Understanding ChatGPT adoption in universities: the impact of faculty TPACK and UTAUT2

Comprendiendo la adopción de ChatGPT en universidades: el impacto del TPACK y UTAUT2 en los docentes

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ABSTRACT

The objective of the field of technology known as artificial intelligence (AI) is to create intelligent devices that can perform tasks that have traditionally required human intelligence. ChatGPT is a program based on AI that provides virtual instructors and a personalized learning environment for students. It raises the bar for top performers by presenting cutting-edge information and encouraging intellectual development. This study aimed to investigate the significance of instructors' Technological Pedagogy Content Knowledge (TPACK) to determine the intention to use ChatGPT in light of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model. The methodology of the study was a quantitative approach and the data was collected from 569 male and female instructors in Saudi universities. The data was analyzed by Path analysis and Smart PLS. The results of the study showed that Effort Expectancy, Social Influence, Hedonic Motivation, and Information Quality did not have a significant influence on Behavioral Intention. However, Facilitating Condition, Learning Value (negatively), and Privacy Risk have significant effects on Behavioral Intention. Moreover, there was a significant moderating role of Instructors' TPACK on the relationship between Privacy Risk and Behavioral Intention. The results shed light on the effect of instructors' TPACK and the lack of the relation among the three knowledge. Instructors' TPACK should be improved with professional development programs in order to adapt a positive intention of using ChatGPT in Saudi universities. Universities are recommended to facilitate sufficient support and resources for the instructors to adopt new technology in their teaching.

Keywords: artificial intelligence; TPACK; ChatGPT; UTAUT2 model; instructors.

RESUMEN

El objetivo de la tecnología de inteligencia artificial (IA) es crear dispositivos inteligentes que realicen tareas que tradicionalmente han requerido inteligencia humana. ChatGPT es un programa basado en IA que proporciona instructores virtuales y un entorno de aprendizaje personalizado para los estudiantes. Eleva el estándar para los mejores intérpretes al presentar información de vanguardia y fomentar el desarrollo intelectual. Este estudio investigó la importancia del Conocimiento Pedagógico Tecnológico del Contenido (TPACK) de los instructores para determinar la intención de usar ChatGPT a la luz del modelo de la Teoría Unificada de Aceptación y Uso de Tecnología 2 (UTAUT2). La metodología fue un enfoque cuantitativo y los datos se recopilaron de 569 instructores en universidades saudíes. Los datos fueron analizados mediante análisis de rutas y Smart PLS. Los resultados mostraron que la Expectativa de Esfuerzo, la Influencia Social, la Motivación Hedónica y la Calidad de la Información no influyeron significativamente en la Intención de Comportamiento. Sin embargo, la Condición Facilitadora, el Valor de Aprendizaje (negativamente) y el Riesgo de Privacidad sí tuvieron efectos significativos en la Intención de Comportamiento. Además, el TPACK de los instructores tuvo un papel moderador significativo en la relación entre el Riesgo de Privacidad y la Intención de Comportamiento. Los resultados destacan la necesidad de mejorar el TPACK de los instructores con programas de desarrollo profesional para fomentar una intención positiva de usar ChatGPT en las universidades saudíes. Se recomienda a las universidades proporcionar suficiente apoyo y recursos para que los instructores adopten la nueva tecnología en su enseñanza.

Palabras clave: inteligencia artificial; TPACK; ChatGPT; modelo UTAUT2; instructores.

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INTRODUCTION

Educational systems have undergone a significant transition due to technology, which has ushered in a new era of almost endless opportunities for students and instructors. By enhancing participation and involvement, technology also breathes new life into the field of education. It allows instructors to design immersive learning environments, and this makes teaching both more engaging and effective (Cooper, 2023). The educational environment is primed for more innovation as technology develops, providing a brighter future for students and instructors worldwide (Dai et al., 2023).

One of the most important reasons to employ technology in the classroom is to better prepare students for the challenges they will face in their future careers. Institutions of higher learning actively use technology in order to provide students with the digital literacy and technological proficiency they will need to succeed in a rapidly evolving global economy (Dergaa et al., 2023). These institutions know that having a solid technical foundation improves students' academic experiences and prepares them for the competitive environment of the modern workplace by teaching them how to effectively navigate the digital space, innovate, collaborate, and communicate (Al-Safadi et al., 2023). The objective of the field of technology known as Generative Artificial Intelligence (GenAI) is to enable a variety of content, not only texts but also videos and images and perform tasks that have traditionally required human intelligence (Luo, 2024). ChatGPT is one of the well-known GenAI tools that is used in education that has multiple educational advantages which significantly impact students' learning experiences. Its 24-hour availability makes it a convenient and valuable tool for students to get their questions answered and enrich their learning (Cooper, 2023). GenAI tools such as ChatGPT are there to help, allowing for more flexible and convenient learning. By enabling students to understand ideas and locate answers whenever needed, this encourages independence and self-paced learning, which makes for a more fruitful and fulfilling educational experience providing a social interaction (Perera & Lankathilaka, 2023; Sharples, 2023).

With the emergence of the advanced technologies, universities work to develop their strategies to keep pace with this development. In order to ensure the promised learning outcomes, studies and research should examine how these technologies would benefit students' learning. The current study aimed to examine universities instructors' acceptance of technologies based on GenAI, such as ChatGPT in Saudi universities. The results of the current study provided a good reference of instructors' skills, knowledge, and acceptance of ChatGPT that affects students' learning. To inspect a deep view, two frameworks were used in this study. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model was used to adapt its variables to the purpose of the study to reveal the expectation and the intention of using ChatGPT, and Technological Pedagogy Content Knowledge (TPACK) framework was added to the variables for better understanding of the effect of the instructors' acceptance.

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) is a thorough model that explores several crucial factors affecting how technology is accepted and used. These significant aspects include Performance Expectancy, which measures the expected advantages. Effort Expectancy evaluates the perceived ease of usage, Social Influence looks at the influence of peers and social norms. Facilitating Conditions assesses the readily available support system, and Hedonic Motivation takes into consideration the pleasure experienced while using technology; Price Value; Habit; Recognizing Habitual Use Patterns; and Voluntariness, which accounts for the flexibility of choice (Qin et al., 2020). These factors determine a person's desire to accept technology, which affects how they use it (Medeiros et al., 2022). This study aimed to examine the acceptance of using AI technologies in education by examining the significance of instructors' TPACK of ChatGPT in light of UTAUT2 model, illuminating how these variables are interrelated and contribute to the ever-changing educational landscape. The benefits of examining instructors' TPACK in using AI technologies in their teaching is to explore the instructors' selection of the technology that is appropriate for different learning settings.

ChatGPT in Education

Artificial intelligence is becoming more and more critical in the educational environment. It efficiently automates administrative processes, allowing instructors to devote more focus to instructing and mentoring students (Eysenbach, 2023). ChatGPT provides instructors with a wealth of data-driven ways to better the learning process by analyzing massive datasets to identify areas for improvement (Järvelä et al., 2023). This gives instructors more control by providing them with the resources they need to design incredibly successful, highly individualized learning experiences that are specifically catered to each student's individual requirements and skills. The broad adoption and integration of ChatGPT in education continues to be a subject of intense attention and scrutiny, since a successful implementation might significantly impact and improve students' learning results across a range of educational contexts (Al-Safadi et al., 2023).

ChatGPT, a sophisticated language model, was created to produce text answers that resemble human speech. ChatGPT is swiftly rising in popularity in educational contexts thanks to its capacity to conduct real-world discussions, respond to inquiries, and give in-depth explanations on various topics (Al-Safadi et al., 2023). Because of its adaptability and versatility, it is a valuable tool for both instructors and students. This innovative technology is at the forefront of transforming the educational environment by encouraging interactive and personalized learning experiences. It is a powerful tool in the hunt for knowledge and skill advancement in the 21st century because of its adaptability to individual needs and capacity to encourage connection.

With ChatGPT, a personalized virtual instructor, students may quickly acquire knowledge and help in various academic fields. It supports academic work and research duties, effectively replies to inquiries, and clarifies complex topics (Pavlik, 2023). Yilmaz and Yilmaz (2023) stated that ChatGPT is a superb teaching tool that can be used for everything from challenging arithmetic problems to exploring intricate scientific ideas. Its fantastic capacity to modify explanations to fit the individual comprehension levels of each student significantly enhances the learning process. Education is more adaptive and accessible than ever before, and ChatGPT may be a flexible and accessible ally in the pursuit of knowledge, whether one spends all night studying or simply seeks some clarification on the weekends. Additionally, ChatGPT offers several ways to help instructors. Its ability to provide instructional content requires developing interesting and instructive courses, customizing explanations to meet the requirements of particular students, and providing additional learning resources (Pavlik, 2023). Using an AI-powered tool can automate processes for instructors and free up time for more one-on-one interactions with students.

ChatGPT Improves Students' Learning

Numerous studies have illuminated ChatGPT's remarkable positive impact on student learning experiences. Cooper (2023) delved into the field of science education and uncovered ChatGPT's considerable value as a resource for students. In addition, Dergaa et al. (2023) conducted an exhaustive investigation into ChatGPT's potential in academic writing, and their findings were overwhelmingly positive. They concluded that ChatGPT plays a crucial role in assisting students in producing well-structured and informative content. Both of these in-depth analyses highlight the crucial role that ChatGPT plays in enhancing students' learning experiences by providing instantaneous and accurate information. They have access to many new tools made possible by modern technology to aid their studies. ChatGPT not only helps students in their pursuit of information but also allows them to make the most of their learning experiences, increasing the likelihood that they will succeed in their studies and beyond (Pavlik, 2023).

In addition, ChatGPT is an exceptional resource for developing critical thinking and problem-solving abilities in a variety of contexts (Eysenbach, 2023). This interactive learning experience allows students to become knowledge seekers, enabling them to actively participate in the search for understanding rather than passively receiving solutions. Simply put, ChatGPT catalyzes the development of inquiring minds and fosters a strong feeling of intellectual curiosity, giving students valuable abilities that go beyond the purview of conventional schooling (Scherer et al., 2019). The ability to find and analyze data with proficiency is now essential in today's internet-dominated world. Students develop a deeper understanding of the vast digital landscape with discernment and caution as they interact with the model, strengthening their capacity to become critical consumers of online content. As they do this, they learn to assess the credibility and pertinence of the information provided (Scherer et al., 2019).

The Acceptance of ChatGPT in Education: Insights from Research

Several studies have investigated the acceptance of AI-powered technology (ChatGPT) and provided valuable insight into the factors that influence the acceptance and impact of these technologies on students' educational experiences.

Alghatrifi and Khalid (2019) used a systematic review of UTAUT and UTAUT2 as a foundational model for information system research on adopting new technologies. The UTAUT and UTAUT2 models provide pertinent insights into the acceptability of technology in education, even though ChatGPT was not this study's primary objective (Dai et al., 2023). These models highlight the relevance of several essential variables when assessing users' intention to embrace technology, including performance expectancy, effort expectancy, social influence, and enabling circumstances (Kasneci et al., 2023). Yilmaz and Yilmaz (2023) argue that teachers and developers may benefit from understanding the importance of these components in making ChatGPT user-friendly, effective, and well-supported to increase its uptake and efficiency in educational contexts. Järvelä et al. (2023) used the UTAUT2 model to examine the factors influencing the acceptability of blended learning. Even though their study focuses on blended learning, they emphasize the importance of performance expectation, effort expectancy, social impact, and enabling factors in education. These elements also influence the adoption of ChatGPT in educational contexts.

The potential advantages of ChatGPT in fostering teaching and learning were investigated by Al-Safadi et al. (2023) and included a wide range of perspectives on the changing AI ecosystem. These studies demonstrate the critical role that several essential elements play in adopting and integrating AI-driven technologies like ChatGPT in educational settings. The perceived utility of such technology is a crucial consideration, and instructors and students alike must acknowledge their real-world worth in enriching the educational process. The simplicity of use is also vital since the usability and accessibility of AI products are essential for widespread adoption (Qin et al., 2020). Additionally, peer and teacher recommendations and other social influences significantly impact how people perceive AI and behave toward the use of it in education. These insights point out the critical factors to consider when investigating and implementing ChatGPT in educational settings, including their potential benefits for providing tailored help and fostering enhanced learning outcomes.

UTAUT2 Model

The Unified Theory of Adoption and Use of Technology 2 (UTAUT2) is a robust model created to explore the complex web of variables that influence the adoption and use of technology (Alghatrifi & Khalid, 2019). The UTAUT2 model is a thorough model that explores several crucial factors affecting how technology is accepted and used. These factors determine a person's desire to accept technology, which affects how they use it (Medeiros et al., 2022; Qin et al., 2020).

Description of UTAUT2 Constructs

Performance Expectancy: This factor emphasizes that adopting a particular technology may considerably improve a person's professional performance. Both students and instructors carefully consider the potential advantages of technology in terms of its ability to enhance learning outcomes and the overall efficacy of instructional techniques (Kopplin, 2022). This idea emphasizes how technology permeates contemporary educational paradigms and is increasingly seen as crucial for enabling students to attain their academic goals and instructors to teach more effectively and engagingly.

Effort Expectancy: The uptake of technology in education is heavily influenced by effort expectations. This includes the user's assessment of how simple or complex the technology is to use (Alghatrifi & Khalid, 2019). Technology's incorporation into the educational process is only possible if it is easier and not burdensome for instructors and students to utilize. The user-friendliness and simplicity of educational technology should thus be given priority to promote technological acceptability and efficacy. Technology may be an excellent tool for improving educational outcomes and learning experiences when it is user-friendly and requires little effort to navigate.

Social Influence: By utilizing outside elements like the opinions and advice of peers and instructors, social influence significantly influences how and whether people decide to adopt new technologies (Azizi et al., 2020). This dynamic is seen in educational settings as the ability of instructors to shape students' technological preferences through the influence of parents, peers, and instructors. The complex web of social impact is influenced by instructors' recommendations for specific technologies, parental advice on screen usage, and peer group preferences (Medeiros et al., 2022). This phenomenon highlights the need to encourage good technology-related behaviors in learning environments, where the combined effect of these external pressures may drastically alter the technological background of students.

Facilitating Conditions: To provide smooth operations and the best user experiences, conducive circumstances must be present. These prerequisites go beyond simple accessibility to hardware, software, and technical assistance in education. They extend to a comprehensive structure that supports the educational setting (Azizi et al., 2020). This model includes a strong support network, well-equipped infrastructure, and abundant resources. It's about giving instructors and students the necessary equipment and resources to succeed, creating an environment that supports learning, while equipping them with the skills they need to successfully navigate the digital world (Foroughi et al., 2023).

Hedonic Motivation: Hedonic motivation explores the desire for pleasure and happiness in the use of technology. This idea is implemented in education by incorporating gamified learning platforms and engaging educational software, both of which are designed to make learning enjoyable. Using gamification approaches, instructors may create immersive and interactive experiences that inspire students to participate actively in their education (Medeiros et al., 2022). These platforms encourage a pleasant learning environment that includes incentives, competition, and amusing challenges (Azizi et al., 2020). Therefore, students are more likely to be passionate and involved, and this will eventually improve their educational performance by turning routine classes into fun learning and development journeys.

Learning Value: Learning value examines instructors' perception of ChatGPT as a learning tool. Studies stated that the effectiveness of technologies is a strong predictor of behavior intention in regard to teaching (Foroughi et al., 2023). Instructors are tasked with providing students with effective tools that improve the students' learning and knowledge; therefore, their perception of ChatGPT as an effective learning tool affects their intention to use it in education (Foroughi et al., 2023). Due to the interactive features of ChatGPT, it has been increasingly used among students recently. It motivates the students to increase their learning value by being involved in the content (Medeiros et al., 2022). In a quickly changing educational environment, where wise choices can influence the future of education, it is crucial to strike a balance between investing in technology and understanding its potential impact on learning outcomes.

Information Quality: Information quality is a measurement based on the students' response to the output information. According to Nookhao and Kiattisin (2023), information quality refers to the construct's understandability, relevance, completeness, personalization, and variety to meet the students' needs. In the current study, information quality represents the aspects of ChatGPT features and serves as an external variable in the UTAUT2 model. It represents the beliefs about the resources themselves (ChatGPT), rather than beliefs about using these resources (Menon & Shilpa, 2023). Because beliefs about e-resource characteristics shape beliefs about using e-resources, information quality has a critical effect on behavioral intention and perceived usefulness of the information system. Therefore, examining the effect of information quality leads to improving the utilization and effectiveness of ChatGPT in education to provide better learning services to students and help them adapt well to the new technology (Menon & Shilpa, 2023).

Privacy Risk: Privacy risk can be defined as a crucial concept that gives users control over accessibility to their personal information. Smith et al., (2023) ranked privacy risk as the second most important factor that determines user choice and preference for a technology tool. Different studies noticed that ChatGPT can collect personal information such as names, contact information, and payment information as well as IP addresses linked to the users' interaction (Smith et al., 2023). Significant privacy risks are related to ChatGPT, which includes creating profiles for users by analyzing their prompts. It is a critical threat that might compromise the users' (students) privacy by allowing access to their personal information (Foroughi et al., 2023). Through the analysis of privacy risk, it can identify and moderate privacy risks, protect students' personal information, and maintain privacy regulations (Smith et al., 2023). Therefore, the degree of privacy risk would negatively affect the willingness to use ChatGPT.

The UTAUT2 model provides a comprehensive and insightful perspective on the factors that influence the adoption and use of technology in education. By delving into the intricate web of determinants, UTAUT2 enables stakeholders to assess instructors' preparedness and enthusiasm for integrating educational technology into their teaching. Its holistic approach enables these key actors to make informed decisions, fostering a more seamless and efficient integration of technology into education (Foroughi et al., 2023).

Instructors' Technological Pedagogy Content Knowledge (TPACK)

To further comprehend the integration of ChatGPT and other AI-driven technologies into education, instructors must contemplate the concept of Technological Pedagogical Content Knowledge (TPACK). The framework examines how instructors' knowledge of technology, pedagogy, and content enhance their teaching practices. This framework fits as a moderator factor to be examined incorporating with the UTAUT2 model (Mohammad-Salehi, Vaez-Dalili & Heidari, 2021). It recognizes the dynamic interaction of three essential components in education: technology, pedagogy (teaching methodologies), and content (Scherer et al., 2019). The framework is the amalgamation of these three knowledge domains, and it influences their instructional design and delivery. It is a critical framework in education that emphasizes how closely technology, pedagogy, and content are related in the context of teaching. Effective instructors know that successful teaching requires a thorough understanding of how these three areas connect and support one another (Alzahrani, 2014). Instructors can create more engaging, interactive, and individualized learning environments when they effectively integrate technology into their teaching practices. Instructors who have a solid understanding of the Technological Pedagogical Content Knowledge (TPACK) framework create dynamic learning environments while smoothly incorporating technology into their teaching practices (Scherer et al., 2019). It is essential to understand how teachers integrate the appropriate technology in each learning setting through examining teachers' TPACK in using AI technologies (Mohammad-Salehi et al., 2021; Ning et al., 2024). The combination of advanced technology and solid pedagogical knowledge has the potential to completely change the face of education and make learning experiences incredibly engaging (Alzahrani, 2014).

Objectives

This study proposed the following hypotheses:

H1: PE has a positive effect on BI to use ChatGPT.
H2: EE has a positive effect on BI to use ChatGPT.

H3: SI has a positive effect on BI to use ChatGPT.
H4: FC has a positive effect on BI to use ChatGPT.
H5: HM has a positive effect on BI to use ChatGPT.
H6: LV has a positive effect on BI to use ChatGPT.
H7: IQ has a positive effect on BI to use ChatGPT.
H8: PR has a positive effect on BI to use ChatGPT.
H9: Instructors' TPACK has a positive moderation of the association between BI to use ChatGPT and the factors of PE, EE, SI, FC, HM, and LV.

Table 1
Research hypotheses

Hypotheses	Connection	Description
H1	PE+BI	Instructors' Performance Expectancy will positively affect BI ChatGPT
H2	EE+BI	Instructors' Effort Expectancy will positively affect BI ChatGPT
H3	SI+BI	Instructors' Social Influence will positively affect BI ChatGPT
H4	FC+BI	Instructors' Facilitating Conditions will positively affect BI ChatGPT
H5	HM+BI	Instructors' Hedonic Motivation will positively affect BI ChatGPT
H6	LV+BI	Instructors' Learning Value will positively affect BI ChatGPT
H7	IQ+BI	Instructors' Information Quality will positively affect BI ChatGPT
H8	PR+BI	Instructors' Privacy Risk will positively affect BI ChatGPT
H9	TPACK[PE, EE, SI, FC, HM, and LV+BI]	Instructors' Technological Pedagogical Content Knowledge positively moderated the association between (PE, EE, SI, FC, HM, and LV) and BI ChatGPT

Note: Table 1 shows the relationship between the nine hypotheses considering Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Learning Value (LV), Information Quality (IQ), Privacy Risk (PR), Technological Pedagogical Content Knowledge (TPACK), and Behavioral Intention (BI). The variables' connections shown in Table 1 provide a well-defined demonstration that the UTAUT2 model is an effective model for examining the acceptance of the use of new technologies.

METHODOLOGY

A quantitative approach was used to collect the data from a sample of (569) instructors in Saudi Universities. A quantitative approach was used to measure the objective with statistical form instructors' responses, examining the impact of instructors' TPACK on their intention to use ChatGPT. This approach was in line with the analysis of the relationship among the variables of the UTAUT2 model (Kopplin, 2022). UTAUT2 is a theoretical model that forms an understanding of the factors that affect the intention of adapting a new technology (Foroughi et al., 2023). To achieve the purpose of the study, (9) variables were examined to reveal the factors that influence the instructors' intention and the acceptance of using ChatGPT in teaching. Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Learning Value (LV), and Behavioral Intention (BI) (Foroughi et al., 2023), Information Quality (IQ) and Privacy

Risk (PR) (Kopplin, 2022), and the Faculty members' TPACK (Alzahrani, 2014). Path analysis and Smart PLS were used for data analysis.

The research followed convenience sampling by sending an electronic survey to Saudi university instructors to collect their responses. Participants were male and female instructors in Saudi universities and had varying levels of experience, from 1 to 5 years, 6 to 10 years, and more than 11 years.

RESULTS

Descriptive statistics

The demographics of a particular population are displayed by gender and years of experience in the descriptive statistics in Table 2. 69.2% of the 569 individuals are male (394 faculty members), and 30.8% are female (175 faculty members). As a result, the gender distribution cumulative percentage comes to 100%. As for years of experience, just 4.9% (28 faculty members) have worked for one to five years, while the majority, 72.6% (413 faculty members), have more than 11 years of experience and a moderate portion, 22.5% (128 faculty members), have six to ten years of experience. According to this data, the workforce is primarily male and highly experienced, with most participants having worked in their field for more than 11 years. These statistics were as a result of the Saudi universities policies that have been limited to specific conditions in employment during the last decade.

Table 2
Descriptive statistics

Demographics		**Frequency**	**Percent**	**Valid Percent**	**Cumulative Percent**
Gender	Male	394	69.2	69.2	69.2
	Female	175	30.8	30.8	100.0
	Total	569	100.0	100.0	
Years of experience	1 to 5 years	28	4.9	4.9	4.9
	6 to 10 years	128	22.5	22.5	27.4
	More than 11 years	413	72.6	72.6	100.0
	Total	569	100.0	100.0	

Validity and Reliability

The measurement model's convergent validity is supported by the factor loadings shown in Table 3, showing a strong factorial structure with high loadings on each construct. Every item appears to load substantially on the factor for which Henseler et al. (2015) designed it, with loadings higher than the generally accepted cutoff of 0.7, as proposed. All loadings for the other constructs – "Hedonic Motivation," "Information Quality," "Learning Value," "Performance Expectancy," "Privacy Risk," "Social Influence," and "Faculty Members' TPACK" – are significantly above the threshold, indicating that each construct is well-defined by its items.

The study tests convergent validity, including average variance extracted (AVE > 0.50) and reliability, including Cronbach alpha > 0.70 and Composite reliability > 0.70 (Hair et al., 2017; Henseler, et al., 2015). The Average Variance Extracted (AVE) values indicate that most constructs have convergent validity. Despite being above the threshold, the indicators "Behavioral Intention," "Effort Expectancy," "Information Quality," "Learning Value" and "Faculty Members' TPACK" have AVEs that suggest caution in interpreting their relevance and potential for additional research. The majority of the constructs demonstrate robust internal consistency as evidenced by high Composite Reliability scores surpassing 0.7. As per Hair et al. (2017), a Cronbach's alpha value of 0.7 or higher is generally regarded as satisfactory, signifying that the items included in the construct measure the same underlying phenomenon.

Table 3

Convergent validity measures (Factor loadings, Alpha, CR and AVE)

Constructs	Items	Factor Loading	Alpha	CR	AVE
Behavioral Intention	BI1	0.764	0.476	0.791	0.654
	BI3	0.851			
Effort Expectancy	EE1	0.862	0.839	0.892	0.674
	EE2	0.853			
	EE3	0.756			
	EE4	0.810			
Facilitating Condition	FC1	0.811	0.898	0.929	0.766
	FC2	0.904			
	FC3	0.917			
	FC4	0.866			
Hedonic Motivation	HM1	0.916	0.769	0.834	0.629
	HM2	0.735			
	HM3	0.714			
Information Quality	IQ1	0.875	0.890	0.924	0.754
	IQ2	0.901			
	IQ3	0.789			
	IQ4	0.902			
Learning Value	LV1	0.733	0.816	0.879	0.647
	LV2	0.854			
	LV3	0.780			
	LV4	0.843			
Performance Expectancy	PE2	0.802	0.841	0.886	0.610
	PE3	0.713			
	PE4	0.808			
	PE5	0.772			
	PE6	0.807			
Privacy Risk	PR1	0.834	0.840	0.903	0.757
	PR2	0.920			
	PR3	0.854			
Social Influence	SI2	0.920	0.824	0.919	0.850
	SI3	0.924			
Teachers' TPACK	TPACK1	0.764	0.839	0.893	0.676
	TPACK2	0.879			
	TPACK3	0.833			
	TPACK4	0.808			

Discriminant validity (HTMT)

A modern method for evaluating discriminant validity in variance-based structural equation modeling such as partial least squares SEM (PLS-SEM) is the Heterotrait-Monotrait (HTMT) ratio of correlations. This approach makes it more evident as to whether, conceptually and empirically, distinct constructs are different. This analysis frequently shows that the data are divided into various classes, each of which may have discriminant validity problems (Table 4).

Table 4
Heterotrait-Monotrait (HTMT) Ratio

Constructs	1	2	3	4	5	6	7	8	9
Behavioral intention									
Effort expectancy	1.103								
Facilitating condition	1.083	0.738							
Hedonic motivation	0.487	0.427	0.338						
Information quality	1.091	0.797	0.977	0.359					
Learning value	1.212	0.969	0.740	0.378	0.793				
Performance expectancy	1.308	0.946	0.697	0.370	0.751	1.183			
Privacy risk	1.236	0.790	0.976	0.357	0.944	0.779	0.741		
Social influence	0.678	0.524	0.549	0.765	0.536	0.493	0.481	0.532	
Teachers' TPACK	1.205	0.916	1.049	0.384	0.975	0.879	0.844	1.068	0.581

Model fitness

The R-square (R^2) value of 0.963 for the Behavioral Intention in the model indicates a very high level of explained variance (Table 5). This suggests that the independent variables included in the study together account for 96.3% of the variability in Behavioral Intention. The adjusted R-square (R^2 adjusted) value of 0.962, which accounts for the number of predictors in the model and is still very high, further supports this. These values indicate a very good model fit, suggesting that the variables considered in this research almost entirely explain the variations in Behavioral Intention. This high degree of explanatory power indicates how well the model captures the factors influencing Behavioral Intention in the context being studied.

Table 5
R^2 and adjusted R^2

Construct	R-square	R-square adjusted
Behavioral intention	0.963	0.962

Assessment of path model

Direct effects

The t-value, p-value, and beta (β) coefficient magnitudes are used to assess direct effects and the hypotheses that go along with them (Figure 1, Table 6). For a two-tailed test at the 5% significance level, a t-value of 1.96 is a commonly accepted threshold in hypothesis testing, and a p-value of less than 0.05 is normally needed to reject the null hypothesis.

Hypothesis 1 (H1) postulates that Performance Expectancy positively affects Behavioral Intention. The results show a significant β coefficient of **1.998,** with a t-value of **30.398** and a p-value of **0.000**. These values are well above the threshold, indicating a strong positive impact of Performance Expectancy on Behavioral Intention. Therefore, H1 is **accepted** [β=1.998, t-value=30.398, p-value=0.000]. Hypothesis 2 (H2) suggests that Effort Expectancy influences Behavioral Intention. However, with a β of **0.017**, a t-value of **0.882**, and a p-value of **0.378**, it does not meet the criteria for significance. Thus, H2 is **rejected** [β=0.017, t-value=0.882, p-value=0.378].

Hypothesis 3 (H3), concerning the effect of Social Influence on Behavioral Intention, shows a β of **0.008**, a t-value of **0.367**, and a p-value of **0.713**. These values do not signify a statistically significant effect, leading to the rejection of H3 [β=0.008, t-value=0.367, p-value=0.713]. Hypothesis 4 (H4) examines the influence of Facilitating Condition on Behavioral Intention. The significant β of **0.134**, t-value of **3.381**, and p-value of **0.001** suggest a positive effect; thus H4 is **accepted** [β=0.134, t-value=3.381, p-value=0.001]. Hypothesis 5 (H5), which predicts the impact of Hedonic Motivation on Behavioral Intention, has a β of **-0.010**, t-value of **0.520**, and p-value of **0.603**, indicating no significant effect and leading to the rejection of H5 [β=-0.010, t-value=0.520, p-value=0.603].

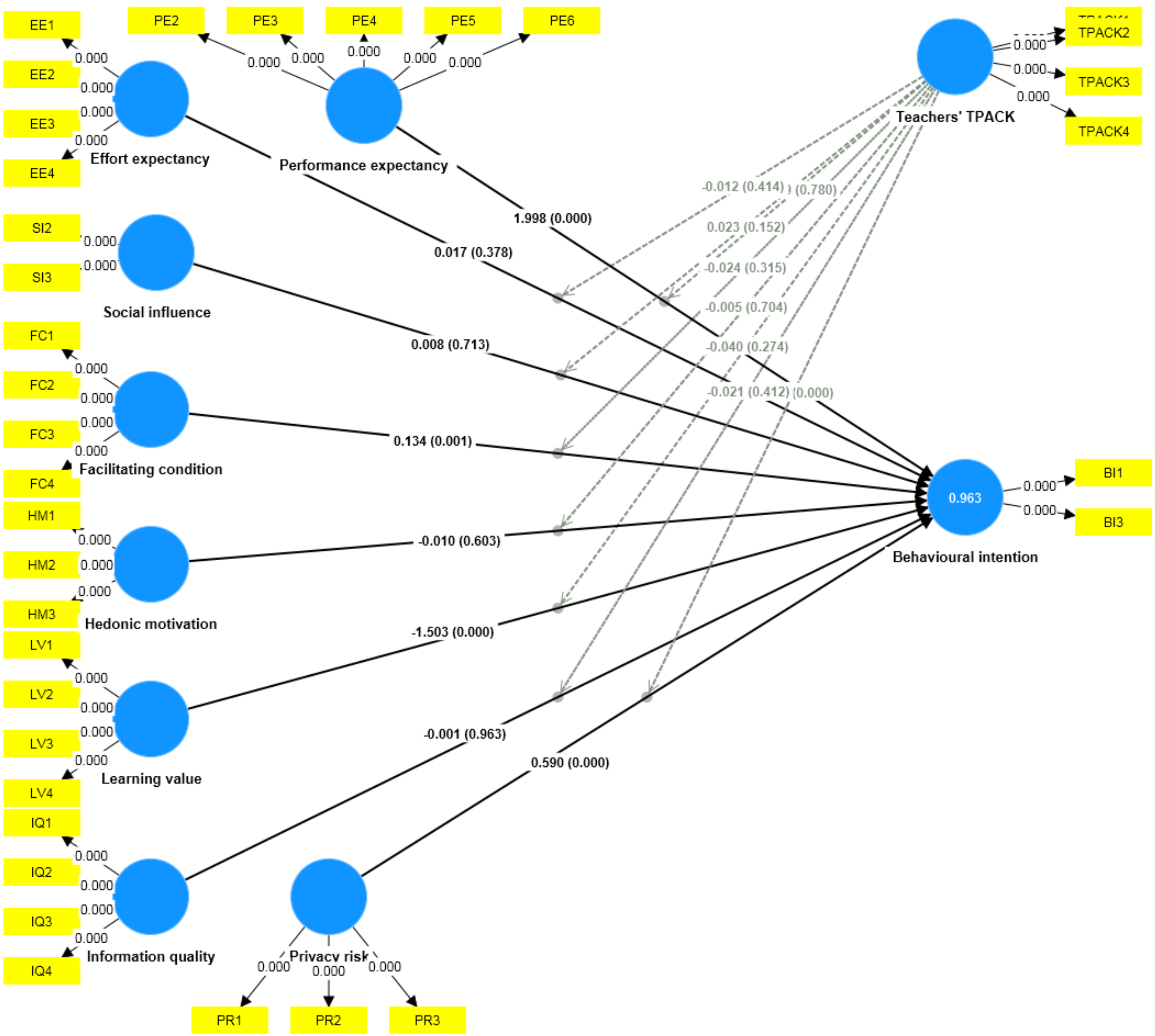
Hypothesis 6 (H6) indicates that Learning Value has a negative effect on Behavioral Intention. With a substantial β of **-1.503**, a t-value of **24.489**, and a p-value of **0.000**, it shows a significant negative influence; thus, H6 is **accepted** [β=-1.503, t-value=24.489, p-value=0.000]. Hypothesis 7 (H7) assesses the influence of Information Quality on Behavioral Intention. The β is negligible at **-0.001**, with a t-value of **0.046** and a p-value of **0.963**, indicating no significant effect and leading to the rejection of H7 [β=-0.001, t-value=0.046, p-value=0.963]. Finally, Hypothesis 8 (H8) posits that Privacy Risk affects Behavioral Intention. The results show a β of **0.590**, a t-value of **25.111**, and a p-value of **0.000**, which suggests a significant effect; thus, H8 is **accepted** [β=0.590, t-value=25.111, p-value=0.000].

According to the results of the hypothesis testing, Effort Expectancy, Social Influence, Hedonic Motivation, and Information Quality do not demonstrate a significant influence on Behavioral Intention. The results also show that Performance Expectancy, Facilitating Condition, Learning Value (negatively), and Privacy Risk have significant effects. These findings demonstrate the intricacy of the variables influencing Behavioral Intention, which serve as a basis for accepting or rejecting the suggested theories.

Table 6
Hypothesis testing of Direct effects

Direct effects	(β)	t-value	p-value
H1. Performance expectancy -> Behavioral intention	1.998	30.398	0.000
H2. Effort expectancy -> Behavioral intention	0.017	0.882	0.378
H3. Social influence -> Behavioral intention	0.008	0.367	0.713
H4. Facilitating condition -> Behavioral intention	0.134	3.381	0.001
H5. Hedonic motivation -> Behavioral intention	-0.010	0.520	0.603
H6. Learning value -> Behavioral intention	-1.503	24.489	0.000
H7. Information quality -> Behavioral intention	-0.001	0.046	0.963
H8. Privacy risk -> Behavioral intention	0.590	25.111	0.000

Figure 1
SEM Model



Moderating effects

The study tests the moderating effect of faculty members' TPACK between all dimensions of UTAUT factors and Behavioral Intention (Figure 1, Table 7). The moderating effects analysis aims to comprehend how introducing a third variable (in this case, Faculty Members' TPACK) affects the relationship between independent variables and the dependent variable (Behavioral Intention). First, we have a significant negative beta (β) coefficient of -0.217, with a t-value of 5.527 and a p-value of 0.000, regarding the direct effect of Faculty Members' TPACK on Behavior Intentions. This implies a significant negative direct relationship between Faculty Members' TPACK and Behavioral Intention, with Behavioral Intention decreasing as Faculty Members' TPACK increases.

For H9a, the interaction term of Faculty Members' TPACK and Performance Expectancy has a β of **0.009**, with a t-value of **0.280** and a p-value of **0.780**, indicating that Faculty Members' TPACK does not significantly moderate the relationship between Performance Expectancy and Behavioral Intention. Therefore, H9a is **rejected**. H9b's interaction of Faculty Members' TPACK and Effort Expectancy shows a β of **-0.012**, a t-value of **0.816**, and a p-value of **0.414**, which is insignificant. Thus, H9b is also **rejected**. In H9c, the β for the interaction of Faculty Members' TPACK and Social Influence is **0.023**, with a t-value of **1.432** and a p-value of **0.152**. This does not meet the standard significance criteria, leading to the rejection of H9c.

The moderating effect of Faculty Members' TPACK and Facilitating Condition in H9d results in a β of **-0.024**, a t-value of **1.004**, and a p-value of **0.315**. These values are not statistically significant. So, H9d is **rejected**. For H9e, the interaction of Faculty Members' TPACK and Hedonic Motivation on Behavioral Intention has a β of **-0.005**, a t-value of **0.380**, and a p-value of **0.704**, indicating no significant moderating effect and leading to the rejection of H9e. The interaction effect in H9f of Faculty Members' TPACK and Learning Value has a β of **-0.040**, a t-value of **1.093**, and a p-value of **0.274**, which is insignificant. Thus, H9f is **rejected**.

In H9g, the interaction of Faculty Members' TPACK and Information Quality yields a β of **-0.021**, a t-value of **0.820**, and a p-value of **0.412**. This is not significant, and H9g is therefore **rejected**. Finally, H9h, which explores the interaction between Faculty Members' TPACK and Privacy Risk, has a β of **0.083**, a t-value of **4.666**, and a p-value of **0.000**. This indicates a significant moderating effect where Faculty Members' TPACK enhances the positive influence of Privacy Risk on Behavioral Intention. So, H9h is **accepted**.

Table 7
Hypothesis testing of Moderating effects

Moderating effects	**(β)**	**t-value**	**p-value**
Teachers' TPACK -> Behavioral intention	-0.217	5.527	0.000
H9a. Teachers' TPACK x Performance expectancy -> Behavioral intention	0.009	0.280	0.780
H9b. Teachers' TPACK x Effort expectancy -> Behavioral intention	-0.012	0.816	0.414
H9c. Teachers' TPACK x Social influence -> Behavioral intention	0.023	1.432	0.152
H9d. Teachers' TPACK x Facilitating condition -> Behavioral intention	-0.024	1.004	0.315
H9e. Teachers' TPACK x Hedonic motivation -> Behavioral intention	-0.005	0.380	0.704
H9f. Teachers' TPACK x Learning value -> Behavioral intention	-0.040	1.093	0.274
H9g. Teachers' TPACK x Information quality -> Behavioral intention	-0.021	0.820	0.412
H9h. Teachers' TPACK x Privacy risk -> Behavioral intention	0.083	4.666	0.000

Therefore, the direct effects analysis shows that while some variables do not significantly affect Behavioral Intention, others do. Regarding moderating effects, Faculty Members' TPACK does not significantly affect the relationships between the other independent variables and Behavioral Intention, except for the significant moderating role of Faculty Members' TPACK on the relationship between Privacy Risk and Behavioral Intention. This suggests that, with the notable exception of considering Privacy Risk, the strength and direction of these relationships are largely unaffected by Faculty Members' TPACK levels.

DISCUSSION

The study used the Unified Theory of Acceptance and Use of Technology (UTAUT2) to run a thorough analysis to investigate instructors' intention of using ChatGPT in education with a moderation of their TPACK.

The study's observation of a negative direct effect of instructors' TPACK on behavioral intention raises the possibility that, although instructors acknowledge the significance of ChatGPT, their lack of preparedness affects the integration of ChatGPT. Reflecting a growing consensus on the significance of technological pedagogical content knowledge (TPACK) and the integration of ChatGPT in educational contexts, these findings are consistent with recent research in education technology and its acceptance (Alghatrifi & Khalid, 2019; Azizi et al., 2020). Previous studies stated that instructors who lack technology use became less interested in using it in their teaching (Sidiropoulos & Anagnostopoulos, 2024; Islam & Islam, 2024). Universities play a critical role in providing instructors with the required technological and pedagogical skills to confront these challenges and effectively benefit what new technologies offer for higher education (Perera & Lankathilaka, 2023).

The study also identified that the effect of performance expectancy and facilitating conditions on behavioral intentions to use ChatGPT align with the UTAUT2 model and the systematic review of new technology adoption by Alghatrifi and Khalid (2019). Azizi et al. (2020), who discovered performance expectancy, corroborate the findings of this study that facilitating conditions were significant predictors of blended learning acceptance in education. Furthermore, an intriguing finding that echoes concerns raised in Dergaa et al. (2023) regarding potential threats of ChatGPT in academic writing is the significant negative moderating effect of instructors' TPACK on the relationship between privacy risk and behavioral intention. This finding suggests that increased pedagogical knowledge may amplify concerns over privacy risks associated with new technologies. Training for technological pedagogical knowledge and an understanding of new research in the field of new technology are required (Luo, 2024; Perera & Lankathilaka, 2023). This would reflect better understanding and use of technology by instructors in searching, planning, and analyzing information. In spite of the fact that ChatGPT offers several tasks, such as referenced texts, images, and presentations, instructors should be concerned about the quality and the reliability of the information (Perera & Lankathilaka, 2023; Sidiropoulos & Anagnostopoulos, 2024). That could be a challenge to help future students actively and positively use deal with ChatGPT. Therefore, instructors play an important role in students' interaction with ChatGPT (Li et al., 2022). While the observed negative impact of learning value on behavioral intention may initially seem counterintuitive, it points to a complex relationship between content value and the willingness to adopt new technologies. This idea is currently at the forefront of educational technology discussions, as Yilmaz and Yilmaz (2023) and Järvelä et al. (2023) noted. These nuanced findings highlight the complex interplay between pedagogical considerations, privacy concerns, and the perceived value of learning content in shaping the adoption of technology in educational settings.

The results of this study provided a better understanding to the challenges using generative AI technologies tools (ChatGPT) in education. Alshahrani (2023) and Cooper (2023), who examined ChatGPT's effects on blended learning and science education, respectively, underline the importance of integrating artificial intelligence (AI) in education. Yilmaz and Yilmaz (2023) argue that teachers and developers may benefit from understanding the importance of these components in making ChatGPT user-friendly, effective, and well-supported to increase its uptake and efficiency in educational contexts. The positive reception and cautious optimism that these works portray, and the present study's alignment with them, point to a wider trend in the academic community toward acknowledging AI's transformative potential while also being aware of its challenges.

Limitations of the current study can be referred to the size of the study sample. While the number of participants was sufficient with the structure of UTAUT2 model analysis, a larger sample would better generalize and represent the study population. Unequal distribution of the gender and experience might cause a bias in the results. Finally, the model should be extended with more factors in future research for more understanding of the intention of adoption of new technology.

RECOMMENDATIONS

The findings recommend that educational institutions should adopt a comprehensive strategy when promoting new technologies such as artificial intelligence in education. Instructors' technological pedagogical content knowledge (TPACK) needs to be improved and their behavioral intention toward technology adopted. Professional development programs that emphasize the pedagogical and technical aspects of emerging technologies could help achieve this. Through this approach, instructors can enhance their self-assurance and preparedness, incorporate these technologies into their teaching methodologies, and, consequently, reduce the detrimental impact of TPACK on behavioral intention. Educational institutions should ensure that the expected performance benefits of new technologies are communicated clearly and that sufficient support and resources are made available to properly facilitate their integration into the learning environment. This is because performance expectancy and facilitating conditions significantly affect behavioral intention.

Proactively addressing privacy concerns is crucial, especially in light of the negative moderating effect of TPACK on the relationship between privacy risks and behavioral intention. To allay these worries, it is recommended that developers and providers of educational technology prioritize the creation of comprehensive privacy safeguards and clear policies. Instructors are more likely to adopt new technologies if they believe they will improve their teaching performance and they can trust the technology to protect their privacy, as evidenced by the significant positive effects of both performance expectancy and privacy risk on behavioral intention. Therefore, to boost adoption rates, educational institutions should prioritize unambiguous examples of the advantages of new technologies and highlight their privacy features. Moreover, instructors may view high-value learning content as incompatible with new technology because of a perceived risk of lowering the quality of direct instruction or interpersonal interaction, as evidenced by the negative effect of learning value on behavioral intention. Therefore, better integration techniques are needed to maintain the educational value of technology while matching it with pedagogical objectives.

CONCLUSION

The study's conclusions shed light on the intricate interactions among variables that shape instructors' intentions to incorporate new ChatGPT technology into their instruction. Although it was discovered that performance expectancy and facilitating conditions had a positive impact on behavioral intentions (suggesting that perceived usefulness and support are important factors in the adoption of technology), instructors' TPACK had a negative direct effect on behavioral intentions. That suggests that there may be a gap between instructors' pedagogical knowledge and their willingness to adopt new technologies. Instructors' concerns regarding data privacy in the context of educational technology is highlighted by the significant negative moderating effect of TPACK on the relationship between privacy risk and behavioral intention, requiring professional development programs in line with technological innovations. Through these development programs, the level of awareness of using ChatGPT effectively will be raised. These findings imply the potential benefits of emerging artificial intelligence technologies for improving educational outcomes, comprehensive support systems such as professional development and that strong privacy models are still required. ChatGPT transforms education by providing each student with individualized help. It facilitates a more effective and exciting learning experience by smoothly adapting to individual learning demands. ChatGPT determines each student's personal understanding level through dynamic interaction, offering explanations and resources that are appropriately tailored to their capacities (Liu et al., 2023).

Future research directions should consider extending the scope of the investigation to understand the underlying reasons behind the negative influence of instructors' TPACK on behavioral intention. Studies could explore qualitative insights from instructors to uncover the nuances of this relationship, such as potential apprehensions or misconceptions about integrating technology into pedagogy. There is also an opportunity to examine the long-term impacts of privacy risks on technology adoption and how these concerns evolve with increased familiarity of technology in educational settings. Additionally, given the rapid advancement of AI tools like ChatGPT, future studies should assess their pedagogical impact and the evolving role of such technologies in shaping educational practices and outcomes. Finally, to provide a global perspective on technology adoption in education, there is a need for cross-cultural research to compare how these factors play out in different educational systems around the world.

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