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Factors Influencing the Adoption of ChatGPT for Innovation Generation: A Moderated Analysis of Innovation Capability and Gender using UTAUT2 framework.

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Abstract

This study aimed to examine the adoption of ChatGPT for innovation generation among students and explore the moderating effects of innovation capability and gender using the UTAUT2 framework. A cross-sectional design was used, collecting data through a structured questionnaire from 446 public university students in Ghana using convenience sampling. Structural equation modeling was employed to analyse the data. The results revealed that hedonic motivation, social influence, and performance expectancy had a statistically significant positive effect on behavioral intention, which in turn significantly affected use behavior. Effort expectancy and facilitating conditions had a positive but statistically insignificant effect on behavioral intention, while facilitating conditions negatively impacted use behavior. Additionally, gender and innovation capability significantly moderated the relationship between facilitating conditions and behavioral intention. Educational institutions and technology providers should design interventions considering hedonic motivation, social influence, and performance expectancy. These interventions should aim to improve facilitating conditions, which are gender-sensitive. Recognising the moderating role of innovation capability, organisations should focus on developing and enhancing innovation capabilities among their members by providing training programs, fostering a culture of creativity and experimentation, and allocating resources towards innovation initiatives. This study contributes to the literature by advancing research on AI adoption in higher education, particularly focusing on critical factors influencing innovation generation through the use of ChatGPT.

Keywords: *ChatGPT, Behavioural intention, Use behavior, Gender, Innovation capability*

1.0 Introduction

The integration of artificial intelligence (AI) technologies in educational settings has gained significant attention due to its potential to revolutionise learning experiences and foster innovation among students (Civit et al., 2024; Guan et al., 2020; Fu et al., 2024; Grassini, Aasen, and Møgelvang 2024). As technology continues to reshape the educational landscape, understanding the factors influencing the adoption of emerging technologies becomes increasingly crucial (Lee and Jones, 2020). A notable AI technology gaining prominence in education is ChatGPT, short for Generative Pre-trained Transformer, developed by OpenAI (Radford et al., 2019). ChatGPT, part of the Transformer architecture family, employs deep learning techniques, specifically a variant of the Transformer known as GPT. AI's pervasive influence spans various economic sectors, including finance (Hidayat, Defitri, and Hilman 2021; Sachan et al., 2024), healthcare (Rahman et al., 2023; Samala and Rawas, 2024), and transportation (Das and Datta, 2024). Its transformative potential extends to education as well (Adıgüzel, Kaya, and Cansu 2023; Tiwari et al., 2023), where AI can significantly enhance student learning through personalised, real-time feedback and tailored learning approaches. Incorporating platforms like ChatGPT into curricula provides students with opportunities for collaborative problem-solving, creative writing, and idea exploration.

Existing literature on ChatGPT adoption in education reveals several key findings. Salifu et al. (2024) demonstrated that behavioral intentions and facilitating conditions significantly influence students' use of ChatGPT. Parker (2024) found that

ChatGPT consistently outperformed average students across various classes. In a related study, Gulati et al. (2024) identified habit as the most influential predictor of behavioral intention to use ChatGPT. Meanwhile, Costa, Costa, and Carvalho (2024) reported that students primarily use ChatGPT for information retrieval and generating initial ideas for specific topics. Despite these insights, notable gaps in the literature on the use of ChatGPT for innovation generation among students remain limited. This gap is partly due to contradictory findings; for instance, Filippi (2023) reported both negative and positive effects of ChatGPT on innovative product design, while Hassan et al. (2024) suggested that ChatGPT might impede students' innovativeness. Conversely, Dai, Liu, and Lim (2023) conceptualise ChatGPT as a student-driven innovation with significant potential to enhance educational experiences. These contradictory findings underscore the need to investigate the role of ChatGPT in generating innovation and the moderating effects of innovation capability in the relationship between the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) constructs and behavioral intention. In this study, innovation capability is defined as an individual's capacity to generate, develop, and implement novel ideas, processes, products, or services (Lawson and Samson, 2001), and is shown to be a significant moderator in technology acceptance models (Iranmanesh et al., 2021; Yang, 2012). Innovation capability is crucial because individuals with high innovation capability are more likely to recognise the potential of new technologies, adapt them to their needs, and integrate them effectively into their workflows. This adaptability could enhance the perceived usefulness and ease of use of technologies like ChatGPT, thereby increasing their acceptance and utilisation.

Moreover, gender differences in technology acceptance (Padilla-Meléndez, del Aguila-Obra, and Garrido-Moreno 2013) warrant investigation. Understanding how gender moderates the acceptance of ChatGPT could provide valuable insights for developing tailored educational strategies that effectively engage and support students of all genders.

This study aims to address these gaps by examining the adoption of ChatGPT for innovation generation among students and exploring the moderating effects of innovation capability and gender using the UTAUT2 framework. By doing so, this research seeks to provide comprehensive insights into the factors driving students' acceptance of ChatGPT, ultimately contributing to the enhancement of educational practices and the promotion of student innovativeness.

Research objectives guiding this study

1. To examine how innovation capability moderates the relationship between UTAUT2 constructs and actual usage behaviors.
2. To explore the influence of gender on the acceptance of ChatGPT among students, taking into account potential variations in perceptions and behaviors.
3. To utilise the UTAUT2 framework to analyse the interaction among UTAUT2 constructs, innovation capability, gender, and ChatGPT adoption.

2.0 Literature review

2.1 Adoption of AI-driven Tools for Innovation Generation

Foundational studies such as Davis's (1989) Technology Acceptance Model (TAM) and its subsequent extensions have shed light on the dynamics of technology acceptance and usage, providing invaluable insights into adoption behavior (Venkatesh and Davis, 2000).

However, the distinctive attributes of AI-driven tools, such as ChatGPT, necessitate further exploration, especially within the context of innovation generation. Additionally, studies have pinpointed perceived ease of use, compatibility with existing workflows, and trust in AI technologies as influential factors shaping adoption intentions (Russo, 2024).). User characteristics and prior experience with AI technologies and individual innovativeness playing pivotal roles in shaping adoption behavior (Zhou et al., 2019). Furthermore, demographic factors such as age, gender, and educational background may impact perceptions of AI technologies and willingness to engage with innovation-oriented tools. In educational settings, the integration of AI-driven tools for innovation generation harbors transformative potential for teaching and learning practices. Moreover, AI-driven tools can facilitate personalised learning experiences, enabling students to receive tailored feedback and guidance aligned with their unique needs and preferences.

2.2 Innovation Capability and Technology Adoption

Previous research indicates that individuals with a strong inclination towards innovation are more likely to embrace novel technologies and engage in creative pursuits (Globocnik, Peña Häufler, and Salomo 2022). However, the relationship between innovation capability and the adoption of AI-powered tools for innovation, such as ChatGPT, remains underexplored, particularly in educational settings. Understanding how students' inherent innovative capacities influence their adoption behaviors can provide valuable insights into promoting AI utilisation in education.

Furthermore, innovation capability is recognised as a crucial driver of organisational performance and competitiveness (Ferreira, Coelho, and Moutinho 2020). Organisations with higher innovation capability are better equipped to adapt to market shifts, meet consumer demands, and create value through novel products, services, or processes (Dodgson et al., 2000). This capability encompasses various elements, including technological proficiency, creative problem-solving skills, and an environment conducive to experimentation and risk-taking. Moreover, innovation capability significantly shapes organisations' readiness to adopt new technologies for innovation purposes. Studies suggest that organisations with higher innovation capability are more inclined to embrace disruptive technologies and seek new avenues for value creation (Tidd et al., 2001). While innovation capability plays

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a crucial role in technology adoption, other factors such as perceived usefulness, ease of use, compatibility with existing systems, organisational readiness for change, and external pressures also influence adoption behaviors (Venkatesh et al., 2003).

2.3 Theoretical Framework: UTAUT2 Model

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, proposed by Venkatesh, Thong, and Xu (2012), offers a comprehensive lens for examining individuals' adoption behavior regarding technology. UTAUT2 integrates elements from various theoretical models, including the original Technology Acceptance Model (TAM) Davis (1986), Theory of Reasoned Action (TRA), Fishbein and Ajzen, (1975) and social cognitive theories, to provide a holistic understanding of technology adoption. By incorporating factors such as perceived usefulness, perceived ease of use, social influence, and facilitating conditions, UTAT2 offers a framework for analysing the adoption of AI-driven tools like ChatGPT for innovation generation among students.

The introduction of the TAM by Davis (1989) marked a significant step in understanding technology adoption. TAM has earned widespread recognition in academic circles for its simplicity and versatility across various contexts, as noted by Venkatesh, Thong, and Xu (2016). As the theory gained broader applicability, it evolved into the (UTAUT) as described by Venkatesh et al. (2003). UTAUT integrates key factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by variables like age, gender, experience, and voluntariness of use, all influencing Behavioral Intention. Building upon UTAUT, UTAUT2 was introduced in (2012), expanding the model to include additional elements like Habit, Hedonic Motivation, and Price Value, as identified by Venkatesh, Thong, and Xu (2012) by incorporating factors such as perceived usefulness, perceived ease of use, social influence, and facilitating conditions, UTAUT2 offers a perspective for analysing the adoption of AI-driven tools like ChatGPT for innovation generation among students. Our research aims to examine the effect of UTAUT2 on the behavioural intention to adopt ChatGPT.

3. Hypothesis development

3.*1 Effect of UTAUT2 constructs on behavioral intention*

Performance expectancy is defined as the extent to which an individual anticipates that utilising a specific technology will enhance their performance in accomplishing particular tasks or objectives (Davis, 1989; Venkatesh et al., 2003). Soliman et al. (2019) emphasised the importance of performance expectancy in the adoption of technology within academic environments. This assertion finds support in numerous studies that have demonstrated the significant impact of performance expectancy on learners' behavioral intention to adopt innovative educational technologies. For instance, Dahri et al. (2024), results suggest that performance and effort expectancy, as well as the accuracy of information provided by AI tools, align with students' expectations. Additionally, the level of student interaction with these tools emerged as a significant predictor of their acceptance and utilisation among students. Gulati et al. (2024) investigation of marketing students revealed that habit was the most important factor influencing behavioural intention. Hence the following hypothesis is proposed.

H1: Performance expectancy significantly influences behavioral intention.

Several studies have indicated that increased levels of effort expectancy positively influence the adoption of technology (Gulati et al., 2024; Candra et al., 2024; Or and Chapman, 2022). Effort expectancy, as defined by Moore and Benbasat (1991) and further expounded upon by Venkatesh et al. (2003), refers to the expectation individuals hold regarding the ease of use associated with a particular technology. Recent scholarship has underscored the significant influence of effort expectancy on learners' behavioral intention to adopt various educational technologies. For instance, Alfalah (2023) and Voicu and Muntean (2023) observed that effort expectancy played a crucial role in the adoption of mobile learning and learning management systems. Similarly, Hunde, Demsash, and Walle (2023) highlighted the impact of effort expectancy in the adoption of e-learning platforms among health science students. In the context of this study, effort expectancy pertains to the extent to which students perceive ChatGPT as user-friendly and requiring minimal effort to engage with. It shows the students' beliefs about the simplicity of using ChatGPT and the ease of interaction it offers. Hence the following hypothesis is proposed.

H2: Effort expectancy significantly influences behavioral intention.

Social influence is defined as the extent to which an individual perceives that influential individuals in their social circle endorse the use of a particular technology (Ajzen, 1991; Fishbein and Ajzen, 1975; Venkatesh et al., 2003). Numerous studies have underscored the pivotal role of social influence in shaping users' behavioral intention to adopt technology in educational settings. This phenomenon has been evidenced across diverse contexts, including mobile learning (Arain et al., 2019), and learning management systems (Celedonio and Picaso, 2023). In the context of this study, social influence pertains to the extent to which students perceive support or encouragement from their peers, teachers, or other influential figures in their social environment regarding the use of ChatGPT. Hence the following hypothesis is proposed.

H3: Social influence significantly influences behavioral intention.

Hedonic motivation denotes the extent to which an individual is driven to use a specific technology for the inherent enjoyment, pleasure, or novelty it provides (van der Heijden, 2004; Venkatesh, Thong, and Xu 2012). Research has underscored the critical role of hedonic motivation in technology adoption across various educational contexts. For instance, Chopdar, Lytras, and Visvizi (2023) identified

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hedonic motivation as a bicycle sharing adoption in India, while Azizi, Roozbahani, and Khatony (2020), Twum et al. (2022), highlighted its influence on the adoption of mobile learning, e-learning platforms, and Gulati et al. (2024) revealed that hedonic motivation influences Behavioral Intention of marketing students to adopt ChatGPT for enhancing their learning potential. In the context of this study, hedonic motivation pertains to the extent to which students find ChatGPT entertaining or enjoyable to use, Hence the following hypothesis is proposed.

H4: Hedonic motivation significantly influences behavioral intention.

Facilitating conditions encompass the extent to which an individual perceives that the requisite resources and support are accessible to effectively utilise a specific technology (Taylor and Todd, 1995; Venkatesh et al., 2003). Research has consistently highlighted the important role of facilitating conditions as a determinant of both learners' behavioral intention and use behavior, establishing it as one of the most significant factors influencing technology usage. Moreover, facilitating conditions have emerged as a critical factor in the adoption of various educational technologies across different contexts, including mobile payment solution (Martinez and McAndrews, 2023), business intelligence solution (Kašparová, 2023), and augmented reality (Faqih, 2022; Zhang et al., 2024) in higher education. In the context of this study, facilitating conditions refer to students' perceptions regarding their access to ChatGPT, as well as the availability of technical support and training resources for ChatGPT.

Hence the following hypotheses were proposed.

H5: Facilitating conditions significantly influence behavior intention

H6: Facilitating conditions significantly influence use behavior.

Behavioral intention refers to an individual's subjective likelihood or intention to use a particular technology in the future (Davis, 1986; Venkatesh, Thong, and Xu 2012). In the context of this study, behavioral intention pertains to the extent to which students intend to utilise ChatGPT in generating innovation higher education process. It serves as a significant indicator of actual technology use and is influenced by the other constructs within the UTAUT2 model. On the other hand, use behavior denotes the tangible utilisation of a technology by individuals following the formation of behavioral intentions towards its adoption (Venkatesh, Thong, and Xu 2012). In this study, use behavior encompasses aspects such as the frequency, duration, and patterns of ChatGPT usage, as well as the extent to which students actively employ ChatGPT to facilitate innovation in their academic endeavors. Moreover, use behavior is also shaped by habit, which reflects ingrained and automatic usage patterns of technology. Hence the following hypothesis is proposed.

H7: Behaviour intention significantly influence use behavior.

Gender is a crucial determinant influencing individuals' perspectives and actions towards technology adoption. While some research suggests no notable gender discrepancies in technology acceptance (Venkatesh and Morris, 2000), others highlight differences in perceived utility, ease of use, and adoption intentions between male and female users (Russel et al., 2022). Furthermore, gender stereotypes and societal expectations can mold individuals' views of technology and their readiness to engage with innovative tools. Despite global advancements in technology access, women continue to be underrepresented in certain sectors, like STEM, and encounter hindrances to full participation in the digital realm (e.g., Hafkin and Huyer, 2006). Contributors to the digital gender gap encompass socioeconomic inequalities, cultural norms, and institutional barriers hindering women's involvement in technology-related domains. Gender emerges as a significant moderator in technology adoption frameworks such as the Technology Acceptance Model (TAM) (Venkatesh and Davis, 2000) and the UTAUT (Venkatesh et al., 2003). While these models assert that perceived utility and ease of use are primary determinants of technology adoption, research indicates gender disparities may shape individuals' perceptions of technology's usefulness, ease of use, and overall acceptance. For instance, studies reveal women often prioritise social influences and subjective norms when assessing new technologies, whereas men may focus on factors like performance expectancy and perceived control.

H8: Gender moderates the relationships between UTAU2 and behavioral intention.

Empirical evidence suggests that there is a positive relationship between innovation capability and technology adoption across various domains (Alaskar, 2023). Furthermore, acknowledging the role of innovation capability holds practical implications, guiding targeted interventions to facilitate adoption processes and bolster innovation advocates within organisations (West and Bogers, 2014). Olugbara et al. (2020) suggest that innovative students demonstrate eagerness to swiftly grasp new technologies, effectively integrating them into their learning endeavors (Turan, Tunc, and Zehir 2015). Moreover, they adeptly employ technology to accomplish desired objectives, such as enhancing academic success and attaining personal goals (Burton-Jones and Volkoff, 2017). Within the context of this study, innovation capability pertains to individuals' capacity to generate novel ideas, solutions, or enhancements within their respective domain or field of expertise, influencing the extent of students' willingness to embrace innovative technological tools like ChatGPT and their perceived ability to acquire and master new technological skills. Hence the following hypothesis is proposed.

H9: Innovation capability moderates relationship between hedonic motivation, facilitating conditions and Behavioral Intention.

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4. Research Methodology

4.1 Research Design

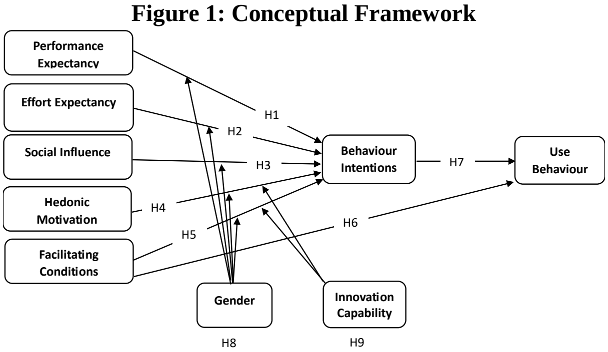
Given that the data for the research originated from a singular moment in time, a cross-sectional research design was used (Wang and Cheng, 2020). A quantitative approach was adopted, using structured questionnaires for data gathering purposes. The study utilised an explanatory research design method, using Structural Equation Modeling (SEM) to perform the analysis.

4.2 Variables and Instruments for data collection

In this study, we are employed components of the well-established UTAUT2 framework, developed by Venkatesh, Thong, and Xu (2012). UTAUT identifies seven predictors of technology usage and intention to use, namely "Performance Expectancy", "Effort Expectancy", "Social Influence", "Facilitating Conditions", "Hedonic Motivation", and "Habit". We propose to modify the list of predictors by excluding "Price Value", given that the current utilisation of ChatGPT is free for all users. While a ChatGPT Plus version is available for a subscription fee of $20 per month, offering benefits such as faster response times and priority access to new features, the basic ChatGPT service remains free for everyone. In addition to the core constructs of the UTAUT2 model, this study incorporates "innovation capability" and "gender" as moderating variables that may influence the relationships between the model predictors and both behavioral intention and use behavior regarding ChatGPT.

Data collection instrument used was a structured questionnaire, and it had eight sections. Section A assessed the personal characteristics of respondents. Under Section A, demographics such as faculty, level/year, age, and gender of students were assessed. Section B-H presented the measurement items for all the independent variables. Thus, performance expectancy (5 items), effort expectancy (3 items), social influence (3 items), facilitating conditions (4 items), hedonic motivation (3 items), behavioural intention (3 items) all adapted from Das and Datta, (2024) and Strzelecki, (2023), and innovation capability (3 items) adapted from Iddris et al., (2023). All measurement items were responded to on a Likert scale of 1-strongly disagree to 5-strongly agree

Figure 1: Conceptual Framework



4.3 Data collection

The target population of the study was public university students in Ghana. The study used convenience sampling to select 446 form the sample size. For easy accessibility, printed questionnaires were administered by the researchers within a space of eleven working/school days to gather data from the students. Questionnaires were administered during break periods, after permissions were sought from the students and the lecturers.

Personal profile for respondents of the study is shown in Table 1. Female respondents dominated the study, comprising 50.4% of the total sample with the minority 49.6% representing males. 10.1% of the respondents were aged less than 21 years, 62.1% were aged between 21-25 years, 24.0% were aged 26-30 years, 2.9% were aged 31-35 years and 0.9% were above 35 years. The majority of the respondents were thus aged between 21-25 years. 74% representing majority of the respondents were Christians, followed by 20.2%, 4.3% of belong to African Tradition and 1.6% had no religion.

Table 1. Respondents Profile

Variable	Respond	Frequency	Percent
Valid	Male	221	49.6
	Female	225	50.4
	Total	**446**	**100.0**
Age	Below 21 years	45	10.1
	21 - 25 years	277	62.1
	26 - 30 years	107	24.0
	31 - 35 years	13	2.9
	Above 35 years	4	.9
	Total	**446**	**100.0**
Religion	Christian	330	74.0
	Moslem	90	20.2
	African Tradition Religion	19	4.3
	No religion	7	1.6
	Total	**446**	**100.0**

4.4 Data validity and reliability

To begin with, we first run exploratory factor analysis (EFA)using SPSS (v.25). The essence was to assess if the measurement items were properly loaded onto their corresponding latent variables. There were nine main variables studied, which were performance expectancy (PERF_EX), effort expectancy (EEF_EX), social influence (SOC_IN), facilitating conditions (FAC_CO), hedonic motivation (HED_MO), innovation capability (INN_CA), gender (G), behavioral intention (BEH_IN) and used behaviour (USE_BE).

4.4.1 Measurement Model (EFA)

Our exploratory factor analysis (EFA) model revealed that all measurement items were appropriately loaded onto their

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corresponding latent variables, demonstrating factor loadings of at least 0.6.

The cumulative variance extracted from the EFA was 75.62%, surpassing the minimum requirement of 50%. The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy, anticipated to be not less than 0.6, had a high value of 0.812, indicating ample sample adequacy. Additionally, Bartlett's test of sphericity, expected to demonstrate statistical significance, to mean there was enough correlation among the measurement items to qualify for EFA (X^2= 8540.52; p < 0.01), indicating there was an adequate correlation to qualify for EFA estimation. The determinant of correlation must not equal zero to ensure positive definiteness in the data used. In our analysis, the determinant for EFA was 3.134E-9, confirming this criterion was met.

4.4.2 Measurement Model (CFA)

Confirmatory Factor Analysis (CFA) was conducted in Amos (v.23) using the variables retained from the EFA. Consistent with the EFA, it was anticipated that the standardised factor loadings in the CFA would be at least 0.5, which was met in this study (Table 2). Each main variable exhibited factor loadings exceeding 0.5, signifying that all measurement items effectively explained their respective latent constructs. When conducting CFA, it was crucial to assess the model fit indices to ascertain the adequacy of the dataset for the estimated model. Among these indices, it was necessary for CMIN/DF to be below 3, PClose to be statistically insignificant (>0.05), and TLI and CFI to exceed 0.9. Additionally, RMSEA and RMR were expected to be 0.08 or less (Iddris, Dogbe, and Kparl 2022). These were achieved for all the latent variables in this dataset.

With the retained variables, Cronbach's Alpha (CA) was calculated using SPSS (v.25), aiming for a minimum alpha score of 0.7. This was met for all latent variables (Table 2), indicating strong internal consistency (reliability) among the measurement items. Convergent validity was evaluated using the Average Variance Extracted (AVE) approach, with a minimum threshold of 0.5 Fornell and Larcker (1981). Additionally, construct reliability (CR) was expected to exceed 0.7, which was all achieved for all the latent constructs.

Table 2: Confirmatory Factor Analysis

	Model Fitness: **CMIN = 495.268; DF = 223; CMIN/DF = 2.221; GFI =.920; PClose = .257; TLI = .960; CFI = .968; RMSEA = .052; RMR = .080**	**Standardised Factor Loadings**
	PERFORMANCE EXPECTANCY (PE): CA = .891; CR = .901; AVE = .644	
PE1	I believe that ChatGPT is useful in generating innovation	.824
PE2	Using ChatGPT increases your chances of achieving innovativeness and creativity	.789
PE3	Using ChatGPT helps you get class innovation project done faster"	.837
PE4	Using ChatGPT increases your productivity in your studies	.783
PE5	I believe that ChatGPT is useful for generating innovation	.779
	EFFORT EXPECTANCY (EE): CA = .994; CR = .994; AVE = .982	
EE1	Learning how to use ChatGPT is easy for me"	.993
EE2	My interaction with ChatGPT is clear and understandable	.994
EE4	It is easy for me to become skillful at using ChatGPT	.986
	SOCIAL INFLUENCE (SI): CA = .896; CR = .892; AVE = .734	
SI1	People who are important to me think I should ChatGPT	.859
SI2	People who influence my behavior believe that I should use ChatGPT	.863
SI3	People whose opinions I value prefer me to use ChatGPT	.849
	FACILITATING CONDITIONS (FC): CA = .842; CR = .843; AVE = .577	
FC1	I have the resources necessary to use ChatGPT	.616
FC2	I have the knowledge necessary to use ChatGPT"	.799
FC3	ChatGPT is compatible with technologies I use	.824
FC4	I can get help from others when I have difficulties using ChatGPT"	.781
	INNOVATION CAPABILITY (FC): CA = .912; CR = .940; AVE = .840	
IC4	I challenge the status quo	.901
IC5	I encourage teammates participation in innovation activities	.932
IC6	I feel proud when I've designed something myself and made it	.917
	HEDONIC MOTIVATION (FC): CA = .715; CR = .782; AVE = .545	
HM1	Using ChatGPT is fun	.771
HM2	Using ChatGPT is enjoyable	.728
HM3	Using ChatGPT is very entertaining"	.715
	BEHAVIORAL INTENTION (FC): CA = .746; CR = .840; AVE = .637	
BI	I intend to continue using ChatGPT in the future"	.717
B2	I will always try to use ChatGPT in my daily life	.850

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B3	I plan to continue to use ChatGPT frequently”	.821

Discriminant validity was confirmed by evaluating the square root of the raw average variance extracted (√AVE) in relation to the correlation coefficients (Iddris et al., 2022). From the analysis, the least √AVE was 0.738, which was greater than the largest correlation score of 0.525 (Table 3). This show that discriminant validity was achieved, indicating the absence of multicollinearity in the dataset as the highest correlation coefficient 0.525 did not exceed 0.7.

Tabel 3. Discriminant Validity

Variables	1	2	3	4	5	6	7	8	9	10
Gender (1)	-									
Age (2)	-.086	-								
Religion (3)	.050	.045	-							
PE (4)	.031	-.047	.017	***.802***						
EE (5)	-.046	.013	.057	-.012	***.991***					
SI (6)	-.010	.042	.028	.394**	.044	***.857***				
FC (7)	.035	.026	.013	.525**	.047	.501**	***.760***			
IC (8)	.091	-.067	-.044	.095*	.095*	-.028	.151**	***.917***		
HM (9)	-.022	.071	-.054	.073	-.024	.058	.134**	.020	***.738***	
BI (10)	-.013	.081	-.054	.167**	.023	.164**	.157**	.080	.311**	***.798***

*** ~ Correlation is significant at the 0.01 level (2-tailed); * ~ Correlation is significant at the 0.05 level (2-tailed); √AVE ~ Bold, Italics and Underline.*

5. Results

5.1 Structural Model

Structural Equation Modelling (SEM) was run in Amos (v.23) to estimate the path analysis, with results presented in (Table 4). The estimation was based on 5000 Bootstrap samples, with Bias-Corrected Confidence Interval of 95%.

5.2 Effect of UTAUT2 constructs on behavioural intention

Table 4 presents the results of the direct effects of UTAUT2 constructs on behavioral intention. The results indicated that the strongest determinant of behavioural intention was hedonic motivation with a coefficient of (0.434), followed by social influence (0.092) and performance expectancy (0.088), collectively explaining 61.4% of the variance in behavioral intention. Effort expectancy (0.005) and facilitating conditions (0.073) also had positive effects on behavioral intention, but these relationships were not statistically significant. Behavioral intention had the highest significant effect on use behavior with a coefficient of (0.786), explaining 78.6% of the variance in use behavior. However, facilitating conditions had a negative impact on use behavior with a coefficient of (-0.058). Three hypotheses among the direct paths were not supported: H2 (effort expectancy and behavioral intention), H5 (facilitating conditions and behavioral intention), and H6 (facilitating conditions and use behavior).

5.3 Moderation effect of Gender

Table 5 presents the results of the moderating effect of gender on the relationship between UTAUT2 constructs and behavioral intention. Gender significantly moderated the relationship between facilitating conditions and behavioral intention, with a coefficient of (0.078). The remaining variables (performance expectancy, effort expectancy, social influence and hedonic motivation) showed no significant moderated relationships between the UTAUT2 constructs and behavioral intention.

5.4 Moderation effect of innovation capability

Table 6 depict the results of the moderating effect of innovation capability in the relationship between hedonic motivation and behavioural intention, as well as the relationship between facilitating conditions and behavioural intention. Innovation capability insignificantly moderated the relationship between hedonic motivation and behaviour intention (-.057). However, innovation capability significantly moderated the relationship between facilitating conditions and behaviour intention (.146).

6. Discussions

Our research focused on the factors affecting students' use of ChatGPT for innovative purposes, employing the UTAUT2.0 framework. The outcomes highlighted the important roles of hedonic motivation, social influence, and performance expectancy in shaping students' intentions to use ChatGPT, subsequently influencing their actual usage.

First, the results indicate that hedonic motivation *(H4)* emerged as the most significant influencer in shaping students' intentions to utilise ChatGPT for innovative purposes. This is in line with the findings of Gulati et al. (2024); Das and Datta (2024); Tiwari et al., (2023). One possible explanation for the prominence of hedonic motivation is the appeal of novelty and creativity inherent in using ChatGPT. Students, particularly those with a desire for innovation, may be drawn

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to the prospect of leveraging an AI-powered tool to generate novel ideas and solutions. The interactive nature of ChatGPT, coupled with its ability to produce diverse and unexpected responses, may evoke a sense of curiosity and excitement among users, thereby enhancing their motivation to engage with the technology for creative endeavors.

Second, the results highlight the effect of social influence *(H3)* on shaping students' intentions to utilise ChatGPT for innovative purposes. This is in line with evidence across different contexts, including mobile learning (Arain et al., 2019), and learning management systems (Celedonio and Picaso, 2023). One plausible explanation for the significance of social influence is the power of peer endorsement and peer learning in shaping students' technology adoption behaviors. Students may be more inclined to use ChatGPT for innovation if they perceive that their peers and classmates endorse and actively engage with the technology for creative endeavors. Observing peers successfully leverage ChatGPT to generate ideas and solutions can serve as a source of social proof, reinforcing students' belief in the efficacy and value of the technology for driving innovation.

Third, the results highlight the effect of performance expectancy *(H1)* on shaping students' intentions to utilise ChatGPT for innovative purposes. This corroborates the findings of Soliman et al. (2019), Gulati et al. (2024), and Grassini, Aasen, and Møgelvang (2024) emphasising the important role of performance expectancy in the adoption of ChatGPT within academic environments. The plausable explanation for the significance of performance expectancy is the perceived utility and effectiveness of ChatGPT in supporting innovation-related tasks and activities. Students who perceive ChatGPT as a valuable tool for generating high-quality ideas, overcoming creative blocks, and facilitating collaborative ideation processes are more likely to exhibit a positive intention to use the technology for innovation. The belief that ChatGPT can enhance their creative output and contribute to the success of innovation projects motivates students to embrace the technology as a means of driving innovation.

Fourth, the findings indicate that behavioral intention *(H7)* had the highest significant effect (0.786) on use behavior, explaining 78.6% of the variance in use behavior. This supports the works of (Davis, 1986; Venkatesh, Thong, and Xu 2012; Grassini, Aasen, and Møgelvang 2024). This substantial effect underscores the important role of behavioral intention as a determinant of actual usage behavior when it comes to utilising ChatGPT for innovation purposes among students. The high coefficient of determination ($R^2 = 0.786$) signifies that a significant proportion of the variance in use behavior can be attributed to variations in behavioral intention. This finding suggests that students' intentions to use ChatGPT for innovation exert a substantial influence on their subsequent actual usage behavior. When students express a strong intention to utilise ChatGPT for innovative endeavors, they are more likely to translate that intention into concrete actions by actively engaging with the technology for innovation-related tasks and activities.

Fifth, Effort expectancy *(H2)*, which refers to the perceived ease of use of a technology, is often considered a crucial determinant of behavioral intention in technology adoption models (Alfalah, 2023; Voicu and Muntean, 2023; Hunde, Demsash, and Walle 2023). However, the insignificance of effort expectancy in predicting students' behavioral intention regarding ChatGPT for innovation suggests that perceptions of ease of use may not be a primary concern for students when considering the adoption of ChatGPT. This unexpected finding prompts a reevaluation of the factors that influence students' intentions to use ChatGPT for innovation and underscores the need for further investigation into the specific barriers and facilitators that shape their adoption decisions. Similarly, facilitating conditions, which encompass the availability of resources, support, and infrastructure necessary for technology adoption, were found to be insignificant predictors of behavioral intention in this study. This supports the findings of Strzelecki (2023), Das and Datta (2024). The insignificance of facilitating conditions suggests that the availability of resources and support may not be key determinants of students' intentions to utilise ChatGPT for innovation, raising questions about the factors that truly drive their adoption decisions.

Sixth, Interestingly, our findings depart from previous studies, particularly regarding the impact of facilitating conditions *(H5)* on usage behavior. While past research suggested a positive correlation between facilitating conditions and technology adoption (Strzelecki, 2023; Pramudito et al., 2023; Bajunaied, Hussin, and Kamarudin 2023), our results indicated a negative influence (Ramírez-Correa et al., 2019). This departure may stem from the accessibility of ChatGPT through students' mobile devices, the familiarity of the technology similar to other search engines like Google, and the availability of assistance from classmates when needed.

Table 4. Direct path analysis

	Direct Paths			Estimate	S.E.	C.R.	P	outcome
H1	PERF_EX	→	BEH_IN	.088	.041	2.116	.034	supported
H2	EFF_EX	→	BEH_IN	.005	.031	.163	.871	Not supported
H3	SOC_IN	→	BEH_IN	.092	.039	2.342	.019	supported

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	Direct Paths			Estimate	S.E.	C.R.	P	outcome
H4	HED_MO	→	BEH_IN	.434	.088	4.933	***	supported
H5	FAC_CO	→	BEH_IN	.073	.049	1.500	.134	Not supported
H6	FAC_CO	→	USE_BE	-.058	.135	-.430	.667	Not supported
H7	BEH_IN	→	USE_BE	.786	.164	4.788	***	supported

Bootstrap Bia-Corrected Confidence Interval at 95%
***Sig. at 1%

Figure 2: Structural Paths

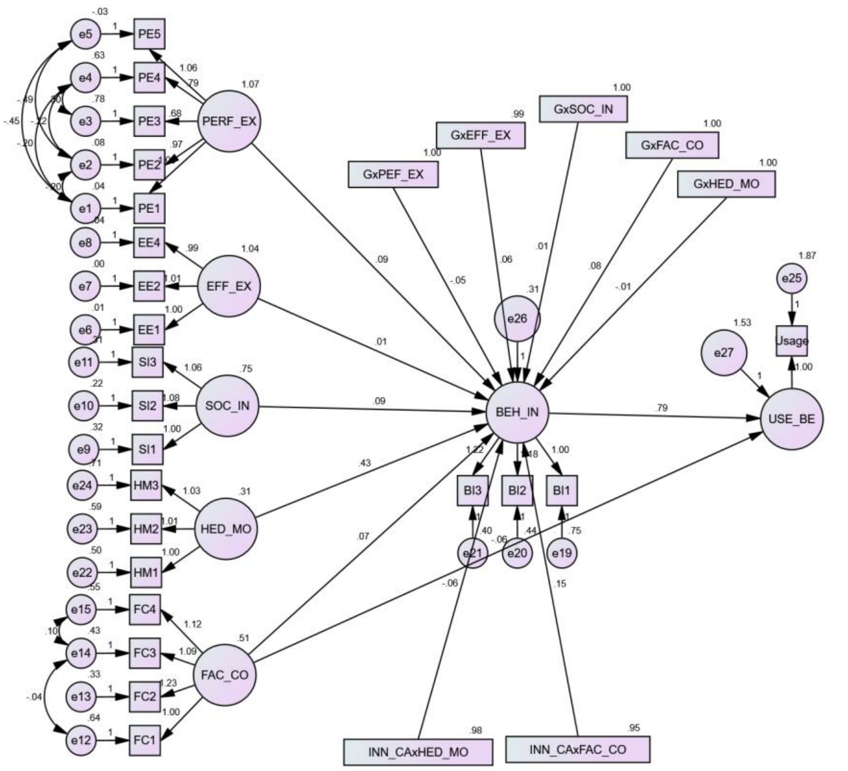

Table 5. Gender as a moderator

Moderating variable			IDV	DV	Estimate	S.E.	C.R.	P	outcome
H8: Gender									
GxPEF_EX	→	BEH_IN	PE	BI	-.054	.032	-1.698	.090	Not supported
GxEFF_EX	→	BEH_IN	EF	BI	.056	.032	1.763	.078	Not supported
GxSOC_IN	→	BEH_IN	SI	BI	.012	.032	.366	.714	Not supported
GxFAC_CO	→	BEH_IN	FC	BI	.078	.032	2.422	.015	supported
GxHED_MO	→	BEH_IN	HM	BI	-.007	.032	-.236	.814	Not supported

Bootstrap Bia-Corrected Confidence Interval at 95%
***Sig. at 1%

Table 6. Innovation capability as a moderator

Moderating variable	IDV	DV	Estimat e	S.E.	C.R.	P	outcome
H:9							

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INN_CAxFAC_CO	→	BEH_IN	EF	BI	.146	.034	4.288	***	supported
INN_CAxHED_MO	→	BEH_IN	SI	BI	-.057	.032	-1.772	.076	Not supported

Bootstrap Bia-Corrected Confidence Interval at 95%

***Sig. at 1%

Seventh, the results of the moderation analysis in this study provided insights into the role of gender in shaping the relationships between key determinants of behavioral intention regarding ChatGPT for innovation among students. While gender *(H8)* was found to insignificantly moderate the relationships between effort expectancy, performance expectancy, social influence, and hedonic motivation as evidenced in prior studies (Merhi et al., 2021; Mardjo, 2018). However, an interesting pattern emerged regarding the relationship with facilitating conditions. Gender positively moderated the relationship between facilitating conditions and behavioral intention, indicating that gender influences how facilitating conditions impact students' intentions to use ChatGPT for innovation. This support the results of (Garg, 2022) that found that men are more likely to have computer abilities in contrast to women. The positive moderation effect of gender on the relationship between facilitating conditions and behavioral intention suggests that social norms, perception of support and access to ChatGPT may influence how gender moderate the relationship and its influence on students' intentions to utilise ChatGPT for innovation. This finding highlights the importance of considering gender-specific differences in the provision of facilitating conditions to promote technology adoption and innovation among students.

Lastly, the results of our study indicate that innovation capability *(H9)* significantly moderates the relationship between facilitating conditions and behavioral intention. This is in line with the assertions of Olugbara et al. (2020), Burton-Jones and Volkoff (2017), and Turan et al. (2015) that suggest innovative students demonstrate eagerness to swiftly grasp new technologies, effectively integrating them into their learning endeavors, and employ technology to naturally accomplish

9. Theoretical contributions

This study contributes to the literature by advancing research on AI adoption in higher education, particularly focusing on critical factors influencing innovation generation through the use of ChatGPT. It addresses unresolved questions in several key ways. First, our research reveals that hedonic motivation significantly influences students' intentions to utilise ChatGPT for innovation. This suggests that individuals perceive ChatGPT as a tool to enhance their ability to generate innovative ideas, thereby motivating their usage (Gulati et al., 2024; Das and Datta, 2024).

Second, our findings corroborate previous research by Arain et al. (2019) and Celedonio and Picaso (2023), demonstrating that peer endorsement and observation play a significant role in shaping students' intentions to use ChatGPT for innovation. This underscores the impact of social influence on technology adoption behaviors (Arain et al., 2019; Celedonio and Picaso, 2023).

Third, the study reveals the positive impact of performance expectancy on students' intentions to use ChatGPT for innovation. This indicates that students who perceive ChatGPT as valuable for generating high-quality ideas are more inclined to intend to use it (Soliman et al., 2019; Gulati et al., 2024).

Fourth, our research underscores the significant influence of behavioral intention on actual technology usage, aligning with the premise of UTAUT2 that behavioral intention is important in technology adoption (Davis, 1986; Venkatesh, Thong, and Xu 2012). This reinforces the idea that individuals' intentions strongly influence their subsequent behavior, shedding light on the mechanisms underlying technology adoption processes. fifth, our findings suggest that gender influences how facilitating conditions impact students' intentions to use ChatGPT for innovation. This emphasises the importance of considering gender-specific differences in technology adoption behaviors beyond UTAUT2's original constructs (Garg, 2022). These insights prompt a reevaluation and refinement of the UTAUT2 framework to explicitly incorporate gender-related variables, enhancing its explanatory power in diverse contexts.

Lastly, our research aligns with the UTAUT2 construct of "Facilitating Conditions" by exploring innovation capability moderation, as discussed by Olugbara et al. (2020) and Burton-Jones and Volkoff (2017). This aspect reflects how individuals perceive organisational and technical support for technology use. The findings suggest that innovative students are more influenced by facilitating conditions in their adoption decisions, highlighting the significance of individual differences in technology adoption behaviors (Olugbara et al., 2020; Burton-Jones and Volkoff, 2017). Additionally, our study extends the UTAUT2 model by incorporating innovation capability, providing a comprehensive framework for future researchers to investigate innovation generation among students.

10. Practical implications

First, Educational institutions and technology providers should design interventions that target specific factors identified in the study, such as hedonic motivation, social influence, and performance expectancy. For example, workshops or training sessions could be organised to highlight the enjoyable and entertaining aspects of using ChatGPT, showcase its value in generating innovative ideas, and emphasise its endorsement by peers and instructors.

Second, Institutions should reevaluate their support services to ensure they effectively facilitate technology adoption. This may involve assessing existing resources and support

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mechanisms to identify and address potential barriers to adoption. Additionally, providing targeted support for groups facing specific challenges, such as female students, can help promote more equitable access to innovative technologies.

Third, interventions aimed at promoting technology adoption and innovation should be gender-sensitive, taking into account the different needs and challenges faced by male and female students. This may involve offering mentorship programs, creating support networks, or providing targeted resources to address gender disparities in technology adoption.

Fourth, educational programs should focus on enhancing students' innovation capability to better equip them for adopting and utilising innovative technologies like ChatGPT. This could involve offering hands-on experiences with innovative tools, and providing opportunities for collaboration and experimentation.

Fifth, creating collaborative learning environments where students can engage with each other and with instructors can help promote technology adoption and innovation. For example, group projects that incorporate the use of ChatGPT for idea generation can encourage students to actively engage with the platform and explore its potential for innovation.

Finally, institutions should continuously monitor and evaluate the effectiveness of interventions aimed at promoting technology adoption and innovation. This may involve collecting feedback from students, tracking adoption rates, and assessing the impact of interventions on learning outcomes and innovation capabilities. Recognising the moderating role of innovation capability, organisations can focus on developing and enhancing innovation capabilities among their employees or members. This may include providing training programs, fostering a culture of creativity and experimentation, and allocating resources towards innovation initiatives.

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