HLRC | HIGHER LEARNING RESEARCH COMMUNICATIONS

Higher Learning Research Communications
2025, Volume 15, Issue 2 Pages 1–30. DOI: 10.18870/hlrc.v15i2.1598

Original Research

WALDEN UNIVERSITY

Integrating AI in Academia: A SEM Evaluation of Research Scholars' Usage Intentions on ChatGPT

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Abstract

Objectives: In this study, we investigate the intentions of research scholars to use ChatGPT in their academic research endeavors by employing an extended Unified Theory of Acceptance and Use of Technology model, the UTAUT2, which examines factors such as performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, ethical concerns, and research excellence. By incorporating "research excellence" into the model, we aim to provide insights into artificial intelligence (AI) adoption in academic research settings and contribute to the broader discourse on the future of academic practices.

Method: We conducted a survey among 400 research scholars in Indian higher education institutions to collect data. We then analyzed the data using Partial Least Squares-Structural Equation Modeling (PLS-SEM).

Results: The analysis revealed that performance expectancy, facilitating conditions, hedonic motivation, habit, and research excellence significantly influence the intention to use ChatGPT, with research excellence emerging as the strongest predictor. Effort expectancy, social influence, and ethical concerns, however, did not significantly impact adoption intentions.

Conclusions: The findings indicate that several key factors, particularly research excellence, play a critical role in influencing research scholars' intentions to integrate ChatGPT into their academic activities. The study demonstrates the importance of these factors in fostering AI adoption within the context of academic research.

Implications for Practice: The results of this study offer valuable insights for researchers, administrators, and policymakers who aim to create environments conducive to effective AI utilization in research academia.

By understanding the factors that influence AI adoption, stakeholders can better support research scholars in integrating ChatGPT into their work, enhancing academic practices, and advancing the use of AI in research.

Keywords: *ChatGPT, research scholars, artificial intelligence, AI, academic research, UTAUT2, PLS-SEM*

Date Submitted: July 8, 2024 | **Date Accepted:** January 1, 2025 | **Date Published:** July 7, 2025

Recommended Citation

Sharma, S., Joshith, V. P., Kavitha, K., & Anthony, A. (2025). Integrating AI in academia: A SEM evaluation of research scholars' usage intentions on ChatGPT. *Higher Learning Research Communications, 15*(2), 1–30. https://doi.org/10.18870/hlrc.v15i2.1598

Introduction

Artificial intelligence (AI) has profoundly influenced individuals by utilizing its systematic reasoning capabilities, from inputs and learning, and analyzing deviations from expected outcomes (Dempere et al., 2023; Kalla & Smith, 2023). AI tools like ChatGPT substantially impact academic research and evaluate the perspectives of scholars (Kamalov et al., 2023; Livberber & Ayvaz, 2023).

AI can be used for knowledge advancement, productivity enhancement, and academic discourse enrichment. Its emergence brought transformative changes to numerous fields, including academia (Dwivedi et al., 2023; Gruetzemacher & Whittlestone, 2022; Makridakis, 2017). In the *NMC Horizon Report: 2018 Higher Education Edition* (Becker, 2018), for example, experts discussed their expectation for a 43% increase in AI use in education between the years 2018 and 2022. Additionally, in the *EDUCAUSE Horizon Report 2019 Higher Education Edition* (Alexander et al., 2019), experts predicted an even broader adoption of AI applications designed for teaching and learning (Zawacki-Richter et al., 2019).

One prominent AI-based technology application, called ChatGPT, uses a "chat" generative pre-trained transformer (GPT) language, and is gaining significant attention in the educational sector (García-Peñalvo, 2021; Taecharungroj, 2023). Developed by OpenAI, ChatGPT is publicly accessible (Kirmani, 2023; Zhou et al., 2023) and aims to achieve Artificial General Intelligence (AGI) by developing to become as intelligent—or more intelligent—than a human. Currently, ChatGPT can accomplish a wide range of tasks (Guentzel & Pennachin, 2007; Kissinger et al., 2023) and particularly excels in producing contextually-relevant and human-like responses, representing a significant advancement in AI-driven conversational agents (Brown et al., 2020; Ghafouri, 2024; Kavitha et al., 2024; Kusal et al., 2022).

Research scholars generally view ChatGPT as a valuable scientific and educational tool with the potential to inspire new topics and research areas (Livberber & Ayvaz, 2023). For example, AI tools like ChatGPT can significantly improve the quality and efficiency of writing scientific articles (Khalifa & Albadawy, 2024), as well as aid in outline development, text expansion, and style refinement (Huang & Tan, 2023). ChatGPT's ability to identify patterns and generate text, based on the learned data, has also made it a valuable tool for research scholars (Bender et al., 2021).

AI tools are highlighted by their significant assistance in research activities and research efficiency, as well as assisting in preparing course materials (Ali & ChatGPT OpenAI, 2023). ChatGPT provides suggestions (Megahed et al., 2024); offers feedback (Firat, 2023); generates human-like text based on given prompts (Brown et al., 2020); translates text (Khan et al., 2023; Lyu et al., 2023); generates assessment tasks (Khan et al., 2023); and assesses student performance (Baidoo-Anu & Ansah, 2023; Cotton et al., 2024; Qadir, 2023).

As AI technologies have been increasingly incorporated into academic research—from generating literature reviews to data collection and manuscript preparation (Rospigliosi, 2023;)—ChatGPT is recognized as a powerful AI tool with the capabilities to address numerous queries and facilitate barnstorming ideas (King & ChatGPT, 2023). ChatGPT can also handle a broad spectrum of text-related queries—from easy questions to complex tasks (Liu et al., 2024). Comprehending ChatGPT's development and evolution is crucial to appreciating its role in scientific research, since it has been found to help researchers (Bang et al., 2023; Biswas, 2023; van Dis et al., 2023).

ChatGPT: Usage and Behavioral Intention

Although extensive research has been conducted on ChatGPT—focusing on the various aspects of the AI technology—investigators have not identified any single study focusing on research scholars' usage and behavioral intentions in academic writing. Also, even though ChatGPT shows significant potential in the educational sector (Dianova & Schultz, 2023; Han & Cai, 2023; Totlis et al., 2023), there is still a considerable lack of comprehensive research on the existing topic in academic research. And, as ChatGPT continues to significantly impact teaching–learning and research outcomes, examining how research scholars intend to embrace ChatGPT in their productivity in research activities becomes essential.

As a prominent AI-based technology application, ChatGPT has been proven to improve output quality substantially, thus increasing the intention to use it (Menon & Shilpa, 2023). This intention is referred to as Behavioral Intention (BI), which is an individual's readiness to utilize a specific technology, such as ChatGPT, for different tasks (Moorthy et al., 2019). Further, BI can be referred to as a motivational factor, as it drives a research scholar's decision to use ChatGPT (Sahu et al., 2023) and indicates the amount of effort they are willing to invest in engaging with this technology (Acosta-Enriquez et al., 2024).

Several researchers explored ChatGPT usage and BI and found that attitudes, beliefs, and behaviors about technology are frequently reflected in an individual's readiness to use it (Almahri et al., 2020; Almaiah & Alamary et al., 2022; Almaiah & Hajjej et al., 2019). Acosta-Enriquez et al. (2024), for example, studied the effect of "intent to use" ChatGPT, in general, while Salifu et al. (2024) studied BI for the specific usage of ChatGPT, specifically among economics students. And Yu et al. (2024) studied factors that influence users' intention to use ChatGPT, users' satisfaction with ChatGPT, and users' intention to continue using ChatGPT.

Selecting research scholars as the target group for this study is highly justified, as these scholars have a profound impact on society and academia. As key drivers of knowledge creation, research scholars spearhead innovation and tackle complex societal issues through their research (Munshi & Marulasiddaiah, 2015), and their contributions lead to scientific advancements, cultural insights, and notable economic effects (Laxmanbhai & Patel, 2023). Within academic institutions, research scholars fulfill diverse roles: They educate future generations, enhance institutional prestige, encourage interdisciplinary collaboration, and uphold research integrity through peer review (Bouter, 2023). Research scholars are also pivotal in securing funding and often rise to leadership positions (Campo, 2014). By focusing this study on research scholars, we were able to highlight the extensive influence these scholars have on advancing knowledge, shaping education, and promoting global cooperation. Research scholars also make significant contributions to academia and society; however, research in this emerging field lacks studies that focus on these important scholars, highlighting the need to address this gap.

Comprehending research scholars' perceptions of ChatGPT, as well as their intentions to integrate it into their studies, could offer valuable insights into the factors that facilitate its successful implementation in academic research. Further, understanding this relationship can provide valuable insights into what and how research scholars decide to adopt and integrate ChatGPT into their research practices. For example, policymakers will find developing regulations to facilitate AI technology growth easier through understanding how research scholars and users interact with ChatGPT. Additionally, the present study's findings can be utilized by

ChatGPT developers to improve the model's functionality, as well as to gain a deeper understanding of user needs and behavior. Moreover, this study's findings can help the AI community gain a better understanding of the use of ChatGPT in academic research and the behavioral intentions of research scholars toward integrating it.

Given the identified research gap and context, this study seeks to address these primary research questions:

1. What factors influence research scholars' intentions to integrate ChatGPT into their academic research activities?
2. How do these factors influence research scholars' intentions to integrate ChatGPT into their academic research activities?

Literature Review: Theoretical Framework and Hypotheses Development

India's education sector is undergoing a digital shift, which is driven by technology and e-Learning usage (Kumari & Tiwari, 2023; Manickam, 2023). The use of ChatGPT, for example, has revolutionized automated literature synthesis by helping with synthesis, generating summary tables, and conducting comparative analyses (Dergaa et al., 2023; Khlaif et al., 2023; Semrl et al., 2023). AI use has also been recognized for improving the quality of communication, providing individualized assistance, and promoting a sense of connection.

AI poses challenges with accountability, surveillance, and agency (Seo et al., 2021). For example, AI offers anonymity to students and aids them in communicating more effectively, but its teaching systems are black-box systems, where students cannot independently confirm the accuracy of the AI's responses (Castelvecchi, 2022; Seo et al., 2021). And researchers worry about the responsibility for errors that might arise from AI's unreliable and opaque responses.

Using AI Tools to Enhance Academic Writing Quality

Although academic research writing poses different challenges for scholars, studies demonstrate that using AI writing tools can increase the quality and efficiency of academic writing, especially in the context of writing and its organization (Khalifa & Albadawy, 2024; Marzuki et al., 2023; Ray, 2023). AI tools have become crucial in enhancing the effectiveness and quality of academic writing, as they allow writers to focus on the creativity and critical elements of the research (Golan et al., 2023). ChatGPT-3, for example, produces coherent, logical, and contextually relevant sentences, which enhances the natural flow of the work (Du et al., 2023; Mhlanga, 2023). AI tools can also be beneficial in promoting the development of ideas, and assisting writers to overcome writing blocks (Gayed et al., 2022). Using GPT-3 and its successor GPT-4 allows users to create compositions that resemble human writing through suggesting the next word or paragraph in a text (Liu et al., 2023).

AI can help improve the quality and effectiveness of writing scientific research articles (Huang & Tan, 2023). As an example, ChatGPT can help develop and curate datasets—a critical aspect of dataset management (Chubb et al., 2022). That said, AI's ability to develop and curate data underscores the importance of maintaining data integrity and enabling efficient data analysis (Christou, 2023; Currie et al., 2023; Garg et al., 2023).

AI can also be helpful for scholars whose first language is not English. ChatGPT, for example, can aid with grammar and sentence structure, suggest suitable vocabulary, and help translate text into different languages (Huang & Tan, 2023). This content targeting skill uses emotional tone analysis (Currie et al., 2023) to analyze tone and ensure the content is convincing and compelling, thereby increasing the chances of funding approval for grant proposals (Eggmann et al., 2023).

Chat GPT Usage Concerns in Academic Research

Generative AI has been given a generally positive review by the public, and many scholars highlight the benefits of ChatGPT (Talan & Kalinkara, 2023), as well. However, maintaining ethical standards and integrity in scientific research is crucial. Due to risks of data fabrication, conflicts of interest, and academic dishonesty that may be associated with AI tools, ethical norms and integrity must be upheld in scientific research. Additionally, critics argue that the current definitions of plagiarism are outdated (Dehouche, 2021; Sadeghi, 2019). These issues raise questions about whether a chatbot, such as ChatGPT, fits within the categories of plagiarism and academic integrity. But despite concerns, researchers have noted the advantages of ChatGPT (Talan & Kalinkara, 2023).

AI engages its audiences and customizes its content for various platforms, but researchers (Garg et al., 2023; Sharma et al., 2023; Tang et al., 2024) agree that its use must also uphold research ethics and ensure research integrity. Even with ChatGPT's bright future, questions remain regarding content accuracy and the ethical considerations for its use (Floridi & Cowls, 2019), and the educational community has expressed concerns regarding plagiarism and academic integrity (Dehouche, 2021; Lampropoulos et al., 2023; Sullivan et al., 2023; Yeo, 2023). Large datasets, for example, can be processed and analyzed using AI tools to quickly assist scholars in producing current and up-to-date literature reviews. Researchers warn that although AI integration streamlines such research and ensures methodological soundness, careful supervision is necessary to maintain rigor and academic integrity (Dergaa et al., 2023; Giray, 2023; Khlaif et al., 2023).

Expanding the UTAUT Model to Address the Research Gap

The UTAUT Model

This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) model, propounded by Venkatesh et al. (2003), as its guiding theoretical framework to address the research gap we identified in our research. The UTAUT is a comprehensive framework for analyzing technology adoption and usage, and it relies upon various theories like the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) (Ajzen, 1991); as well as the Technology Adoption Model (TAM) (Davis, 1989). The UTAUT incorporates these theories, presenting four key concepts: (1) performance expectancy; (2) effort expectancy; (3) social impact; and (4) facilitating factors (Venkatesh et al., 2003).

As a sociopsychological model, the UTAUT attempts to forecast and explain the variables affecting users' acceptance and usage of a particular technology (Venkatesh, 2022; Venkatesh et al., 2016). In the context of information systems, the UTAUT model uses key constructs, such as performance expectancy, effort expectancy, social influence, hedonic motivation, and price value, to investigate the intricate dynamics surrounding technology adoption (Venkatesh et al., 2016). The UTAUT model can also be adopted to represent the unique features of AI technology in the context of AI tools (Hasija & Esper, 2022; Venkatesh, 2022). For example, the model has been applied to study AI tools, and chatbots are among them (Balakrishnan et al., 2022; Mogaji et al., 2021).

Expanded UTAUT2 Model

In our expansion of the original UTAUT model, called UTAUT2, this study provides a thorough framework for forecasting the variables that influence technology adoption in various contexts—particularly in the context of information systems, such as ChatGPT (Khan et al., 2023; Tamilmani et al., 2021). The UTAUT2 model is well-suited for conducting research in ChatGPT, as it is very effective at predicting individual behavioral intentions (BIs) and is good at *using* information technology like AI (Cabrera-Sánchez et al., 2021). This expansion provides more accurate insights into technology adoption in academic research settings and acknowledges research scholars' distinct needs, concerns, and motivations (Tijssen & Winnink, 2022).

For this study, the factors "Ethical Concerns" and "Research Excellence" were added (as displayed in Figure 1), specifically to investigate research scholars' adoption of ChatGPT for academic research work (Tijssen & Winnink, 2022). Ethics and research excellence are relevant factors for scholars who prioritize quality research (Lindhult, 2019) and address a unique motivational aspect, which allows for context-specific adaptation (Araújo et al., 2017). Incorporating Ethical Concerns into this study addresses potential risks and moral implications of using ChatGPT, ensuring that research scholars will consider the ethical dimensions of AI use in their academic work (Bin-Nashwan et al., 2023). Research Excellence can significantly enhance the predictive power of a group of researchers, as well, and includes aspects like fostering innovation, knowledge sharing, and network building (Weggeman & Groeneveld, 2005). By including the Research Excellence factor, the model recognizes that scholars' technology adoption is likely influenced by how it contributes to their academic pursuits (Liu et al., 2020).

In the following sections, each factor (or key construct) for the expanded UTAUT2 is discussed. A hypothesis is given for each of the factors.

Performance Expectancy

Performance expectancy (PE) is one of the key constructs in UTAUT2. This construct explains the degree to which individuals believe that using a particular technology will bring them significant performance or expected outcomes (Venkatesh et al., 2012). Further, individual views and expectancies about technology, as well as how it will improve the output, will influence their intentions toward integrating it (Almahri et al., 2020; Emon et al., 2023).

In this study, research scholars' expectations about ChatGPT's ability to accurately generate literature reviews, as well as brainstorm ideas for manuscript preparation, can directly influence their attitudes toward adopting the tool. As a result, research scholars' performance expectations can shape their BIs to integrate ChatGPT into their academic research processes. Consequently, the following hypothesis was formulated:

> **H1:** Performance expectancy significantly influences research scholars' BIs to integrate ChatGPT into their academic research activities.

Effort Expectancy

Effort expectancy (EE) refers to the perceived ease of use associated with a system or technology (Balakrishnan et al., 2022). EE is one of the strong predictors of user's willingness to adopt new technologies (Mensah & Onyancha, 2022; Nikulina & Wynstra, 2022; Onaolapo & Oyewole, 2018).

In this study, EE reflects research scholars' perceptions of ChatGPT's usability and accessibility in effectively meeting their professional needs. Consequently, the following hypothesis was formulated:

> **H2:** Effort expectancy significantly influences research scholars' BI to integrate ChatGPT into their academic research activities.

Social Influence

Social Influence (SI) refers to the degree to which an individual's beliefs are affected by the opinions and actions of others, thereby affecting their intention and actual use of a particular technology (Huang & Chueh, 2022; Wang et al., 2022). SI plays an essential role in determining whether an individual adopts a particular technology, as it reflects the influence of peer groups, mentors, or society (Hamundu et al., 2023; Gatzioufa & Saprikis, 2022). Additionally, previous research shows that SI positively impacts students' intention to use ChatGPT (Emon et al., 2023).

In this study, SI is defined as the degree to which research scholars' perceptions and use of ChatGPT are shaped by the opinions or behaviors of their peers or academic community, ultimately affecting their usage of ChatGPT. Consequently, the following hypothesis was formulated:

> **H3:** Social influence significantly influences research scholars' BIs to integrate ChatGPT into their academic research activities.

Facilitating Conditions

Facilitating Conditions (FC) refers to the degree to which individuals believe that the necessary technological infrastructure and resources are in place to support the adoption and use of modern technologies (Chatterjee et al., 2022). FC has been proven to significantly influence university students' willingness to adopt AI-based technologies, such as ChatGPT (Rahim et al., 2022; Almahri et al., 2020; Grover et al., 2020). When adequate resources, technical support, and compatibility with existing systems are available, individuals tend to exhibit positive usage behavior towards that technology (Canziani & MacSween, 2021).

In this study, FC is represented by the availability of resources, technical support, and compatibility with existing AI-based tools that facilitate research scholars' use of ChatGPT for different academic research activities, including writing. Consequently, the following hypothesis was formulated:

> **H4**: Facilitating conditions significantly influence research scholars' BIs to integrate ChatGPT into their academic research activities.

Hedonic Motivation

Hedonic Motivation (HM) refers to the drive or desire to engage in technological activities for pleasure, happiness, and satisfaction (Venkatesh et al., 2012). The enjoyment derived from using technology can turn a practical task into a more enjoyable and engaging experience (Salifu et al., 2024). Previous studies have shown that HM positively influences students' intention to use AI-based technologies, including chatbots (Sebastián et al., 2022; Grover et al., 2020).

In this study, HM reflects the research scholars' enjoyment and satisfaction in using ChatGPT, which drives their adoption and continued use of the tool for academic research activities. Consequently, the following hypothesis was formulated:

> **H5:** Hedonic motivation significantly influences research scholars' BIs to integrate ChatGPT into their academic research activities.

Habit

Habit (HT) is an instinctive behavior repeated frequently, tends to occur subconsciously, and can develop unintentionally (Kurz et al., 2014). In the context of technology, HTs are ingrained behaviors that guide individuals' regular and automatic use of technology (Varma & Marler, 2013). HT is often seen as a crucial factor in behavioral change (Verplanken & Sato, 2011; Yue et al., 2021) and has been shown to positively influence students' intention to use chatbots (Rahim et al., 2022).

In the present study, HT refers to the habitual use of ChatGPT by research scholars as an integral part of their academic research activities, including academic writing. Consequently, we formulated the following hypothesis:

> **H6:** Habit significantly influences research scholars' BIs to integrate ChatGPT into their academic research activities.

Ethical Concerns

Ethical concerns (EC) arise from the considerations and guidelines that outline acceptable and unacceptable behavior in the use of technology (Ramachandran, 2019). Assessing technological applications from the user's perspective is essential, as addressing ethical concerns can foster trust and ensure responsible usage (Rahim et al., 2022).

In this study, ethical concerns encompass establishing clear guidelines, ensuring transparency, promoting accountability, safeguarding data privacy, and fostering the responsible use of ChatGPT by research scholars in their academic research activities. Consequently, the following hypothesis was formulated:

> **H7:** Ethical concerns significantly influence research scholars' BIs to integrate ChatGPT into their academic research activities.

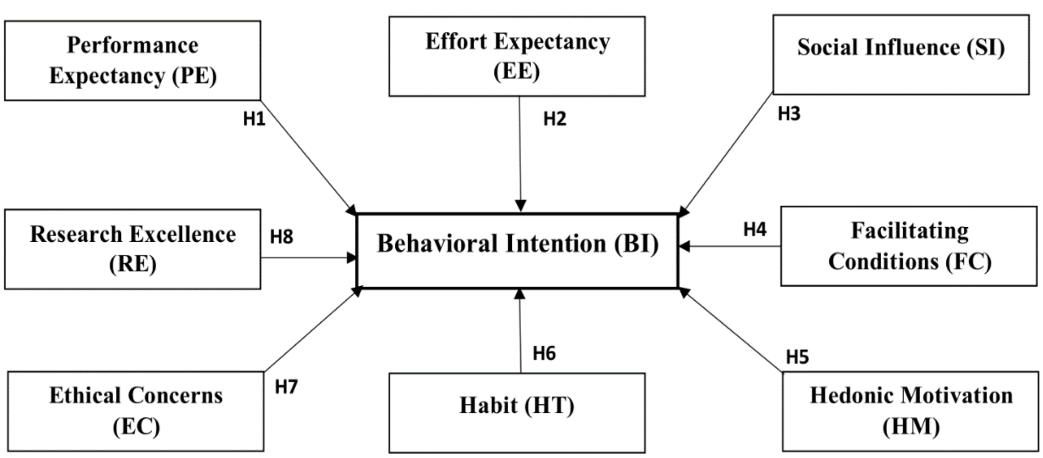
Research Excellence

Research Excellence (RE) refers to maintaining high-quality standards in planning, conducting, and reporting research, which can be optimized through the use of different AI-based technologies, including chatbots such as ChatGPT. It also denotes the ability to enhance the quality and impact of research activities by integrating such tools. Further, the growing influence of ChatGPT in academic research activities, particularly in academic writing, is increasingly recognized (Picazo-Sanchez & Ortiz-Martin, 2024).

In this study, research excellence refers to ChatGPT's role in facilitating comprehensive literature reviews, aiding data analysis, improving writing quality, preparing manuscripts, and addressing ethical concerns promptly, thus supporting research scholars in their academic research activities. Consequently, the following hypothesis was formulated:

> **H8:** Research excellence significantly influences research scholars' BIs to integrate ChatGPT into their academic research activities.

Figure 1. *Conceptual Model*



Methodology

Research Design

This study employed a quantitative research design to determine the factors influencing research scholars' intentions to integrate ChatGPT into their research activities. Many studies on ChatGPT acceptance in the field of education have used a quantitative research approach, often incorporating constructs from the UTAUT2 model and employing PLS-SEM techniques to examine relationships among the defined constructs (Biloš & Budimir, 2024; Grassini et al., 2024). Following this example, our study employed the PLS-SEM technique in the extended UTAUT2 model. Consistent with this approach, we developed a structured survey questionnaire as our primary data collection tool.

Survey Instrument, Sampling, and Data Collection

The questionnaire used in this study consists of a three-part survey. The first section provides respondents with information about the study's purpose, clear instructions, and a request for participation and consent. The second section includes a research instrument with items in a 5-point Likert scale for the constructs of PE, SI, HM, FC, EE, HT, and BI, collectively referred to as the UTAUT2 constructs (see Appendix A). The UTAUT2 constructs were then derived from the research work of Venkatesh et al. (2012) and tailored to fit the context of ChatGPT. The researchers developed the final section of the questionnaire, comprising items for the constructs of Ethical Concerns (EC) and Research Excellence (RE), by drawing on the works of Shaw et al. (2000) and Twum et al. (2022).

The questionnaire was validated and finalized by a panel of experts, comprised of two academicians and two research scholars who specialize in educational technology and AI. This expert validation ensured the questionnaire items were relevant, precise, and reliable for the study's context.

Following expert validation, we conducted a pilot survey with 100 research scholars from Indian higher education institutions (HEIs). Each participant had prior experience using ChatGPT, and these participants were excluded from the subsequent full-scale survey. The pilot study demonstrated strong reliability with a Cronbach's alpha 0.927 (Ursachi et al., 2015). Subsequently, a full-scale survey was conducted over 12 weeks, from April 2024 to June 2024. Responses were gathered from 400 research scholars across various HEIs in India. Purposive sampling was employed to ensure participants had relevant ChatGPT experience (Campbell et al., 2020).

The survey questionnaire was distributed both in person and online through Google Forms. The detailed demographic details of the respondents (n = 400) are presented in Table 1. Reliability and convergent validity of the sampled participants are presented in Table 2.

Table 1. *The Demographic Details of the Respondents* (n = *400*)

Demographic Category	Frequency (*n*)	Percentage (*%*)
PhD Type		
Part time	128	32
Full time	272	68
PhD Stream		
Sciences	166	41.5
Non-sciences	234	58.5
Gender		
Male	192	48
Female	208	52
PhD Year		
First-year student	78	19.5
Second-year student	65	16.25
Third-year student	84	21
Fourth-year student	99	24.75
Fifth-year student	74	18.5
University Type		
Central government	137	34.25
State government	167	41.75
Private	96	24

Data Analysis

The demographic details in Table 1 show that the majority (68%) of respondents are pursuing their PhD full time, while the remaining respondents (32%) are part-time scholars. Regarding academic disciplines, 41.5% are enrolled in sciences and 58.5% in non-sciences. Gender distribution shows a balanced representation with 48% male and 52% female participants. Further, 19.5% of respondents are in their first year of their PhD program, 16.25% are in their second year, 21% are in their third year, 24.75% are in their fourth year, and 18.5% are in their fifth year. Regarding university affiliations, 34.25% of respondents are from central government universities, 41.75% are from state government universities, and 24% are from private universities. This demographic diversity ensures a comprehensive understanding of research scholars' perspectives on integrating ChatGPT into their research activities.

To validate the proposed extended UTAUT2 conceptual model, the Partial Least Squares-Structural Equation Modeling (PLS-SEM) method was performed with SmartPLS 4.0 software (Sarstedt & Cheah, 2019). This structural equation modeling (SEM) method allows for simultaneous evaluation of measurement and structural models, and ensures thorough analysis (J. Hair et al., 2014; Meet & Kala, 2021). Moreover, the PLS-SEM is particularly effective for analyzing complex relationships between observed and latent variables, and accommodates small and large sample sizes without requiring normal distribution assumptions (El Maalmi et al., 2021). Additionally, the accuracy of the PLS-SEM in assessing complex models and validating explanatory power makes it the ideal choice for our study (Usakli & Rasoolimanesh, 2023).

Measurement Model Evaluation

The measurement model was evaluated by assessing each of the construct's reliability and validity properties. The internal consistency and item reliability were measured using the metrics of Cronbach's alpha (α) and Composite reliability (CR). As Fornell and Larcker (1981) outlined, reliable constructs typically show

Cronbach's α and CR values above 0.7 (Lance et al., 2006). Our findings (detailed in Table 2) demonstrate that all of the study's constructs exhibit a desired level of reliability and internal consistency, with Cronbach's α values of each item and CR values of each construct exceeding the 0.7 threshold (Mohamad et al., 2021).

During our study, we used convergent validity, which ensures that items measuring the same construct are correlated. The validity was confirmed using the metrics of factor loadings and average variance extracted (AVE) for each construct (Chin & Yao, 2014). During our initial measurement model evaluation, some items exhibited factor loadings lower than the threshold value and were removed from the final model evaluation. This refinement ensured all remaining items demonstrated strong convergent validity, as indicated by their satisfactory factor loadings and AVE values meeting the 0.5 thresholds (Hair et al., 2009; Hair & Hult et al., 2021). According to Fornell and Larcker (1981), however, an AVE value of 0.4 or above is acceptable if the same construct's CR is higher than 0.6. Therefore, constructs with borderline AVE values were retained since they were close to the threshold and met the necessary CR criteria (see Table 2).

Table 2. *Reliability and Convergent Validity*

Constructs and Items	Mean	SD	Factor Loading	VIF
Performance Expectancy (PE) α = 0.729, CR=0.783, AVE=0.475				
PE1	2.757	0.429	0.665	1.03
PE2	2.712	0.453	0.68	1.045
PE3	2.752	0.432	0.722	1.117
PE4	2.748	0.434	0.689	1.126
Effort Expectancy (EE) α = 0.714, CR=0.786, AVE=0.480				
EE1	2.72	0.449	0.697	1.098
EE2	2.638	0.481	0.709	1.195
EE3	2.55	0.497	0.735	1.108
EE4	2.632	0.482	0.627	1.089
Social Influence (SI) α = 0.718, CR=0.811, AVE=0.522				
SI1	2.783	0.413	0.661	1.317
SI2	2.795	0.404	0.76	1.366
SI3	2.812	0.39	0.836	1.427
SI4	2.775	0.418	0.613	1.287
Facilitating Conditions (FC) α = 0.698, CR=0.769, AVE=0.455				
FC1	2.73	0.444	0.652	1.064
FC2	2.533	0.499	0.647	1.072
FC3	2.737	0.44	0.652	1.12
FC4	2.587	0.492	0.744	1.143
Hedonic Motivation (HM) α = 0.685, CR=0.765, AVE=0.450				
HM1	2.785	0.411	0.628	1.103
HM2	2.68	0.466	0.707	1.075
HM3	2.493	0.5	0.695	1.18
HM4	2.513	0.5	0.652	1.151

Habit (HT) α = 0.710, CR=0.767, AVE=0.453				
HT1	2.61	0.488	0.633	1.094
HT2	2.505	0.5	0.679	1.131
HT3	2.555	0.497	0.645	1.149
HT4	2.595	0.491	0.731	1.139
Ethical Concerns (EC) α = 0.725, CR=0.790, AVE=0.487				
EC1	1.955	0.385	0.623	1.604
EC2	1.982	0.403	0.668	1.761
EC3	1.978	0.409	0.688	1.273
EC4	1.817	0.489	0.802	1.1
Research Excellence (RE) α = 0.712, CR=0.843, AVE=0.519				
RE1	2.61	0.488	0.737	1.29
RE2	2.652	0.476	0.679	1.571
RE3	2.667	0.471	0.749	1.691
RE4	2.65	0.477	0.735	1.411
RE5	2.62	0.485	0.701	1.219
Behavioral Intention (BI) α = 0.743, CR=0.828, AVE=0.492				
BI1	2.638	0.481	0.71	1.244
BI2	2.712	0.453	0.658	1.315
BI3	2.663	0.473	0.771	1.447
BI4	2.63	0.483	0.717	1.373
BI5	2.72	0.449	0.646	1.14

The discriminant validity, which ensures that constructs intended to be distinct are indeed different from one another (Hubley, 2014), was checked using the heterotrait–monotrait (HTMT) ratio metric. The HTMT ratio compares the average correlations of items across constructs measuring different concepts to the average correlations of items within the same construct (Henseler et al., 2015). According to Kline (2011), an HTMT value below 0.85 indicates adequate discriminant validity. By ensuring that all HTMT ratios were below this threshold (see Table 3), we confirmed that each construct was unique and not overly correlated with others in the model.

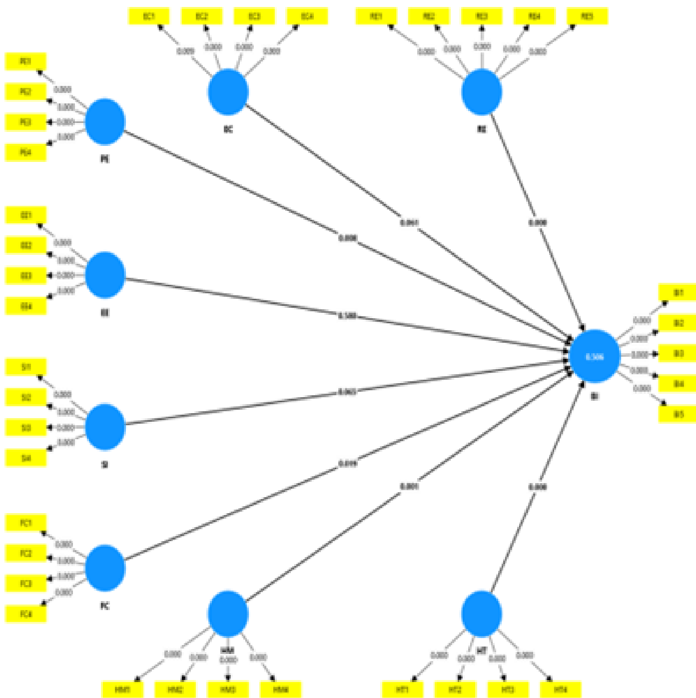
Table 3. *HTMT Criterion for Discriminant Validity*

	BI	EC	EE	FC	HM	HT	PE	RE
BI								
EC	0.213							
EE	0.56	0.297						
FC	0.676	0.205	0.83					
HM	0.818	0.251	0.719	0.756				
HT	0.821	0.246	0.771	0.645	0.712			
PE	0.819	0.194	0.824	0.783	0.816	0.757		
RE	0.809	0.17	0.66	0.766	0.699	0.804	0.638	
SI	0.294	0.12	0.341	0.44	0.415	0.344	0.344	0.249

Structural Model Evaluation

Prior to the evaluation of the structural model and testing the hypothesized relationships, we conducted an assessment to identify potential collinearity issues among indicators by validating the Variance Inflation Factor (VIF) against a criterion set at 3 and detailed in Table 2 (Ringle et al., 2023). Further, we examined the proposed relationships within the extended UTAUT2 conceptual model in the Structural Model Evaluation (see Figure 2).

Figure 2. *SEM Output*



This examination involved assessing the strength and significance of the proposed paths between constructs to test the hypothesized relationships (Nikolopoulou et al., 2020). The analysis focused on understanding how each exogenous construct influences the endogenous constructs in the model. Path coefficients (β) were examined to determine the strength and direction of these relationships through the bootstrapping procedure (see Table 4), while R-squared (R^2) as the goodness-of-fit measure was used to assess how well the model explains the variance in the endogenous constructs (Camilleri, 2024).

Table 4. *Bootstrapping Results of Hypotheses Testing*

Hypothesis	Path	β Values	*p*-Values	Decision
H1	PE → BI	0.127**	0.008	Confirmed
H2	EE → BI	0.027	0.580	Not Confirmed
H3	SI → BI	0.075	0.065	Not Confirmed
H4	FC → BI	0.118**	0.009	Confirmed
H5	HM → BI	0.18**	0.001	Confirmed
H6	HT → BI	0.184***	0.000	Confirmed
H7	EC → BI	0.066	0.061	Not Confirmed
H8	RE → BI	0.442***	0.000	Confirmed

Note: ****p* <0.001, ***p* <0.01

Based on the hypothesis testing results, hypotheses H1, H4, H5, H6, and H8 were confirmed as indicated by their significant β values (see Table 4). Constructs, such as Performance Expectancy (PE), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT), and Research Excellence (RE), specifically, demonstrated statistically significant positive relationships with BI (Table 4). Among these, the most significant path was from RE to BI with a β value of 0.442, underscoring its strong influence.

In contrast to the statistically significant positive relationships, the least significant supported path was from FC to BI (see Table 4). Conversely, hypotheses H2, H3, and H7 were not confirmed, with constructs EE, SI, and EC showing non-significant relationships with BI (Table 4).

In PLS path models, squared correlation values are classified as substantial, moderate, and weak, respectively (Hair et al., 2014). The R^2 statistic quantifies the proportion of variance in the dependent variable explained by the independent variables (Hair et al., 2019; Mohd Rahim et al., 2022).

In this study, the R^2 value for the endogenous construct BI is 0.506 (Figure 2), which is considered moderate. This finding suggests that the model successfully explains a substantial portion of the variance in the dependent variable, BI.

Discussion

In this study, we examine the elements that affect scholars' intentions to use ChatGPT, a large language model revolutionizing online interactions and daily task completion, by employing an extended UTAUT2 model, thereby expanding its applicability to the context of ChatGPT. The findings of this study are pertinent to researchers, policymakers, and educators in universities and colleges. Understanding the extended version of UTAUT2 can help guide administrators and policymakers in creating supportive environments that facilitate the effective utilization of AI tools in research endeavors. By focusing on these aspects of AI, and specifically ChatGPT, more tailored solutions for research scholars, including essential resources, training programs, and technical support, can be developed (Eager & Brunton, 2023; Koos & Wachsmann, 2023).

UTAUT2 provides researchers with a comprehensive framework for understanding the adoption of AI tools, such as ChatGPT, in academic research activities. By incorporating the constructs of UTAUT—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), Habit (HT)—and the additional extensions of Ethical Concerns (EC) and Research Excellence (RE) to create UTAUT2, this model offers valuable insights into the factors influencing AI adoption in research academia (Al Farsi, 2023; Ahmad et al., 2023). As examples, the empirical results of this study indicate that five constructs from the UTAUT2 model—PE, FC, HM, HT, and RE have a significant positive relationship with the BI to use ChatGPT among research scholars in India. These results align with findings from previous studies by (Romero-Rodríguez et al., 2023).

Research Excellence

In this study, the model's emphasis on RE suggests that researchers should consider how AI tools can improve the quality and impact of their outputs, and potentially influence policy decisions, industry practices, and public understanding of various fields of study (Palacios-Marqués et al., 2019; Romero-Rodríguez et al., 2023). The specificity of this research lies in its focus on early-career scholars and doctoral students, who are often at the forefront of technology adoption in academia. As digital natives, these younger researchers are significant for AI adoption, represent the future of academic research, and are typically more open to new technologies (Koos & Wachsmann, 2023).

The most substantial positive relationship with the BI to use ChatGPT among research scholars in India (β = 0.442, $p < 0.001$) was found for RE, indicating that scholars perceive ChatGPT as a tool that significantly enhances research quality and productivity across various domains and offers benefits like improved writing style and streamlined problem-solving processes (Azaria et al., 2024). ChatGPT's natural language interaction capabilities and ability to generate coherent text have transformed scientific communication and information synthesis (Ferrante & Lanera, 2023). This finding extends the UTAUT2 model by incorporating a domain-specific factor relevant to academic research (Teo, 2011; Wong et al., 2024).

Habit and Hedonic Motivation

HT was the second most influential factor for BI, followed by HM. These results suggest that scholars find using ChatGPT enjoyable and have integrated it into their regular research routines, a finding consistent with that of Palacios-Marqués et al. (2019). The strong positive relationship between HT and HM (β = 0.184, $p < 0.001$; β = 0.18, $p < 0.01$, respectively) indicates that these constructs significantly influence the intention to use ChatGPT.

Additionally, the UTAUT2 model highlights the importance of habit and BI in influencing user behavior toward ChatGPT use (Romero-Rodríguez et al., 2023). Strzelecki (2024) found that students demonstrate a high level of comfort in adopting new technology, and the frequency of their usage contributes to the development of routine actions (Strzelecki, 2024). Furthermore, the impact of hedonic motivation on the intention to use ChatGPT indicates its significant role in shaping user behavior (Foroughi et al., 2023).

Performance Expectancy

PE showed a significant positive relationship with BI (β = 0.127, $p < 0.01$) in this study, as well, suggesting that scholars believe ChatGPT can enhance their research productivity and quality (Firat, 2023; Liao, 2011). This finding aligns with the goal-oriented nature of research scholars who value tools that improve efficiency and effectiveness (Emon et al., 2023). University students, when embracing new technologies like ChatGPT, evaluate AI's benefits compared to traditional methods, as well as its ease of learning and use. These considerations play a crucial role in their decision-making process regarding the adoption of ChatGPT and its potential utility in enhancing their academic endeavors.

Facilitating Conditions

FC had a positive influence on BI (β = 0.118, p < 0.01). This finding indicates that the availability of resources and support for using ChatGPT is crucial for adoption intentions (Puspitasari et al., 2019). The impact of FC on technology adoption is evident across various contexts.

Studies on Muslim Sacco mobile apps (Hamzah et al., 2023) and e-wallet usage (Boon et al., 2023) found significant positive influences on user intentions. Similarly, research on massive open online course (MOOC) adoption, in Thailand and Pakistan, revealed that *facilitating conditions* (such as resources and support) are a key predictor of BIs (Chaveesuk et al., 2022). These findings underscore the crucial role of FC in shaping user engagement with diverse technological platforms and services.

Effort Expectancy, Social Influence, and Ethical Concerns

Interestingly, EE, SI, and EC did not show significant relationships with BI. The non-significance of EE might stem from the advanced technological literacy of research scholars, which reduces the importance of perceived ease of use (Nyembezi & Bayaga, 2015). The lack of significance for SI suggests that scholars' decisions to use ChatGPT are more influenced by a personal assessment of its benefits rather than peer or institutional pressure (Jowarder, 2023).

In this study, the non-significance of EC is notable. This result may potentially indicate that, while scholars are aware of ethical issues, they may prioritize the benefits of ChatGPT instead, or they may feel confident in their ability to use the tool ethically (Lampropoulos et al., 2023).

Implications

The implications of this study extend beyond individual researchers to encompass broader institutional and societal impacts. The findings highlight, for example, the necessity of creating policies and guidelines for the ethical use of AI in research for universities and research institutions. These measures will help address potential concerns and promote responsible adoption (Xue et al., 2024). Also, a more specifically designed AI could have far-reaching effects on the nature and quality of academic output for academic researchers, such as influencing the academic community, industry practices, and public understanding of various fields of study.

This research helps shape the future landscape of scholarly work and knowledge dissemination in research activities by providing a nuanced understanding of AI adoption in academia. Research scholars' adoption of ChatGPT could help accelerate the development and refinement of AI tools specifically designed for academic research. Further development and refinement could potentially lead to more sophisticated and specialized AI assistants in the future (Balel, 2023; Vicente-Yagüe-Jara et al., 2023).

Limitations and Future Research Suggestions

The findings of this study can be interpreted in light of several significant limitations, which provide avenues for future research on AI usage. For example, the sample was limited to research scholars in India, which may not be generalizable to other countries or academic contexts. Future studies could expand to different geographical regions and academic levels.

Future studies could explore ChatGPT adoption among research scholars across different countries, as well as other generative AI tools, and potentially incorporate additional constructs and moderating factors. Such varied research would provide a more comprehensive understanding of AI adoption in education across different cultural and demographic settings.

The UTAUT2 model used in this study is limited by its reliance on self-reported data, where individuals report their intentions rather than actual behaviors. Self-reporting can introduce inaccuracies and validity issues, and can compromise the reliability of the model's findings, which becomes a limitation of this model. This extended model also opens up opportunities for further research in diverse contexts. Excluding moderators, such as gender, age, and experience, would simplify the study by focusing directly on the relationships between key constructs and facilitating the development of straightforward models to analyze direct correlations. Additionally, the cross-sectional nature of the data in this study limits causal inferences. Further research using longitudinal studies, for example, could provide insights into how ChatGPT adoption evolves over time.

In this study, we focused on BI, rather than the actual usage of ChatGPT. Future research could examine the relationship between "intention to use" ChatGPT and "actual use" of ChatGPT in academic writing. Additionally, qualitative methods could provide deeper insights into scholars' motivations and concerns regarding ChatGPT adoption.

Finally, the non-significance of ethical concerns warrants further investigation—perhaps through more nuanced measures or qualitative exploration. Future studies could also examine potential moderating factors, such as academic discipline, research experience, or institutional policies, on AI use in academia.

Conclusion

Research scholars have adopted ChatGPT, which represents a significant shift in academic practices with far-reaching implications. As AI tools become more prevalent in academia, institutions must balance the potential benefits with ethical considerations and maintain research integrity.

This research employed an extended UTAUT2 model and a PLS-SEM approach to examine ChatGPT adoption among research scholars in Indian higher education institutions. By analyzing both BI and actual usage patterns, while following the UTAUT2 model, this study provided insights into how the ChatGPT interface might influence these scholars' intentions to use the technology in their academic work and day-to-day lives.

Integrating AI into research processes may help reshape individual scholarly practices, as well as broaden higher education dynamics, such as teaching methods, publication processes, and interdisciplinary collaboration. This study highlights the importance of implementing PE, FC, HM, HT, EC, and RE in driving ChatGPT adoption intentions.

The strong influence of RE in our study suggests that ChatGPT is perceived as a valuable tool for enhancing scholarly output. The academic community, however, must remain conscious of potential pitfalls, such as over-reliance or ethical misuse, when using ChatGPT and other AI. As these tools evolve, their impact on academic research and knowledge production will likely grow, necessitating ongoing adaptation and thoughtful integration within the scholarly ecosystem.

References

Acosta-Enriquez, B. G., Ballesteros, M. A. A., Jordan, O. H., Roca, C. L., & Tirado, K. S. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: Effect of intent to use, verification of information and responsible use. *BMC Psychology*, *12*(255). https://doi.org/10.1186/s40359-024-01764-z

Ahmad, F. B., Al-Nawaiseh, S. J., & Al-Nawaiseh, A. J. (2023). Receptivity level of faculty members in universities using digital learning tools: A UTAUT perspective. *International Journal of Emerging Technologies in Learning*, *18*(13), 209–219. https://doi.org/10.3991/ijet.v18i13.39763

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

Alexander, B., Ashford-Rowe, K., Barajas-Murphy, N., Dobbin, G., Knott, J., McCormack, M., Pomerantz, J., Seilhamer, R., & Weber, N. (2019). *EDUCAUSE Horizon Report: 2019 higher education edition*. EDUCAUSE. https://library.educause.edu/-/media/files/library/2019/4/2019horizonreport

Al Farsi, G. (2023). The efficiency of UTAUT2 model in predicting student's acceptance of using virtual reality technology. *International Journal of Interactive Mobile Technologies*, *17*(12), 17–27. https://doi.org/10.3991/ijim.v17i12.36951

Ali, F., & ChatGPT OpenAI. (2023). Let the devil speak for itself: Should ChatGPT be allowed or banned in hospitality and tourism schools? *Journal of Global Hospitality and Tourism*, *2*(1), 1–6. https://doi.org/10.5038/2771-5957.2.1.1016

Almahri, F. A. J., Bell, D., & Merhi, M. (2020). Understanding student acceptance and use of chatbots in the United Kingdom universities: A structural equation modelling approach. *2020 6th International Conference on Information Management (ICIM)*, 284–288. https://doi.org/10.1109/ICIM49319.2020.244712

Almaiah, M. A., Alamri, M. M., & Al-Rahmi, W. (2019). Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education. *IEEE Access*, *7*, 174673–174686. https://doi.org/10.1109/ACCESS.2019.2957206

Almaiah, M. A., Hajjej, F., Lutfi, A., Al-Khasawneh, A., Alkhdour, T., Almomani, O., & Shehab, R. (2022). A conceptual framework for determining quality requirements for mobile learning applications using Delphi method. *Electronics*, *11*(5), Article 788. https://doi.org/10.3390/electronics11050788

Araújo, L. S., Cruz, J. F. A., & Almeida, L. S. (2017). Achieving scientific excellence: An exploratory study of the role of emotional and motivational factors. *High Ability Studies*, *28*(2), 249–264. https://doi.org/10.1080/13598139.2016.1264293

Azaria, A., Azoulay, R., & Reches, S. (2024). ChatGPT is a remarkable tool—for experts. *Data Intelligence*, *6*(1), 240–296. https://doi.org/10.1162/dint_a_00235

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the era of generative artificial intelligence (AI): Understanding the potential benefits of ChatGPT in promoting teaching and learning. *Journal of AI*, *7*(1), 52–62. https://doi.org/10.61969/jai.1337500

Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change*, *180*, Article 121692. https://doi.org/10.1016/j.techfore.2022.121692

Balel, Y. (2023). The role of artificial intelligence in academic paper writing and its potential as a co-author: Letter to the editor. *European Journal of Therapeutics*, *29*(4), 984–985. https://doi.org/10.58600/eurjther1691

Bang, Y., Cahyawijaya, S., Lee, N., Dai, W., Su, D., Wilie, B., Lovenia, H., Ji, Z., Yu, T., Chung, W., Do, Q. V., Xu, Y., & Fung, P. (2023). A multitask, multilingual, multimodal evaluation of ChatGPT on reasoning, hallucination, and interactivity. *Computation and Language*. https://doi.org/10.48550/arXiv.2302.04023

Becker, S. A., Brown, M., Dahlstrom, E., Davis, A., DePaul, K., Diaz, V., & Pomerantz, J. (2018). *EDUCAUSE Horizon Report: 2018 higher education edition*. EDUCAUSE. https://library.educause.edu/~/media/files/library/2018/8/2018horizonreport.pdf

Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, 610–623. https://doi.org/10.1145/3442188.3445922

Biloš, A., & Budimir, B. (2024). Understanding the adoption dynamics of ChatGPT among Generation Z: Insights from a modified UTAUT2 model. *Journal of Theoretical and Applied Electronic Commerce Research*, *19*(2), 863–879. https://doi.org/10.3390/jtaer19020045

Bin-Nashwan, S. A., Sadallah, M., & Bouteraa, M. (2023). Use of ChatGPT in academia: Academic integrity hangs in the balance. *Technology in Society*, *75*, Article 102370. https://doi.org/10.1016/j.techsoc.2023.102370

Biswas, S. (2023). ChatGPT and the future of medical writing. *Radiology*, *307*(2). https://doi.org/10.1148/radiol.223312

Boon, L. K., Fern, Y. S., Yee, T. X., & Ling, T. C. (2023). Investigating the e-wallet usage continuance intention in Malaysia post-COVID 19 pandemic. *International Journal of Business and Technology Management, 5*(1), 333–350. https://doi.org/10.55057/ijbtm.2023.5.1.26

Bouter, L. (2023). Why research integrity matters and how it can be improved. *Accountability in Research, 31*(8), 1277–1286. https://doi.org/10.1080/08989621.2023.2189010

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., Hesse, C., … Amodei, D. (2020). Language models are few-shot learners. *Computation and Language*. https://doi.org/10.48550/arXiv.2005.14165

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

Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. *Technological Forecasting and Social Change*, *201*, Article 123247. https://doi.org/10.1016/j.techfore.2024.123247

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing*, *25*(8), 652–661. https://doi.org/10.1177/1744987120927206

Campo, M. A. (2014). Leadership and research administration. *Research Management Review*, *20*(1), 1–6. https://files.eric.ed.gov/fulltext/EJ1038832.pdf

Canziani, B., & MacSween, S. (2021). Consumer acceptance of voice-activated smart home devices for product information seeking and online ordering. *Computers in Human Behavior*, *119*, Article 106714. https://doi.org/10.1016/j.chb.2021.106714

Castelvecchi, D. (2022). Are ChatGPT and AlphaCode going to replace programmers? *Nature*. https://doi.org/10.1038/d41586-022-04383-z

Chatterjee, S., Chaudhuri, R., Vrontis, D., & Basile, G. (2022). Digital transformation and entrepreneurship process in SMEs of India: A moderating role of adoption of AI-CRM capability and strategic planning. *Journal of Strategy and Management*, *15*(3), 416–433. https://doi.org/10.1108/JSMA-02-2021-0049

Chaveesuk, S., Khalid, B., Bsoul-Kopowska, M., Rostańska, E., & Chaiyasoonthorn, W. (2022). Comparative analysis of variables that influence behavioral intention to use MOOCs. *PLOS ONE*, *17*(4), Article e0262037. https://doi.org/10.1371/journal.pone.0262037

Chin, C.-L., & Yao, G. (2014). Convergent validity. In A. C. Michalos (Ed.), *Encyclopedia of quality of life and well-being research* (pp. 1275–1276). Springer. https://doi.org/10.1007/978-94-007-0753-5_573

Christou, P. A. (2023). How to use artificial intelligence (AI) as a resource, methodological and analysis tool in qualitative research? *The Qualitative Report, 28*(7), 1968–1980. https://doi.org/10.46743/2160-3715/2023.6406

Chubb, J., Cowling, P., & Reed, D. (2022). Speeding up to keep up: Exploring the use of AI in the research process. *AI and Society*, *37*(4), 1439–1457. https://doi.org/10.1007/s00146-021-01259-0

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, *61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Currie, G., Singh, C., Nelson, T., Nabasenja, C., Al-Hayek, Y., & Spuur, K. (2023). ChatGPT in medical imaging higher education. *Radiography*, *29*(4), 792–799. https://doi.org/10.1016/j.radi.2023.05.011

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

Dehouche, N. (2021). Plagiarism in the age of massive generative pre-trained transformers (GPT-3). *Ethics in Science and Environmental Politics*, *21*, 17–23. https://doi.org/10.3354/esep00195

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

Dergaa, I., Chamari, K., Zmijewski, P., & Saad, H. B. (2023). From human writing to artificial intelligence generated text: Examining the prospects and potential threats of ChatGPT in academic writing. *Biology of Sport*, *40*(2), 615–622. https://doi.org/10.5114/biolsport.2023.125623

Dianova, V. G., & Schultz, M. D. (2023). Discussing ChatGPT's implications for industry and higher education: The case for transdisciplinarity and digital humanities. *Industry and Higher Education*, *37*(5), 593–600. https://doi.org/10.1177/09504222231199989

Du, H., Teng, S., Chen, H., Ma, J., Wang, X., Gou, C., Li, B., Ma, S., Miao, Q., Na, X., Ye, P., Zhang, H., Luo, G., & Wang, F.-Y. (2023). Chat with ChatGPT on intelligent vehicles: An IEEE TIV perspective. *IEEE Transactions on Intelligent Vehicles*, *8*(3), 2020–2026. https://doi.org/10.1109/TIV.2023.3253281

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). Opinion paper: "So what if ChatGPT wrote it?": Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Eager, B., & Brunton, R. (2023). Prompting higher education towards AI-augmented teaching and learning practice. *Journal of University Teaching and Learning Practice*, *20*(5). https://doi.org/10.53761/1.20.5.02

Eggmann, F., Weiger, R., Zitzmann, N. U., & Blatz, M. B. (2023). Implications of large language models such as ChatGPT for dental medicine. *Journal of Esthetic and Restorative Dentistry*, *35*(7), 1098–1102. https://doi.org/10.1111/jerd.13046

El Maalmi, A., Jenoui, K., & El Abbadi, L. (2021, November 3–5). Comparison study between CB-SEM and PLS-SEM for sustainable supply chain innovation model [Conference paper]. In R. Saidi, B. El Bhiri, Y. Maleh, A. Mosallam, & M. Essaaidi, M. (Eds.), *Advanced technologies for humanity* (pp. 537–552). International Conference on Industrial Engineering and Operations Management—ICATH 2021, Monterrey, Mexico. https://doi.org/10.1007/978-3-030-94188-8_48

Emon, M. M. H., Hassan, F., Nahid, M. H., & Rattanawiboonsom, V. (2023). Predicting adoption intention of artificial intelligence ChatGPT. *AIUB Journal of Science and Engineering*, *22*(2), 189–199. https://doi.org/10.53799/ajse.v22i2.797

Ferrante, G., & Lanera, C. (2023). ChatGPT in scientific research: A guide to informed use. *PubMed*, *47*(3), 203–207. https://doi.org/10.19191/ep23.3.a639.051

Firat, M. (2023). What ChatGPT means for universities: Perceptions of scholars and students. *Journal of Applied Learning and Teaching*, *6*(1). https://doi.org/10.37074/jalt.2023.6.1.22

Floridi, L., & Cowls, J. (2019). A unified framework of five principles for AI in society. *Harvard Data Science Review*, *1*(1). https://doi.org/10.1162/99608f92.8cd550d1

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

Fornell, C., & Larcker, D. F. (1981b). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382–388. https://doi.org/10.1177/002224378101800313

Foroughi, B., Senali, M. G., Iranmanesh, M., Khanfar, A., Ghobakhloo, M., Annamalai, N., & Naghmeh-Abbaspour, B. (2023). Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. *International Journal of Human–Computer Interaction, 40*(17), 4501–4520. https://doi.org/10.1080/10447318.2023.2226495

García-Peñalvo, F. J. (2021). Avoiding the dark side of digital transformation in teaching. An institutional reference framework for eLearning in higher education. *Sustainability*, *13*(4), 2023. https://doi.org/10.3390/su13042023

Garg, R. K., Urs, V. L., Agrawal, A. A., Chaudhary, S. K., Paliwal, V., & Kar, S. K. (2023). Exploring the role of ChatGPT in patient care (diagnosis and treatment) and medical research: A systematic review. *Health Promotion Perspectives*, *13*(3), 183–191. https://doi.org/10.34172/hpp.2023.22

Gatzioufa, P., & Saprikis, V. (2022). A literature review on users' behavioral intention toward chatbots' adoption. *Applied Computing and Informatics, 18*(3/4). https://doi.org/10.1108/ACI-01-2022-0021

Gayed, J. M., Carlon, M. K. J., Oriola, A. M., & Cross, J. S. (2022). Exploring an AI-based writing assistant's impact on English language learners. *Computers and Education: Artificial Intelligence*, *3*, Article 100055. https://doi.org/10.1016/j.caeai.2022.100055

Ghafouri, M. (2024). ChatGPT: The catalyst for teacher-student rapport and grit development in L2 class. *System*, *120*, Article 103209. https://doi.org/10.1016/j.system.2023.103209

Giray, L. (2023). Prompt engineering with ChatGPT: A guide for academic writers. *Annals of Biomedical Engineering*, *51*(12), 2629–2633. https://doi.org/10.1007/s10439-023-03272-4

Goertzel, B., & Pennachin. C. (Eds.). (2007). *Artificial general intelligence*. Springer.

Golan, R., Reddy, R., Muthigi, A., & Ramasamy, R. (2023). Artificial intelligence in academic writing: A paradigm-shifting technological advance. *Nature Reviews Urology*, *20*(6), 327–328. https://doi.org/10.1038/s41585-023-00746-x

Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding university students' acceptance of ChatGPT: Insights from the UTAUT2 model. *Applied Artificial Intelligence*, *38*(1), Article 2371168. https://doi.org/10.1080/08839514.2024.2371168

Grover, T., Rowan, K., Suh, J., McDuff, D., & Czerwinski, M. (2020, March 17–20). Design and evaluation of intelligent agent prototypes for assistance with focus and productivity at work [Conference presentation]. *Proceedings of the 25th International Conference on Intelligent User Interfaces (IUI '20)* (pp. 390–400). Cagliari, Italy. ACM. https://doi.org/10.1145/3377325.3377507

Gruetzemacher, R., & Whittlestone, J. (2022). The transformative potential of artificial intelligence. *Futures*, *135*, Article 102884. https://doi.org/10.1016/j.futures.2021.102884

Hair, J. F., Jr., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis* (7th ed.). Pearson.

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Evaluation of reflective measurement models. In *Partial least squares structural equation modeling (PLS-SEM)* (pp. 75–90). Springer. https://doi.org/10.1007/978-3-030-80519-7_4

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

Hair, J. F., Jr, Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hamundu, F. M., Solihat, I., Hendrian, & Wahyu, M. (2023). Determinants of behavior intention to adopt peer-to-peer lending services among Indonesia MSMES. *International Journal of Business and Society*, *24*(1), 543–558. https://doi.org/10.33736/ijbs.5633.2023

Hamzah, N., Haji-Othman, Y., & Cheumar, M. T. (2023). The influence of facilitating condition and perceived usefulness on intention to use mobile applications in Uganda. *Malaysian Journal of Social Sciences and Humanities*, *8*(4), Article e002257. https://doi.org/10.47405/mjssh.v8i4.2257

Han, A., & Cai, Z. (2023, June 19–23). Design implications of generative AI systems for visual storytelling for young learners [Conference presentation]. In *Proceedings of the 22nd Annual ACM Interaction Design and Children Conference (IDC23)* (pp. 470–474). Chicago, IL, USA. ACM. https://doi.org/10.1145/3585088.3593867

Hasija, A., & Esper, T. L. (2022). In artificial intelligence (AI) we trust: A qualitative investigation of AI technology acceptance. *Journal of Business Logistics*, *43*(3), 388–412. https://doi.org/10.1111/jbl.12301

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Huang, D.-H., & Chueh, H.-E. (2022). Behavioral intention to continuously use learning apps: A comparative study from Taiwan universities. *Technological Forecasting and Social Change*, *177*, Article 121531. https://doi.org/10.1016/j.techfore.2022.121531

Huang, J., & Tan, M. (2023). The role of ChatGPT in scientific communication: Writing better scientific review articles. *American Journal of Cancer Research*, *13*(4), 1148–1154.

Hubley, A. M. (2014). Discriminant validity. In *Encyclopedia of quality of life and well-being research* (pp. 1664–1667). Springer. https://doi.org/10.1007/978-94-007-0753-5_751

Jowarder, M. I. (2023). The influence of ChatGPT on social science students: Insights drawn from undergraduate students in the United States. *Indonesian Journal of Innovation and Applied Sciences*, *3*(2), 194–200. https://doi.org/10.47540/ijias.v3i2.878

Kalla, D., & Smith, N. (2023). Study and analysis of Chat GPT and its impact on different fields of study. *International Journal of Innovative Science and Research Technology*, *8*(3), 827–833. https://doi.org/10.5281/zenodo.10250455

Kamalov, F., Calonge, D. S., & Gurrib, I. (2023). New era of artificial intelligence in education: Towards a sustainable multifaceted revolution. *Sustainability*, *15*(16), Article 12451. https://doi.org/10.3390/su151612451

Kavitha, K., Joshith, V. P., & Sharma, S. (2024). Beyond text: ChatGPT as an emotional resilience support tool for Gen Z—a sequential explanatory design exploration. *E-Learning and Digital Media*. https://doi.org/10.1177/20427530241259099

Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update*, *5*, Article 100145. https://doi.org/10.1016/j.cmpbup.2024.100145

Khan, R. A., Jawaid, M., Khan, A. R., & Sajjad, M. (2023). ChatGPT—reshaping medical education and clinical management. *Pakistan Journal of Medical Sciences*, *39*(2). https://doi.org/10.12669/pjms.39.2.7653

Khlaif, Z. N., Mousa, A., Hattab, M. K., Itmazi, J., Hassan, A. A., Sanmugam, M., & Ayyoub, A. (2023). The potential and concerns of using AI in scientific research: ChatGPT performance evaluation. *JMIR Medical Education*, *9*, Article e47049. https://doi.org/10.2196/47049

King, M. R., & ChatGPT. (2023). A conversation on artificial intelligence, chatbots, and plagiarism in higher education. *Cellular and Molecular Bioengineering*, *16*(1), 1–2. https://doi.org/10.1007/s12195-022-00754-8

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

Kissinger, H., Schmidt, E., & Huttenlocher, D. (2023, February 24). Opinion: ChatGPT heralds an intellectual revolution. *The Wall Street Journal*. https://www.wsj.com/articles/chatgpt-heralds-an-intellectual-revolution-enlightenment-artificial-intelligence-homo-technicus-technology-cognition-morality-philosophy-774331c6

Kline, R. B. (2011). *Principles and practice of structural equation modeling* (3rd ed). The Guilford Press.

Koos, S., & Wachsmann, S. (2023). Navigating the impact of ChatGPT/GPT4 on legal academic examinations: Challenges, opportunities and recommendations. *Media Iuris*, *6*(2), 255–270. https://doi.org/10.20473/mi.v6i2.45270

Kumari, N., & Tiwari, J. K. (2023). E-Learning use and integration in NEP-2020. *International Journal of Creative Research Thoughts*, *11*(11), b398–b405. https://doi.org/10.56975/ijcrt.v11i11.246079

Kurz, C., Wu, X., Wand, M., Thormählen, T., Kohli, P., & Seidel, H.-P. (2014). Symmetry-aware template deformation and fitting. *Computer Graphics Forum*, *33*(6), 205–219. https://doi.org/10.1111/cgf.12344

Kusal, S., Patil, S., Choudrie, J., Kotecha, K., Mishra, S., & Abraham, A. (2022). AI-based conversational agents: A scoping review from technologies to future directions. *IEEE Access*, *10*, 92337–92356. https://doi.org/10.1109/ACCESS.2022.3201144

Lampropoulos, G., Keramopoulos, E., Diamantaras, K., & Evangelidis, G. (2023). Integrating augmented reality, gamification, and serious games in computer science education. *Education Sciences*, *13*(6), Article 618. https://doi.org/10.3390/educsci13060618

Lance, C. E., Butts, M. M., & Michels, L. C. (2006). The sources of four commonly reported cutoff criteria: What did they really say? *Organizational Research Methods*, *9*(2), 202–220. https://doi.org/10.1177/1094428105284919

Laxmanbhai, P. B., & Patel, H. A. (2023). A study of the impact of economic status on the opinion of beneficiary candidates of the scheme of developing high quality research about the scheme benefits. *PARIPEX—Indian Journal of Research*, *12*(4), 80–83. https://doi.org/10.36106/paripex/2106181

Liao, C. H. (2011). How to improve research quality? Examining the impacts of collaboration intensity and member diversity in collaboration networks. *Scientometrics*, *86*(3), 747–761. https://doi.org/10.1007/s11192-010-0309-2

Lindhult, E. (2019). Scientific excellence in participatory and action research: Part I. Rethinking research quality. *Technology Innovation Management Review*, *9*(5), 6–21. https://doi.org/10.22215/timreview/1237

Liu, Q., Geertshuis, S., & Grainger, R. (2020). Understanding academics' adoption of learning technologies: A systematic review. *Computers and Education*, *151*, Article 103857. https://doi.org/10.1016/j.compedu.2020.103857

Liu, X., Zheng, Y., Du, Z., Ding, M., Qian, Y., Yang, Z., & Tang, J. (2024). GPT understands, too. *AI Open, 5*, 208–215. https://doi.org/10.1016/j.aiopen.2023.08.012

Liu, Y., Han, T., Ma, S., Zhang, J., Yang, Y., Tian, J., He, H., Li, A., He, M., Liu, Z., Wu, Z., Zhao, L., Zhu, D., Li, X., Qiang, N., Shen, D., Liu, T., & Ge, B. (2023). Summary of ChatGPT-related research and perspective towards the future of large language models. *Meta-Radiology, 1*(2), Article 100017. https://doi.org/10.1016/j.metrad.2023.100017

Livberber, T., & Ayvaz, S. (2023). The impact of artificial intelligence in academia: Views of Turkish academics on ChatGPT. *Heliyon*, *9*(9), Article e19688. https://doi.org/10.1016/j.heliyon.2023.e19688

Makridakis, S. (2017). The forthcoming artificial intelligence (AI) revolution: Its impact on society and firms. *Futures*, *90*, 46–60. https://doi.org/10.1016/j.futures.2017.03.006

Manickam, D. K. (2023). A study on education system to utilize new techniques for digital education in India. *ICTACT Journal on Management Studies*, *09*(03), 1535–1543. https://doi.org/10.21917/ijms.2023.0267

Marzuki, Widiati, U., Rusdin, D., Darwin, & Indrawati, I. (2023). The impact of AI writing tools on the content and organization of students' writing: EFL teachers' perspective. *Cogent Education*, *10*(2), Article 2236469. https://doi.org/10.1080/2331186X.2023.2236469

Meet, R. K., & Kala, D. (2021). Trends and future prospects in MOOC researches: A systematic literature review 2013–2020. *Contemporary Educational Technology*, *13*(3), Article ep312. https://doi.org/10.30935/cedtech/10986

Megahed, F. M., Chen, Y.-J., Ferris, J. A., Knoth, S., & Jones-Farmer, L. A. (2024). How generative AI models such as ChatGPT can be (mis)used in SPC practice, education, and research? An exploratory study. *Quality Engineering*, *36*(2), 287–315. https://doi.org/10.1080/08982112.2023.2206479

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

Mensah, M., & Onyancha, O. B. (2022). Ghanaian academic libraries' use of social media: A structural equation modelling approach. *Information Development*, *38*(2), 323–342. https://doi.org/10.1177/0266666921999429

Mhlanga, D. (2023). Open AI in education, the responsible and ethical use of ChatGPT towards lifelong learning. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4354422

Mogaji, E., Balakrishnan, J., Nwoba, A. C., & Nguyen, N. P. (2021). Emerging-market consumers' interactions with banking chatbots. *Telematics and Informatics*, *65*, Article 101711. https://doi.org/10.1016/j.tele.2021.101711

Mohamad, M. A., Amron, M. T., & Noh, N. H. (2021, December 1–3). Assessing the acceptance of e-Learning via technology acceptance model (TAM). In, *2021 6th IEEE international conference (virtual mode) on recent advances and innovations in engineering*, 1–5. Kedah, Malaysia. IEEE. https://doi.org/10.1109/ICRAIE52900.2021.9704019

Mohd Rahim, N. I., A., Iahad, N., Yusof, A. F., & Al-Sharafi, M. A. (2022). AI-based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach. *Sustainability*, *14*(19), Article 12726. https://doi.org/10.3390/su141912726

Moorthy, K., Chun T'ing, L., Ming, K. S., Ping, C. C., Ping, L. Y., Joe, L. Q., & Jie, W. Y. (2019). Behavioral intention to adopt digital library by the undergraduates. *International Information and Library Review*, *51*(2), 128–144. https://doi.org/10.1080/10572317.2018.1463049

Munshi, M. M., & Marulasiddaiah, M. B. M. (2015). Engagement of research scholar in research. *IOSR Journal of Business and Management*, *17*(3), 13–15.

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2020). Acceptance of mobile phone by university students for their studies: An investigation applying UTAUT2 model. *Education and Information Technologies*, *25*(5), 4139–4155. https://doi.org/10.1007/s10639-020-10157-9

Nikulina, A., & Wynstra, F. (2022). Understanding supplier motivation to engage in multiparty performance-based contracts: The lens of expectancy theory. *Journal of Purchasing and Supply Management*, *28*(2), Article 100746. https://doi.org/10.1016/j.pursup.2022.100746

Nyembezi, N., & Bayaga, A. (2015). Analysis of the effect of effort expectancy on school learners' adoption and use of cloud computing. *Journal of Communication*, *6*(1), 113–119.

Onaolapo, S., & Oyewole, O. (2018). Performance expectancy, effort expectancy, and facilitating conditions as factors influencing smart phones use for mobile learning by postgraduate students of the University of Ibadan, Nigeria. *Interdisciplinary Journal of E-Skills and Lifelong Learning*, *14*(1), 095–115. https://doi.org/10.28945/4085

Palacios-Marqués, D., García, M. G., Sánchez, M. M., & Mari, M. P. A. (2019). Social entrepreneurship and organizational performance: A study of the mediating role of distinctive competencies in marketing. *Journal of Business Research*, *101*, 426–432. https://doi.org/10.1016/j.jbusres.2019.02.004

Picazo-Sanchez, P., & Ortiz-Martin, L. (2024). Analysing the impact of ChatGPT in research. *Applied Intelligence*, *54*(5), 4172–4188. https://doi.org/10.1007/s10489-024-05298-0

Puspitasari, N., Firdaus, M. B., Haris, C. A., & Setyadi, H. J. (2019). An application of the UTAUT model for analysis of adoption of integrated license service information system. *Procedia Computer Science*, *161*, 57–65. https://doi.org/10.1016/j.procs.2019.11.099

Qadir, J. (2023). Engineering education in the era of ChatGPT: Promise and pitfalls of generative AI for education. *2023 IEEE Global Engineering Education Conference (EDUCON)*, 1–9. https://doi.org/10.1109/EDUCON54358.2023.10125121

Rahim, N. I. M., Iahad, N. A., Yusof, A. F., & Al-Sharafi, M. A. (2022). AI-based chatbots adoption model for higher-education institutions: A hybrid PLS-SEM-neural network modelling approach. *Sustainability*, *14*(19), Article 12726. https://doi.org/10.3390/su141912726

Ramachandran, A. (2019). User adoption of chatbots. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3406997

Ray, P. P. (2023). ChatGPT: A comprehensive review on background, applications, key challenges, bias, ethics, limitations and future scope. *Internet of Things and Cyber-Physical Systems*, *3*, 121–154. https://doi.org/10.1016/j.iotcps.2023.04.003

Ringle, C. M., Sarstedt, M., Sinkovics, N., & Sinkovics, R. R. (2023). A perspective on using partial least squares structural equation modelling in data articles. *Data in Brief*, *48*, Article 109074. https://doi.org/10.1016/j.dib.2023.109074

Romero-Rodríguez, J.-M., Ramírez-Montoya, M.-S., Buenestado-Fernández, M., & Lara-Lara, F. (2023). Use of ChatGPT at university as a tool for complex thinking: Students' perceived usefulness. *Journal of New Approaches in Educational Research*, *12*(2), 323–339. https://doi.org/10.7821/naer.2023.7.1458

Rospigliosi, P. (2023). Artificial intelligence in teaching and learning: What questions should we ask of ChatGPT? *Interactive Learning Environments*, *31*(1), 1–3. https://doi.org/10.1080/10494820.2023.2180191

Sadeghi, M. (2019). A shift from classroom to distance learning: Advantages and limitations. *International Journal of Research in English Education*, *4*(1), 80–88. https://doi.org/10.29252/ijree.4.1.80

Sahu, P., Kumari, A., & Mahima, M. H. (2023). User attitudes and behavioural intentions towards ChatGPT: An exploratory study. *International Journal of Novel Research and Development*, *8*(4), d627–d636.

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

Sarstedt, M., & Cheah, J.-H. (2019). Partial least squares structural equation modeling using SmartPLS: A software review. *Journal of Marketing Analytics*, *7*(3), 196–202. https://doi.org/10.1057/s41270-019-00058-3

Sebastián, M. G. d. B., Sarmiento Guede, J. Ramón., & Antonovica, A. (2022). Application and extension of the UTAUT2 model for determining behavioral intention factors in use of the artificial intelligence virtual assistants. *Frontiers in Psychology*, *13*, Article 993935. https://doi.org/10.3389/fpsyg.2022.993935

Semrl, N., Feigl, S., Taumberger, N., Bracic, T., Fluhr, H., Blockeel, C., & Kollmann, M. (2023). AI language models in human reproduction research: exploring ChatGPT's potential to assist academic writing. *Human Reproduction*, *38*(12), 2281–2288. https://doi.org/10.1093/humrep/dead207

Seo, K., Tang, J., Roll, I., Fels, S., & Yoon, D. (2021). The impact of artificial intelligence on learner–instructor interaction in online learning. *International Journal of Educational Technology in Higher Education*, *18*(1), Article 54. https://doi.org/10.1186/s41239-021-00292-9

Sharma, S. C., Ramchandani, J. P., Thakker, A., & Lahiri, A. (2023). ChatGPT in plastic and reconstructive surgery. *Indian Journal of Plastic Surgery*, *56*(04), 320–325. https://doi.org/10.1055/s-0043-1771514

Shaw, D., Shiu, E., & Clarke, I. (2000). The contribution of ethical obligation and self-identity to the theory of planned behaviour: An exploration of ethical consumers. *Journal of Marketing Management*, *16*(8), 879–894. https://doi.org/10.1362/026725700784683672

Strzelecki, A. (2024). Students' acceptance of ChatGPT in higher education: An extended unified theory of acceptance and use of technology. *Innovative Higher Education*, *49*(2), 223–245. https://doi.org/10.1007/s10755-023-09686-1

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning and Teaching*, *6*(1), 1–10. https://doi.org/10.37074/jalt.2023.6.1.17

Taecharungroj, V. (2023). "What can ChatGPT do?" Analyzing early reactions to the innovative AI chatbot on Twitter. *Big Data and Cognitive Computing*, *7*(1), Article 35. https://doi.org/10.3390/bdcc7010035

Talan, T., & Kalinkara, Y. (2023). The role of artificial intelligence in higher education: ChatGPT assessment for anatomy course. *International Journal of Management Information Systems and Computer Science*, *7*(1), 33–40. https://doi.org/10.33461/uybisbbd.1244777

Tang, A., Li, K.-K., Kwok, K. O., Cao, L., Luong, S., & Tam, W. (2024). The importance of transparency: Declaring the use of generative artificial intelligence (AI) in academic writing. *Journal of Nursing Scholarship*, *56*(2), 314–318. https://doi.org/10.1111/jnu.12938

Teo, T. (2011). Factors influencing teachers' intention to use technology: Model development and test. *Computers and Education*, *57*(4), 2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008

Tijssen, R., & Winnink, J. (2022). Global and local research excellence in Africa: New perspectives on performance assessment and funding. *Science, Technology and Society*, *27*(3), 368–387. https://doi.org/10.1177/09717218221078236

Totlis, T., Natsis, K., Filos, D., Ediaroglou, V., Mantzou, N., Duparc, F., & Piagkou, M. (2023). The potential role of ChatGPT and artificial intelligence in anatomy education: A conversation with ChatGPT. *Surgical and Radiologic Anatomy*, *45*(10), 1321–1329. https://doi.org/10.1007/s00276-023-03229-1

Twum, K. K., Ofori, D., Keney, G., & Korang-Yeboah, B. (2022). Using the UTAUT, personal innovativeness and perceived financial cost to examine student's intention to use e-learning. *Journal of Science and Technology Policy Management*, *13*(3), 713–737. https://doi.org/10.1108/JSTPM-12-2020-0168

Ursachi, G., Horodnic, I. A., & Zait, A. (2015). How reliable are measurement scales? External factors with indirect influence on reliability estimators. *Procedia Economics and Finance*, *20*, 679–686. https://doi.org/10.1016/S2212-5671(15)00123-9

Usakli, A., & Rasoolimanesh, S. M. (2023). Which SEM to use and what to report? A comparison of CB-SEM and PLS-SEM. In F. Okumus, S. M. Rasoolimanesh, & S. Jahani, S. (Eds.), *Cutting edge research methods in hospitality and tourism* (pp. 5–28). Emerald Publishing Limited. https://doi.org/10.1108/978-1-80455-063-220231002

van Dis, E. A. M., Bollen, J., Zuidema, W., van Rooij, R., & Bockting, C. L. (2023). ChatGPT: Five priorities for research. *Nature*, *614*(7947), 224–226. https://doi.org/10.1038/d41586-023-00288-7

Varma, S., & Marler, J. H. (2013). The dual nature of prior computer experience: More is not necessarily better for technology acceptance. *Computers in Human Behavior*, *29*(4), 1475–1482. https://doi.org/10.1016/j.chb.2013.01.029

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1–2), 641–652. https://doi.org/10.1007/s10479-020-03918-9

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

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

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems*, *17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Verplanken, B., & Sato, A. (2011). The psychology of impulse buying: An integrative self-regulation approach. *Journal of Consumer Policy*, *34*(2), 197–210. https://doi.org/10.1007/s10603-011-9158-5

Vicente-Yagüe-Jara, M. I., López-Martínez, O., Navarro-Navarro, V., & Cuéllar-Santiago, F. (2023). Writing, creativity, and artificial intelligence. ChatGPT in the university context. *Comunicar*, *31*(77). https://doi.org/10.3916/C77-2023-04

Wang, J., Li, X., Wang, P., Liu, Q., Deng, Z., & Wang, J. (2022). Research trend of the unified theory of acceptance and use of technology theory: A bibliometric analysis. *Sustainability*, *14*(1), Article 10. https://doi.org/10.3390/su14010010

Weggeman, M. P., & Groeneveld, M. J. (2005). Applying the business excellence model to a research organization. *Research-Technology Management*, *48*(4), 9–13. https://doi.org/10.1080/08956308.2005.11657319

Wong, L. W., Tan, G. W. H., Ooi, K. B., Lin, B., & Dwivedi, Y. K. (2024). Artificial intelligence-driven risk management for enhancing supply chain agility: A deep-learning-based dual-stage PLS-SEM-ANN analysis. *International Journal of Production Research*, *62*(15), 5535–5555. https://doi.org/10.1080/00207543.2022.2063089

Xue, L., Rashid, A. M., & Ouyang, S. (2024). The unified theory of acceptance and use of technology (UTAUT) in higher education: A systematic review. *SAGE Open*, *14*(1). https://doi.org/10.1177/21582440241229570

Yeo, M. A. (2023). Academic integrity in the age of Artificial Intelligence (AI) authoring apps. *TESOL Journal*, *14*(3), Article e716. https://doi.org/10.1002/tesj.716

Yu, C., Yan, J., & Cai, N. (2024). ChatGPT in higher education: Factors influencing ChatGPT user satisfaction and continued use intention. *Frontiers in Education*, *9*. https://doi.org/10.3389/feduc.2024.1354929

Yue, P., Wu, Y., Zhang, Y., Chen, Y., Li, J., Xu, Y., & Liu, Y. (2021). Contemplation-action-maintenance model of behaviour change for persons with coronary heart disease: A qualitative study. *Journal of Clinical Nursing*, *30*(9–10), 1464–1478. https://doi.org/10.1111/jocn.15699

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), Article 39. https://doi.org/10.1186/s41239-019-0171-0

Zhou, C., Li, Q., Li, C., Yu, J., Liu, Y., Wang, G., Zhang, K., Ji, C., Yan, Q., He, L., Peng, H., Li, J., Wu, J., Liu, Z., Xie, P., Xiong, C., Pei, J., Yu, P. S., & Sun, L. (2023). A comprehensive survey on pretrained foundation models: A history from BERT to ChatGPT. *ArXiv*. https://doi.org/10.48550/arXiv.2302.09419

Appendix A

Constructs	Items
Performance Expectancy (PE)	PE1. Using ChatGPT significantly enhanced the quality of my research activities. PE2. ChatGPT helps me to complete my research tasks more efficiently. PE3. Integrating ChatGPT leads to more innovative research ideas. PE4. ChatGPT provides valuable insights that contribute to my research success.
Effort Expectancy (EE)	EE1. I find it easy to use ChatGPT for my research activities. EE2.Learning to use ChatGPT does not require significant effort from my side. EE3. I am comfortable in navigating the functionalities of ChatGPT. EE4. Using ChatGPT requires minimal time investment for effective results.
Social Influence (SI)	SI1. My peer group actively supports the use of ChatGPT in research activities. SI2. I often see colleagues in my field using ChatGPT for academic research purposes. SI3. There is a general belief among my peers that ChatGPT is beneficial for research & academic tasks. SI4. My mentors support the integration of ChatGPT in research activities.
Facilitating Conditions (FC)	FC1. I have access to the necessary resources to use ChatGPT in my research effectively. FC2. Technical support is always available to help me integrate ChatGPT into my academic work. FC3. I have a reliable internet connection to use ChatGPT without interruptions. FC4. I have access to the necessary software and tools to utilize ChatGPT effectively.
Hedonic Motivation (HM)	HM1. I enjoy using ChatGPT for my research tasks. HM2. Engaging with ChatGPT makes the research more enjoyable for me. HM3. Using ChatGPT adds an element of fun to my research activities. HM4. I look forward to exploring the upcoming features of ChatGPT at work.
Habit (HT)	HT1. I regularly use ChatGPT as part of my research routine. HT2. Using ChatGPT has become a habitual part of my research work. HT3. I find myself using ChatGPT automatically when I need research assistance. HT4. I consistently turn to ChatGPT when I encounter challenges in my research.

Ethical Concerns (EC)	EC1. I am concerned about the ethical implications of using ChatGPT in my research. EC2. I worry that relying on ChatGPT may lead to plagiarism in my academic research work. EC3. There are ethical guidelines that I need to follow when using ChatGPT. EC4. I feel doubtful about the accuracy and reliability of information generated by ChatGPT.
Research Excellence (RE)	RE1. I believe that using ChatGPT contributes to achieving high standards in my academic activities. RE2. ChatGPT supports my efforts to produce original and high-quality research work. RE3. I feel that integrating ChatGPT aligns with my goals of research excellence. RE4. I see ChatGPT as a tool that enhances my scholarly contributions. RE5. Using ChatGPT helps me maintain productive academic research practices.
Behavioral Intention (BI)	BI1. I intend to use ChatGPT for my academic research activities in the future. BI2. I plan to incorporate ChatGPT into my scholarly works regularly. BI3. I am motivated to explore how ChatGPT can enhance my research outcomes. BI4. I will recommend the use of ChatGPT to my colleagues for their academic research activities. BI5. Using ChatGPT will become a significant part of my research activities.

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