the BI role in terms of the relationship between students' perception to accept and use Gemini in educational context. The current study tries to overcome the gap by applying the UTAUT model to postulate the following hypotheses:

H10: BI mediates the connection between PE and Google Gemini Usage

H11: BI mediates the connection between EE and Google Gemini Usage

H12: BI mediates the connection between SI and Google Gemini Usage

H13: BI mediates the connection between FC and Google Gemini Usage

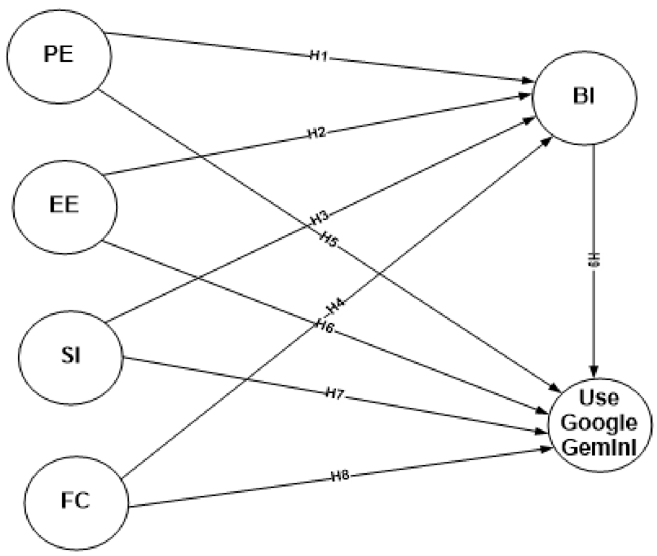

Figure 1. The conceptual model.

Methods

Participants

The population for this research is all the undergraduate college students within Saudi universities who utilize Gemini for learning. The participants of this study were students from four Saudi regions. The seven universities that were involved were part of King Faisal University (East), Taibah University (West), North Border University (North,) and

Jazan University (South). Hence, the scores indicated good participation by the students from the seven universities. Out of all the participants, we had approximately 75 students from each university. Out of 525 administered questionnaires, we collected 400 forms that were filled out completely and used for data analysis. Among these forms collected, more males participated in the given topic, with 290 participants, than female participants, with only 110 participants. If we take age groups of students, it is identified that a maximum number of 56% of students fall in the age of 19-25 years. Also, surprisingly, the social sciences and humanities students' sharing was slightly higher than that of other groups. In analysing the distribution of academic disciplines among participants, it was observed that there was higher participation from students in social sciences and humanities (250 participants) compared to those in natural, applied, and basic sciences (150 participants). The latter group included students from colleges such as the College of Science, College of Medicine, College of Pharmacy, and College of Engineering.

Measurement scales

In collecting data, this study utilized a pre-administered survey questionnaire among students. As a whole, the questionnaire form consists of three main sections. On the first page of the questionnaire, we provided some facts about the topic, the aim and the objective of the study and informed the participant to participate in the study by filling out the questionnaire voluntarily. In Part One, the questions on the participants' demographic profiles, including questions about gender and study discipline, were asked. Part Two has the scales of PE, EE, SI and FC. The scale questions were derived from Strzelecki (2023) and Strzelecki & ElArabawy (2024) and were originally developed based on the UTAUT framework introduced by Venkatesh et al. (2003). The questions used a five-point Likert scale ranging from strongly agree to strongly disagree. Part Three of the questionnaire has five variables measuring the intention and use of ChatGPT in learning, which were derived from the work of Strzelecki (2023) and Strzelecki and ElArabawy (2024). The credibility of the questionnaire form was established regarding content validity and face validity by twelve professors, and few modifications were made to the format and content of the questionnaire questions.

Data analysis

In order to verify the research hypotheses, the PLS-SEM analysis was conducted. According to Hair et al. (2019), PLS-SEM yields a lower bias estimation where the data are non-parametric. Therefore, PLS-SEM might be appropriate for analyzing data in this study. SmartPLS program Version 4 was employed for the inner and outer model estimation.

Results

Like many other quantitative studies, in order to assess research hypotheses, Henseler et al. (2009) pointed out that the researchers have to establish the convergent validity, discriminant validity, and reliability of the constructs before performing a PLS-SEM test. As mentioned by Hair et al. (2019), acceptable levels of convergent validity comprise the outer loadings and the criterion average variance extracted (AVE) threshold equal to or greater than 0.5. The results revealed factor loading values from 0.513 to 0.955. These were higher than the minimum threshold of 0.5 (Table 1). Moreover, in Table 2, AVE values ranged from 0.661 to 0.823 (exceeding the cutoff value of 0.5). Therefore, all the constructs displayed good levels of convergent validity with 0.7, as Hair et al., 2019 recommended. Moreover, as presented in Table 3, it is clear that the square root of AVE was significantly higher than its relative correlations. Hence, discriminant validity for all the variables was achieved at acceptable levels and could be deemed adequate.

Table 1. Cross-loadings and VIF values.

	Behavior Intention	Effort Expectancy	Facilitating Conditions	Performance Expectancy	Social Influence	Use Google Gemini	VIF
BI1	**0.852**	-0.061	-0.206	0.124	0.315	0.749	1.838
BI2	**0.904**	-0.079	-0.248	0.188	0.337	0.808	2.065
BI3	**0.662**	-0.021	-0.156	-0.058	0.427	0.445	1.258
EE1	-0.086	**0.946**	0.509	0.089	-0.134	-0.100	4.295
EE2	-0.063	**0.940**	0.451	0.077	-0.152	-0.072	3.936
EE3	-0.044	**0.920**	0.444	0.074	-0.124	-0.064	4.350
EE4	-0.054	**0.909**	0.404	0.076	-0.127	-0.065	3.742
FC1	-0.106	0.561	**0.874**	-0.025	-0.042	-0.083	3.903
FC2	-0.164	0.539	**0.855**	-0.009	-0.058	-0.124	4.104
FC3	-0.201	0.466	**0.955**	-0.042	-0.072	-0.186	4.335
FC4	-0.324	0.374	**0.940**	-0.157	-0.066	-0.311	3.962
PE1	0.043	0.057	-0.042	**0.832**	-0.278	0.133	2.230
PE2	0.075	0.144	-0.040	**0.767**	-0.138	0.132	1.455
PE3	0.132	0.014	-0.088	**0.843**	-0.138	0.157	1.699
PE4	-0.064	0.001	0.079	**0.513**	-0.125	-0.013	1.670
SI1	0.475	-0.084	-0.069	-0.181	**0.886**	0.428	1.586
SI2	0.273	-0.158	-0.052	-0.188	**0.799**	0.237	2.108
SI3	0.263	-0.163	-0.047	-0.182	**0.863**	0.239	2.540
Use_1	0.738	-0.057	-0.209	0.095	0.298	**0.767**	1.485
Use_2	0.797	-0.072	-0.239	0.187	0.369	**0.941**	4.096
Use_3	0.630	-0.092	-0.143	0.206	0.317	**0.875**	4.259

Table 2. The validity and reliability of latent variables.

Factors	Cronbach's alpha (a)	Composite reliability (C.R.)	Average variance extracted (AVE)
Behavior Intention	0.738	0.852	0.661
Effort Expectancy	0.948	0.962	0.863
Facilitating Conditions	0.935	0.949	0.823
Performance Expectancy	0.800	0.833	0.563
Social Influence	0.820	0.886	0.722
Use Google Gemini	0.826	0.898	0.746

Table 3. Fornell–Larcker criterion matrix and HTMT results.

Dim.	AVE square root	Pearson's correlation matrix 1	2	3	4	5	6
1. Behavior Intention	0.813	1					
2. Effort Expectancy	0.929	-0.070	1				
3. Facilitating Conditions	0.907	-0.254	0.493	1			
4. Performance Expectancy	0.725	0.149	0.069	-0.091	1		
5. Social Influence	0.850	0.426	-0.145	-0.068	-0.183	1	
6. Use Google Gemini	0.864	0.544	-0.084	-0.232	0.208	0.382	1
	HTMT						
1. Behavior Intention							
2. Effort Expectancy		0.077					
3. Facilitating Conditions		0.257	0.555				
4. Performance Expectancy		0.187	0.109	0.066			
5. Social Influence		0.523	0.177	0.072	0.305		
6. Use Google Gemini		0.449	0.093	0.215	0.182	0.426	

In PLS, the reliability of the construct should also be assessed by two more coefficients – composite reliability (CR) and Cronbach's alpha (CA). As Hair et al. (2019) noted, a CR and CR of 0.7 should be used as a measure of reliability in identifying whether the level of reliability is excellent or not. Table 2 stated that CR and CA ranged from 0.833 (Performance Expectancy) to 0.852 (behavior intention), respectively, exceeding the cutoff value of 0.7. Accordingly, the reliability of the study's latent variables was satisfied. Likewise, to ensure the estimation of discriminant validity, the researchers employed Fornell and Larcker's, where the square root of the AVE should exceed the intercorrelation for each factor, as shown in Table 3. Furthermore, the "Heterotrait-Monotrait" (HTMT) ratio, which is admitted as a more robust approach compared to Fornell and Larcker's (1981), was examined. The probable worries regarding discriminant validity occur when HTMT scores (Table 3) surpass 0.90. As shown in Table 3, all ratios fall below 0.9, thus confirming the discriminant validity. Hair et al. (2019) also identified that the existence of multicollinearity is an issue when the variance inflation factor (VIF) exceeds the value of five as a threshold. Table 2 shows that the highest value of VIF was 4.335. Hence, the possibility of a multicollinearity issue was not a problem. Additionally, the researchers evaluated the chance of common method bias (CMB) that might occur in this paper as cross-sectional data gathered from the same respondents. To deal with this issue, Podsakoff et al. (2003) suggested that researchers would employ Harman's one-factor test. The exploratory factor analysis found that the single dimension explained 43% of the overall variance, which signaled a low likelihood of CMB. As revealed in Figure 2 and Table 4, the PLS-SEM outcomes revealed that BI was positively, directly and significantly impacted by PE (β = 0.192, t=2.067, p<.001), EE (β = 0.109, t=2.226, p<.001), and SI (β = 0.466, t=7.523, p<.001), which approve H1, H2, and H3. It is worth noting that the weak negative correlation between BI and EE in Table 3 (-0.070) and the positive and significant path coefficient in Table 4 (H2: β = 0.109) are not necessarily contradictory, considering the effects of multiple variables simultaneously. In a multivariate context, the positive impact of EE on BI might become evident when controlling for the effects of other constructs like PE, SI, and FC.

However, FC failed to positively affect BI (β = -0.259, t=5.375, p<.001), rejecting H4. Similarly, the study results signaled that PE is the only factor positively and significantly impacting Geminin Usage (β = 0.102, t=3.067, p<.001) supporting H5. Conversely, all the other factors of the UTAUT framework failed to positively and significantly impact the usage of Google Gemini by university students, rejecting H6 (β = -0.028, t=1.158, p=247), H7 (β = 0.057, t=1.633, p=.103) and H8 β = -0.001, t=0.032, p=974). Finally, the results showed a high positive direct impact of BI on Gemini usage (β = 0.805, t=31.194, p<.001) supporting H9.

Finally, the negative correlations observed in the Fornell-Larcker Table 3 are generally consistent with the hypotheses testing results, particularly for the relationships involving Facilitating Conditions (FC) and their negative impacts. These findings reinforce the conclusion that despite the perceived ease of use and social influence, the lack of adequate resources and support (facilitating conditions) plays a significant role in hindering the intention and actual usage of Google Gemini among students.

Table 4. Hypotheses testing results.

	Relationship	β	T statistics	P value	Results
H1	Performance Expectancy -> Behavior Intention	0.192	2.067	0.039	Support
H2	Effort Expectancy -> Behavior Intention	0.109	2.226	0.026	Support
H3	Social Influence -> Behavior Intention	0.466	7.523	0.000	Support
H4	Facilitating Conditions -> Behavior Intention	-0.259	5.375	0.000	Reject
H5	Performance Expectancy -> Use Google Gemini	0.102	3.067	0.002	Support
H6	Effort Expectancy -> Use Google Gemini	-0.028	1.158	0.247	Reject
H7	Social Influence -> Use Google Gemini	0.057	1.633	0.103	Reject
H8	Facilitating Conditions -> Use Google Gemini	-0.001	0.032	0.974	Reject
H9	Behavior Intention -> Use Google Gemini	0.805	24.194	0.000	Support
Specific indirect effects					
H10	Performance Expectancy -> Behavior Intention -> Use Google Gemini	0.155	2.038	0.042	Support
H11	Effort Expectancy -> Behavior Intention -> Use Google Gemini	0.087	2.208	0.027	Support
H12	Social Influence -> Behavior Intention -> Use Google Gemini	0.375	6.794	0.000	Support
H13	Facilitating Conditions -> Behavior Intention -> Use Google Gemini	-0.208	5.206	0.000	Reject

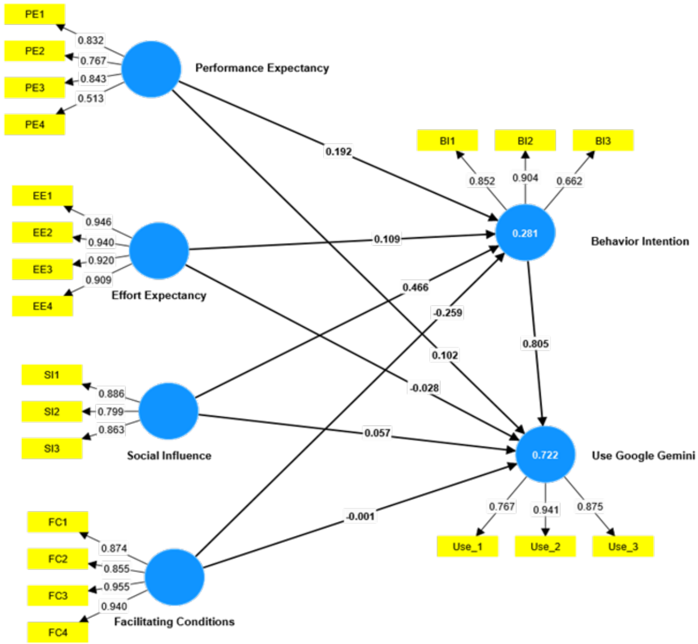

Figure 2. Results of the inner model.

As for the indirect, specific impact, the study results showed that BI could mitigate the insignificant direct impacts by mediating significantly between PE and Gemini Usage (β = 0.155, t=2.038, p<.001), which supports H10. Similarly, BI successfully mediates the relationship between EE and Gemini Usage (β = 0.087, t=2.208, p<.05), SI and Gemini Usage (β = 0.375, t=6.794, p<.001), supporting H11 and H12. However, BI failed to positively mediate the impact of FC on Gemini Usage (β = -0208, t=5.206, p<.001), rejecting H12.

Discussion

This paper addresses students' acceptance and use of Gemini in their learning process. For this reason, the questionnaire survey developed using the UTAUT framework was directed at students in Saudi universities. The findings showed that PE has a positive but insignificant effect on the BI of students who adopt Gemini in education. As discussed earlier, PE refers to students' perception of using Gemini to enhance their academic performance (Brachten et al., 2021). However, this result confirms that students are unsure that Gemini would significantly impact their academic performance. On the other hand, the findings confirmed that PE significantly and positively impacts the BI to use Gemini in education. This aligns with previous research results that students use the AI tool in their educational activities because they believe it may assist them in critical activities and enhance their performance (e.g., Sevnarayan & Potter, 2024).

The results also showed that EE in educational activities significantly and positively affects the BI to use Gemini. This means that EE students perceive Gemini as a simple AI tool to utilize. They perceive it as intuitive, user-friendly, and effortlessly incorporated into daily activities that stimulate the BI of students (Menon & Shilpa, 2023). This finding concurs that Gemini requires minimal effort to incorporate it into their regular learning routines like other AI tools, e.g. ChatGPT (Hasanein & Sobaih, 2023; Wang & Zhao, 2023; Chaka, 2024; Tian et al., 2024). However, the result is not in line with the UTAUT framework (Venkatesh, 2022) as EE has a negative, albeit significant impact on BI of students to adopt Gemini in educational activities. This could be because the spread of the Gemini tool among Saudi students is recent. Therefore, students' acceptance of Gemini did not directly affect their use of Gemini in their educational activities.

Regarding the effect of SI on BI to use Gemini in educational activities, there was an agreement with UTAUT and previous research (Venkatesh et al., 2003; García-Peñalvo, 2024) that the BI to use Gemini in educational activities is positively affected by SI. This means that teachers and peers have an effect on students' BI when using Gemini. Empirical research (e.g., Menon & Shilpa, 2023) has shown that when peers use Gemini for learning, it has the ability to improve other students' BI performance. On the other hand, SI's influence on Gemini's use was positive but not significant. The effect of teachers and peers was enough to stimulate the BI of students to use Gemini but not their definite use of Gemini in their education activities.

The results showed a positive and significant relationship concerning the effect of FC on BI to adopt Gemini in their teaching. This means that technical mobility, access to appropriate instruction and tools, and broad incentive programs for integration (Strzelecki, 2023; Menon & Shilpa, 2023; Oye et al., 2014) were enough to stimulate students' BI to use Gemini but were not enough to affect their actual use of Gemini in education. There was a negative but insignificant effect on the facilities and support given by institutions to students regarding AI tools, particularly Gemini. This concurs with the work of Sobaih et al. (2024), who state that the support universities in Saudi Arabia give for using AI in learning is often limited and absent. Hence, they also found FC's negative but insignificant effect on students' use of ChatGPT in their education.

This research study confirmed the mediation role of BI in the relationship between EE, PE, SI and the adoption of Gemini in teaching by university students. This result supported the UTAUT framework and the work of Sobaih et al. (2024), who confirmed a mediating role of BI in the relationship between EE, PE, SI and the adoption of AI in learning. Although EE and SI had no direct effect on the use of Gemini, BI confirmed the indirect relationship. This means that BI was able to change these relationships, reflecting its great importance in driving students' use of Gemini in learning. On the other hand, BI did not have any mediating role in linking FC and students' use of Gemini. This is because the current level of FC given by institutions to their students was not significant enough to affect their BI in using Gemini in their education. These findings are unlike the study of Sobaih et al. (2024), which confirmed this mediation effect of FC in the link between acceptance and use of ChatGPT among Saudi students. This could be because students did not have enough support from their institutions to facilitate their use of Gemini in their education activities despite it being a new AI tool for them to use. Gemini is less common among students, and they may not have developed their BI to actually use it in their education without external support. The findings encourage scholars to undertake further studies to understand the actual usage of AI tools in education. There is a need for more studies that analyze how these tools could be better integrated into students' learning while considering their long-term consequences as well as addressing any associated ethical concerns (Sobaih, 2024).

Conclusion

This study responds to university students' growing usage of AI tools in education. The study examined students' acceptance and use of Gemini for educational activities. The study confirmed that BI to adopt Gemini is significantly affected by PE. Students believe it assists them in educational activities. On the other hand, the results showed that PE has a positive but insignificant effect on the BI of students who adopt Gemini in education. Students are not sure that Gemini would significantly affect their academic performance. On the other hand, despite EE having an insignificant effect on BI to use Gemini, it has a direct positive effect on the use of Gemini because they found its ease of access. As the individual's decisions in Saudi society are affected by peers, the BI to use Gemini is significantly affected by SI, but SI did not confirm a significant influence on the real adoption of Gemini in educational activities. In the same context, FC had a significant effect on BI to use bua significant effect on BI use, but it did not significantly affect the actual use of Gemini. The external support given to students was not enough to change the BI effect in the relationship between FC and the use of Gemini for learning. The study confirmed that BI mediates the link between EE, PE, SI and the use of Gemini by university students. The study of value is not only for Saudi higher education but also for other countries' higher education sectors.

Acknowledgements

This research was funded by the Deanship of Scientific Research, Vice Presidency for Graduate Studies and Scientific Research, King Faisal University, Saudi Arabia, grant number "GrantA139".

References

Al-Emran, M., AlQudah, 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, 71*, 4985-4999. https://doi.org/10.1109/

TEM.2023.3237789

Anayat, S., Rasool, G., & Pathania, A. (2023). Examining the context-specific reasons and adoption of artificial intelligence-based voice assistants: A behavioural reasoning theory approach. *International Journal of Consumer Studies, 47*(5), 1885-1910. https://doi.org/10.1111/ijcs.12963

Asem, A., Abdullah, Y. R. A. G., Mohammad, A. A., & Ziyad, I. A. (2024). Navigating digital transformation in alignment with Vision 2030: A review of organizational strategies, innovations, and implications in Saudi Arabia. *Journal of Knowledge Learning and Science Technology, 3*(2), 21-29. https://doi.org/10.60087/jklst.vol3.n2.p29

Ashrafimoghari, V., Gürkan, N., & Suchow, J. W. (2024). *Evaluating large language models on the GMAT: Implications for the future of business education*. https://doi.org/10.48550/arXiv.2401.02985

Asrif, Y., & Fatmi, H. (2024). *A cognitive revolution: Generative artificial intelligence in higher education*. arXiv preprint. https://doi.org/10.48550/arXiv.2401.02985

Brachten, F., Kissmer, T., & Stieglitz, S. (2021). The acceptance of chatbots in an enterprise context – A survey study. *International Journal of Information Management, 60*, 102375. https://doi.org/10.1016/j.ijinfomgt.2021.102375

Carlà, M. M., Gambini, G., Baldascino, A., Giannuzzi, F., Boselli, F., Crincoli, E., ... & Rizzo, S. (2024). Exploring AI-chatbots' capability to suggest surgical planning in ophthalmology: ChatGPT versus Google Gemini analysis of retinal detachment cases. *British Journal of Ophthalmology*. https://doi.org/10.1136/bjo-2023-325143

Chaka, C. (2024). Reviewing the performance of AI detection tools in differentiating between AI-generated and human-written texts: A literature and integrative hybrid review. *Journal of Applied Learning and Teaching, 7*(1), 115-126. https://doi.org/10.37074/jalt.2024.7.1.14

Chan, C. K. Y., & Zhou, W. (2023). *Deconstructing student perceptions of Generative AI (GenAI) through an Expectancy Value Theory (EVT)-based instrument*. arXiv preprint. https://doi.org/10.48550/arXiv.2305.01186

Chang, W., & Park, J. (2024). A comparative study on the effect of ChatGPT recommendation and AI recommender systems on the formation of a consideration set. *Journal of Retailing and Consumer Services, 78*, 103743. https://doi.org/10.1016/j.jretconser.2024.103743.

Cheong, R. C. T., Pang, K. P., Unadkat, S., Mcneillis, V., Williamson, A., Joseph, J., ... & Paleri, V. (2023). Performance of artificial intelligence chatbots in sleep medicine certification board exams: ChatGPT versus Google Bard. *European Archives of Oto-Rhino-Laryngology, 281*, 2137-2143. https://doi.org/10.1007/s00405-023-08381-3

Duong, C. D., Vu, T. N., & Ngo, T. V. N. (2023). Applying a modified technology acceptance model to explain higher education students' usage of ChatGPT: A serial multiple mediation model with knowledge sharing as a moderator. *The International Journal of Management Education, 21*(3), 100883.https://doi.org/10.1016/j.ijme.2023.100883

Fagan, M., Kilmon, C., & Pandey, V. (2012). Exploring the adoption of a virtual reality simulation: The role of perceived ease of use, perceived usefulness and personal innovativeness. *Campus-Wide Information Systems, 29*(2), 117-127. https://doi.org/10.1108/10650741211212368

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39–50. https://doi.org/10.2307/3151312

García-Peñalvo, F. J. (2024). Generative artificial intelligence in higher education: A 360 perspective [Conference Presentation]. In *IFE Conference Special Event; Artificial Intelligence in Education Summit, Tecnológico de Monterrey, Monterrey, México*. https://bit.ly/48W0GNX.

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

Hasanein, A. M., & Sobaih, A. E. E. (2023). Drivers and consequences of ChatGPT use in higher education: Key stakeholder perspectives. *European Journal of Investigation in Health, Psychology and Education, 13*(11), 2599-2614. https://doi.org/10.3390/ejihpe13110181

Henseler, J., Ringle, C., & Sinkovics, R. (2009). *The use of partial least squares path modeling in international marketing*. https://www.researchgate.net/publication/229892421_The_Use_of_Partial_Least_Squares_Path_Modeling_in_International_Marketing

Ismail, F. M. M., Crawford, J., Tan, S., Rudolph, J., Tan, E., Seah, P., ... & Kane, M. Artificial intelligence in higher education database (2024): Introducing an open-access repository. *Journal of Applied Learning and Teaching, 7*(1), 140-148. https://doi.org/10.37074/jalt.2024.7.1.35

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society, 62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280.

Latif, E., & Zhai, X. (2024). Fine-tuning ChatGPT for automatic scoring. *Computers and Education: Artificial Intelligence*, 100210. https://doi.org/10.1016/j.caeai.2024.100210.

Lee, G. G., Latif, E., Shi, L., & Zhai, X. (2023). *Gemini pro defeated by GPT-4v: Evidence from education*. ArXiv preprint. https://doi.org/10.48550/arXiv.2401.08660

Magsamen-Conrad, K., Upadhyaya, S., Joa, C. Y., & Dowd, J. (2015). Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. *Computers in Human Behavior, 50*, 186-196. https://doi.org/10.1016/j.chb.2015.03.032.

Mardiansyah, K., & Surya, W. (2024). *Comparative analysis of ChatGPT-4 and Google Gemini for spam detection on the SpamAssassin public mail corpus*. http://dx.doi.org/10.21203/rs.3.rs-4005702/v1

Menon, D., & Shilpa, K. (2023). Chatting with ChatGPT: Analyzing the factors influencing users' intention to use the open AI's ChatGPT using the UTAUT model. *Heliyon, 9*(11). https://doi.org/10.1016/j.heliyon.2023.e20962.

Metwally, A. B., Ali, S. A., & Mohamed, A. T. (2024, January). Thinking responsibly about responsible AI in risk management: The darkside of AI in RM. In *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (pp. 1-5). http://dx.doi.org/10.1109/ICETSIS61505.2024.10459684

Oye, N. D., A. Iahad, N., & Ab. Rahim, N. (2014). The history of UTAUT model and its impact on ICT acceptance and usage by academicians. *Education and Information Technologies, 19,* 251-270. https://doi.org/10.1007/s10639-012-9189-9

Perera, P., & Lankathilake, M. (2023). Preparing to revolutionize education with the multi-model GenAI tool Google Gemini? A journey towards effective policy making. *Journal of Advances in Education and Philosophy, 7*(8), 246-253. http://dx.doi.org/10.36348/jaep.2023.v07i08.001

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology, 88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Popenici, S. (2023). The critique of AI as a foundation for judicious use in higher education. *Journal of Applied Learning and Teaching, 6*(2), 378-384. https://doi.org/10.37074/jalt.2023.6.2.4.

Popenici, S., Rudolph, J., Tan, S., & Tan, S. (2023). A critical perspective on generative AI and learning futures.: An interview with Stefan Popenici. *Journal of Applied Learning and Teaching, 6*(2), 311-331. https://doi.org/10.37074/jalt.2023.6.2.5

Rane, N., Choudhary, S., & Rane, J. (2024a). *Gemini or ChatGPT? Efficiency, performance, and adaptability of cutting-edge generative Artificial Intelligence (AI) in finance and accounting.* http://dx.doi.org/10.2139/ssrn.4731283

Rane, N., Choudhary, S., & Rane, J. (2024b). *Gemini Versus ChatGPT: Applications, performance, architecture, capabilities, and implementation.* http://dx.doi.org/10.2139/ssrn.4723687

Rudolph, J., Ismail, F. M. M., & Popenici, S. (2024). Higher education's generative artificial intelligence paradox: The meaning of chatbot mania. *Journal of University Teaching and Learning Practice, 21*(06). https://doi.org/10.53761/54fs5e77

Rudolph, J., Tan, S., & Tan, S. (2023). War of the chatbots: Bard, Bing Chat, ChatGPT, Ernie and beyond. The new AI gold rush and its impact on higher education. *Journal of Applied Learning and Teaching, 6*(1), 364-389. https://doi.org/10.37074/jalt.2023.6.1.23

Sevnarayan, K., & Potter, M. A. (2024). Generative artificial intelligence in distance education: Transformations, challenges, and impact on academic integrity and student voice. *Journal of Applied Learning and Teaching, 7*(1), 104-114. https://doi.org/10.37074/jalt.2024.7.1.41

Sobaih, A. E. E. (2024). Ethical concerns for using artificial intelligence chatbots in research and publication: Evidences from Saudi Arabia. *Journal of Applied Learning and Teaching, 7*(1), 93-103. https://doi.org/10.37074/jalt.2024.7.1.21

Sobaih, A. E. E., Elshaer, I. A., & Hasanein, A. M. (2024). Examining students' acceptance and use of ChatGPT in Saudi Arabian higher education. *European Journal of Investigation in Health, Psychology and Education, 14*(3), 709-721. https://doi.org/10.3390/ejihpe14030047

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments,* 1–14. https://doi.org/10.1080/10494820.2023.2209881

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

Terblanche, N., & Kidd, M. (2022). Adoption factors and moderating effects of age and gender that influence the intention to use a non-directive reflective coaching chatbot. *SAGE Open, 12*(2), https://doi.org/10.1177/21582440221096136

Tian, W., Ge, J., & Zheng, X. (2024). AI Chatbots in Chinese higher education: Adoption, perception, and influence among graduate students—an integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology, 15*, 1268549. https://doi.org/10.3389/fpsyg.2024.1268549

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research, 308,* 641-652. https://doi.org/10.1007/s10479-020-03918-9

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), 425-478. https://doi.org/10.2307/30036540

Wang, Y., & Zhao, Y. (2023). *Gemini in reasoning: Unveiling commonsense in multimodal large language models.* arXiv preprint arXiv:2312.17661. https://doi.org/10.48550/arXiv.2312.17661

Yeadon, W., & Hardy, T. (2024). The impact of AI in physics education: A comprehensive review from GCSE to university levels. *Physics Education, 59*(2), 025010. https://doi.org/10.1088/1361-6552/ad1fa2

Appendix

Appendix A: Research Instrument

	Scale Variables and Items
	Performance Expectancy (PE) (Venkatesh et al., 2003)
PE1	"Google Gemini is an invaluable asset for enhancing my academic endeavors."
PE2	"Employing Google Gemini significantly increases the likelihood of achieving crucial objectives in academic pursuits."
PE3	"Google Gemini optimizes productivity in academic endeavors by streamlining task and project completion."
PE4	"Engaging with Google Gemini has the potential to enhance my academic performance."
	Effort Expectancy (EE) (Venkatesh et al., 2003)
EE1	"I perceive learning to use Google Gemini as straightforward."
EE2	"The interaction with Google Gemini is clear and easily understandable."
EE3	"Google Gemini boasts a user-friendly and intuitive interface."
EE4	"I effortlessly develop proficiency in utilizing Google Gemini."
	Social Influence (SI) (Venkatesh et al., 2003)
SI1	"The individuals who hold significant influence in my life strongly advocate for the use of Google Gemini."
SI2	"The people who influence my actions endorse the utilization of Google Gemini."
SI3	"The perspectives of those whom I deeply respect indicate a recommendation for incorporating Google Gemini into my activities."
	Facilitating Conditions (FC) (Venkatesh et al., 2003)
FC1	"I possess sufficient resources to effectively utilize Google Gemini."
FC2	"I have acquired the necessary skills to proficiently use Google Gemini."
FC3	"Google Gemini aligns with the technological tools I employ."
FC4	"In the event of challenges with Google Gemini, external support and assistance are readily available."
	Behavioral Intention (BI) (Ajzen and Fishbein, 1972)
BI1	"I have made the decision to persist in using Google Gemini going forward."
BI2	"I am fully committed to employing Google Gemini as an integral tool for my academic endeavors."
BI3	"I am determined to maintain a consistent usage of Google Gemini."
	Google Gemini Use (Venkatesh et al., 2012)
Use1	"I plan to apply the knowledge and skills gained from Google Gemini in my educational pursuits."
Use2	"The knowledge and skills acquired through Google Gemini will prove beneficial to my classroom endeavors."
Use3	"Utilizing Google Gemini has contributed to enhancing my academic performance."