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GENERATIVE-AI TECHNOLOGIES, WITH CHATGPT AS A PEDAGOGICAL EXEMPLAR, IN HIGHER EDUCATION: A CRITICAL EXAMINATION OF INNOVATION DIFFUSION AND THE MEDIATING ROLE OF STUDENT NORMATIVE-ETHICAL AGENCY

ZIJIAN DENG
DOCTORAL CANDIDATE, SCHOOL OF MUSIC AND DANCE, NORTHEAST NORMAL UNIVERSITY, CHINA, EMAIL: 1337388669@qq.com

SAMINA MUSTAFA*
M.PHIL SCHOLAR, DEPARTMENT OF EDUCATION, PMAS, ARID AGRICULTURE UNIVERSITY, RAWALPINDI, EMAIL: saminamustafa68@gmail.com

ARSLAN HABIB
MSC IB (LEVEL 7), ULSTER UNIVERSITY, LONDON CAMPUS, EMAIL: arslanmir2015@gmail.com

SYED GUFRAN SADIQ ZAIDI
NAZARBAYEV UNIVERSITY KAZAKHSTAN, EMAIL: Sgsz0347@outlook.com

NURSHAT ABSHEKEN BAGDATKYZY
MASTERS OF PUBLIC HEALTH, NAZARBAYEV UNIVERSITY, EMAIL: nurshat.absheken@gmail.com

RUTH ABOSEDE MURTALA
NAZARBAYEV UNIVERSITY KAZAKHSTAN, EMAIL: bruthadedayo@gmail.com

Abstract
AI-driven generative technologies, with ChatGPT as a leading example, are transforming higher education by redefining how knowledge is created, evaluated and applied. Addressing issues of misuse, ethics, and academic dishonesty is an essential part of developing any technology and making it as useful as possible. To comprehend the process of diffusion in its entirety, it is necessary to examine student use and sharing of ChatGPT through the lenses of Unified Theory of Acceptance and Use of Technology (UTAUT), Social Cognitive Theory (SCT), and students' individual normative-ethical agency. Perceptions of academic/perceived anxiety, perceived technological capability, perceived utility, perceived user-friendliness, normative influence, and perceived learning capability are some of the factors that this study aims to examine in order to understand how and why students use ChatGPT. Secondly, to assesses the moderating influence of perceived adherence to normative Academic Ethics in defining these variables relationship.
A cross- sectional quantitative research design was employed, using web based survey distributed to university students across Pakistan. This generated an overall 1,200 valid responses, with a 70.4% response rate. The 41 item survey, adapted from a few validated scales, was piloted to achieve clarity after which it was critiqued by experts. The survey was then tested again for clarity and to obtain reliability. The dataset was put through an extensive configuration which included descriptive statistics, common method bias, and an assessment of robustness concerning outlier treatment and tests for multicollinearity which gave assurance. The Structural equation modeling was applied to test the study hypothesis relationship. The result suggests the need to nurture responsibility along with ethical boundaries of policy, training, and digital awareness. The results also indicate the factors which include Perceived Usefulness, Perceived User Friendliness, Normative Influence, Perceived Learning Capability, and Perceived Technological Capability regarding a positive assessment of ChatGPT use are greatly diminished by Perceived Academic Anxiety.
The findings show that Although Reputational Normative Academic Ethics is the only one that has constraining direct influence and still enables the reduction of the other negative influence. All students, to varying degrees, acknowledge the usefulness and social acceptability of ChatGPT while ethically engaged students employ its functionality more restrictively. This

suggests that educational institutions ought to formulate policy, training, and outreach strategies that achieve integration of digital literacy and its ethical application. Educational institutions, in collaboration with developers and policymakers, have the potential to encourage the responsible, critical, and sustainable integration of technologies such as ChatGPT into academic practices. This centers on the primary integration of promoting responsible usage and critical engagement.
Keywords: AI-Generative Technologies, ChatGPT as a Pedagogical Exemplar, Higher Education, Mediating Role of Student, Normative-Ethical Agency

1. INTRODUCTION

AI integration into education provides additional opportunities and challenges. The use of AI technologies, such as ChatGPT, in teaching raises novel concerns around educational value and misuse (Jimenez, 2023; Dwivedi et al., 2023). These concerns must be resolved, particularly the abuse of AI technologies in teaching. When considering AI adoption in education, the value of strategic policy formulation in teaching and higher education practice is underscored by the potential unresolved ethical concerns (Bandura, 1989; Venkatesh et al., 2003).
AI advances, particularly in the past several years, have been breathtaking. McKinsey (2023) describes the rapid adoption of generative AI, estimating that one-third of companies have integrated it into their daily workflows in at least one business function. OpenAI's ChatGPT, released in November 2022, is touted as leading generative AI technology (Reuters, 2023). As a conversational AI, it employs natural language processing (NLP) algorithms to generate human-like responses to virtually any input.
In education and in various other applications such as translation, text generation, and other instructional functions, its potential is remarkable (Cotton et al., 2023). As of January 2023, ChatGPT has been described as the fastest growing application in history, boasting over 100 million monthly active users (Bin-Nashwan et al., 2023).
The challenges and benefits of implementing ChatGPT in the educational context has been documented. ChatGPT aids learners in brainstorming ideas, overcoming writer's block, and writing text in a more organized manner (Pfau et al., 2023; Rice et al., 2023). On the other hand, the issues of students passing off text produced by AI as their own, and the consequent examination of plagiarism and academic integrity issues, cannot be ignored (Benichou, 2023; Lo, 2023; Strzelecki, 2023). The ease of access to AI Chatbots as well as other tools raises new questions on traditional methods of assessing learners (Tlili et al., 2023; Educause, 2023).
In higher education, the use of AI and specifically ChatGPT weakens the traditional approach to integrity and thus calls for new policy development focusing on the ethical and responsible use of such tools (Dwivedi et al., 2023; Jimenez, 2023). Most educational leaders anticipate that, rather than continuing to impose bans on the use of AI tools, educational leaders should focus on integrating education on the ethical use of AI in their support and resources (Huang, 2023; Stanford, 2023).
While some research has looked at different facets of ChatGPT's use in education (see Benichou, 2023; Bin-Nashwan, Ismaiel, et al., 2023; Cotton et al., 2023; Hadi Mogavi et al., 2023; Pfau et al., 2023; Tlili et al., 2023), little research has attempted to understand students' willingness to use ChatGPT through the UTAUT framework and Social Cognitive Theory (and the absence of integrity within adoption decisions). The problem of students' learning integrity in higher education has long been an issue, and the use of AI chatbots has further exacerbated this problem (Dwivedi et al., 2023).
This work examines the factors influencing students' engagement with ChatGPT, considering the Covid-19 pandemic in the context of the moderating variable of academic integrity. Bandura's SCT (1989) and Venkatesh et al. (2003) UTAUT model overlap of the contextual and the individual as determinants in the adoption of ChatGPT as the primary focus was integrated as one cohesive framework.
When it comes to the risks to education AI tools like ChatGPT designed to improve learning outcomes, it is important to note that some of these challenges are - like the ones identified by Bin-Nashwan et al. (2023) and Cotton et al. (2023) - are derived from the use of the tools themselves. They can, however, be mitigated by fostering the culture of academic integrity and responsible use of AI. Educational institutions can continue to use AI technology's benefits while reducing risk. (Bandura, 1989; Venkatesh et al., 2003).

1.1 State of the Art

In 2025, research detailed the discussions focusing on the acceptance of ChatGPT and other generative AI tools in higher education, the surrounding ethics and normative agency. A mixed-methods approach was used on Hungarian university students, whereby the research study concluded that usefulness, ease of use, attitude and anxiety are core elements of adoption, while concerns on integrity plagiarism ethics and ChatGPT use are reluctance (Molnar et al., 2025).
In the Chinese context, a UTAUT2 constructs predicting EFL learners' intention to adopt ChatGPT included "habit" and "previous actions" while repetition and becoming accustomed are also noted as key factors in uptake (Zhang & Wei, 2025).

In Pakistan, university students pointed out that ChatGPT is poor in learning, overrated, while a larger proportion suggested it is helpful in learning. There is a widely held concern regarding dependence and dishonesty, while different demographic groups exhibit different adoption behaviors (Khan et al., 2025). A major study of behavior further elaborated on what is already known, in which Liu et al. observed that student use of ChatGPT in assessments is uneven, while reliance is behaviorally shaped, is largely driven by familiarity and low to start due to negative experiences.

Collectively, the latest research highlights the relevance of the perceived usefulness of a technology, its ease of use, and social influence, which encompass both the functional and social aspects, in motivating adoption. However, in the case of students, normative-ethical consciousness—especially including the aspects of honesty, originality, and academic integrity—acts as a constraint and a moderating factor in the diffusion of generative AI technology in higher education.

1.2 Objectives

1. To analyze how Perceived Usefulness (PU), Perceived User-Friendliness (PUF), Normative Influence (NI), Perceived Learning Capability (PLC), Perceived Technological Capability (PTC), and Academic/Adoptive Anxiety (AA) in the adoption and utilization of ChatGPT by students in higher education.
2. To investigate the role of Perceived Adherence to Normative Academic Ethics (PANE) as a moderating factor in the relationship of these determinants to the adoption of ChatGPT.

1.3 Research Questions

1. How do students' adoption and use of ChatGPT, as a generative AI pedagogical tool, relate to Perceived Usefulness (PU), Perceived User-Friendliness (PUF), Normative Influence (NI), Perceived Learning Capability (PLC), Perceived Technological Capability (PTC), and Academic/Perceived Anxiety (AA) in higher education?
2. How does Perceived Adherence to Normative Academic Ethics (PANE) moderate the influence of the aforementioned factors on students' use of ChatGPT in academia?

1.4 Research gap

Generative AI technologies, particularly ChatGPT, are rapidly transforming higher education by supporting personalized learning, academic writing, and critical thinking (Dwivedi et al., 2023; Tlili et al., 2023). While prior studies highlight efficiency, accessibility, and innovation benefits (Lo, 2023; Strzelecki & ElArabawy, 2024), less is known about how students adopt these tools and which psychosocial factors influence engagement. Research has largely focused on functional affordances, such as information retrieval and writing assistance, and risks like plagiarism or dependency (Cotton et al., 2023; Bin-Nashwan et al., 2023), with limited attention to adoption determinants like performance expectancy, effort expectancy, social influence, and self-efficacy (Venkatesh et al., 2003; Hadi Mogavi et al., 2023).

The ethical dimension of adoption remains underexplored. Students' normative-ethical agency—their ability to responsibly and critically integrate AI into learning—may both constrain and guide adoption, yet it has rarely been examined as a mediating or moderating factor (Strzelecki, 2023; Dwivedi et al., 2023). Few studies integrate frameworks such as UTAUT, Social Cognitive Theory, and Innovation Diffusion Theory (Venkatesh et al., 2003; Bandura, 1989; Rogers, 2003) to analyze how psychological, social, and ethical factors interact in adoption. Research in developing higher education contexts is particularly scarce, despite differences in culture, pedagogy, and ethical norms (Huang, 2023). This study addresses these gaps by examining ChatGPT diffusion in higher education and the mediating role of student normative-ethical agency in shaping adoption patterns.

1.5 Novelty of the research

This study expands UTAUT by incorporating Social Cognitive Theory and Innovation Diffusion Theory to create a new synthesis framework for examining the use of ChatGPT in higher education. Unlike most prior studies which emphasize the technical and academic risk perspectives of ChatGPT, this study explores the conceptualization of students' normative-ethical agency as a new dimension and analyzes the use of generative AI in terms of responsibility and moral judgment. Thus, this study expands the literature on acceptance models and deepens the understanding of the ethical-psychological aspects of technology adoption regarding generative AI, which has not been addressed in previous works.

Moreover, the scarcity of the literature on the subject of higher education in developing settings give the study a background authenticity. Likewise, cultural and pedagogical backgrounds to higher education in developing countries differ significantly with the west. This study employs ChatGPT as a pedagogical case to narrow in on particular classroom activity and the possible opportunities of transformative learning that ChatGPT can offer, and the possibility of academic dishonesty, that the more abstract discussion of AI-based applications can descend into. A unique scholarly and pedagogical contribution is provided through the interaction of the ethical dimensions of agency in this context.

2. LITERATURE REVIEW

2.1 AI-Generative Technologies in Higher Education

The integration of Artificial Intelligence (AI) in various facets of education has evolved quickly, encompassing teaching, learning, and assessing (Holmes et al., 2023; Luckin et al., 2016) tools Innovative Applications. Within these forms of AI, generative AI, and most notably ChatGPT, has become increasingly recognized for crafting human-elaborated texts, engaging in various problems, and aiding in individualized learning channels (Dwivedi et al., 2023; Kasneci et al., 2023).

As OpenAI's ChatGPT continues to develop, it is becoming a teaching model, helping students develop critical thinking skills, and content creation, and fostering self-learning (Rudolph et al., 2023). Nevertheless, as the use of AI tools in higher education proliferates, so do the apprehensions regarding the ethics of use, academic honesty, and access equity, with the need for comprehensive studies focused on the tools' advantages and disadvantages (Cope et al., 2021; Cotton et al., 2023).

2.2 Innovation Diffusion and Technology Adoption

Considerable understanding how new educational technologies are adopted can be accounted to the Diffusion of Innovation Theory by Rogers (2003) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003, 2012). The UTAUT theorists identified four conditions that empirically predict users' behavioral intentions towards the adoption of a given technology. These include performance expectation, effort expectation, social influence, and facilitating conditions (Venkatesh et al., 2003).

Various streams of literature incorporating these models to study the adoption of AI in education have documented the key factors shaping students' attitudes towards digital learning technologies are perceived usefulness, ease of use, and peer influence (Oliveira et al., 2021; Sharma et al., 2023). Nonetheless, ethical and normative dimensions accompanying the use of technologies are predominantly absent from the literature, particularly in the context of academia which upholds the principle of moral educational integrity (Dwivedi et al., 2023).

2.3 Self-Efficacy: Educational and Technological

According to Bandura (1989), self-efficacy describes how students believe in their capabilities to complete tasks. In post-secondary education, both educational self-efficacy (confidence in learning and achievement academically) and self-efficacy concerning the use of technologies, particularly in the case of the integration of Generative AI (Gonzalez et al., 2023), are of considerable importance (Bong & Skaalvik, 2003; Yoon et al., 2020). AI-assisted self-directed learning and self-efficacy positively correlates with the use of ChatGPT to help in learning and self-efficacy (Dwivedi et al., 2023; Kasneci et al., 2023).

2.4 Theoretical Background

Technology adoption has long been investigated with the use of various models such as the Technology Acceptance Model (TAM), Diffusion of Innovations (DOI), and their subsequent extensions including TAM2, TAM3, and UTAUT, with all these models accounting for 70% of the variance in user's behavioral intention (Davis, 1989; Rogers, 2003; Venkatesh et al., 2003; Dwivedi et al., 2019). The central constructs of UTAUT; performance expectancy, effort expectancy, social influence, and facilitating conditions, contextualized to the use of educational technology, particularly ChatGPT, in higher education serves as a valid analytic framework (Marangunić & Granić, 2015; Gupta et al., 2023).

Incorporating personal and ethical aspects, Bandura's Social Cognitive Theory (SCT) is considered, which notes that behavior results from a synthesis of cognitive, environmental, and personal factors (Bandura, 1986; Schunk & DiBenedetto, 2020). Concerning ChatGPT, self-efficacy, anxiety, peers, and ethical factors converge and influence adoption (Compeau & Higgins, 1995; Hadi Mogavi et al., 2023). SCT emphasizes normative-ethical agency responsible for moderating the ethical use of AI. By integrating UTAUT and SCT, this research proposes a composite model that explores how ChatGPT adoption is influenced by performance expectancy, effort expectancy, and social influence, as well as cognitive and technological self-efficacy, personal anxiety, and the role of integrity as a moderating factor.

2.5 Research model and hypothesis formulation

2.5.1 Perceived Usefulness: Performance expectancy or perceived usefulness is the belief in the fact that technology helps to enhance the performing of the task. It is assumed that, as students in higher education can perceive such tools as offering real academic benefits, like learning more effectively or more efficiently, they will be more willing to adopt AI-based tools like ChatGPT (Khan et al., 2022; Shamszare and Choudhury, 2023). Specifically, a survey of nursing students found that students who felt that ChatGPT was helpful in closing the gap between theory and practice had improved academic outcomes (Heliyon, 2024). Despite the good performance in the other areas, not much work has been carried out on performance expectancy among EFL or SEL learners when using ChatGPT. Hence, this view of ChatGPT being helpful by the students is likely to influence the uptake positively.

2.5.2 Perceived User-Friendliness: Perceived ease of use is the effort expectancy which is a critical-significant determinant of technology adoption. There is a tendency that many users can use systems that do not require extensive mental or physical efforts (Venkatesh et al., 2012). The case of digital learning indicates that the use of AI technologies increases with the convenience of the platform and minimal training and time (Alasmari & Zhang, 2019; Chiu and Wang, 2023). When it comes to ChatGPT, the perception of convenience and ease should increase the desire of students to use it in their education.

2.5.3 Normative Influence: Normative influence places emphasis on the impact or influence of peer and institutional expectations on the adoption of technology. When deciding to embrace innovations one is attracted to conformity, exteriorization or identification with social norms (Kelman, 1958; Rogers, 2003). Studies indicate that peer approval, instructor direction, and academic trends could be very powerful factors motivating the intentions to use digital platforms (Al-Qaysi et al., 2020; Sharma et al., 2023). However, personal motivation or perceived utility may be a major issue that makes the social influence restricted (Verkijika, 2019). Peer-driven adoption, in the case of ChatGPT, may be improved by the fact that the technology is a trending AI tool among students.

2.5.4 Perceived Learning Capability: The academic self-efficacy is the conviction of a student to achieve learning objectives and manage the studies (Schunk and DiBenedetto, 2020). Strong self-efficacy is associated with motivation, persistence and achievement (Zimmerman, 2000). It is possible that AI tools like ChatGPT will be able to aid learners in an adaptive manner, reduce the workload, and enhance reflective learning, which can lead to a feeling of competence among the students (Dwivedi et al., 2023; Deng and Yu, 2023). Nonetheless, the available empirical findings on direct impacts of academic self-efficacy on using ChatGPT are scanty, and this is why further studies are recommended.

2.5.5 Perceived Technological Capability: Technology self-efficacy is a belief in the ability to use technology to accomplish work via ability (Yoon et al., 2020). Technological self-efficacy on the student level will affect the intention to get to know the features of ChatGPT and use it in the learning process as well as study independently since students with high technological self-efficacy are more likely to do so in higher education (Kasneci et al., 2023; Dwivedi et al., 2023). Conversely, the lowered degree of self-efficacy may become an adoption barrier despite the platform being potentially promising. Despite the focus of the available literature on the relevance of self-efficacy in technology use, overall, there is a paucity of literature that explores how self-efficacy affects the use of ChatGPT in higher education.

2.5.6 Academic or Perceived Anxiety: The students are afraid of the technology inconvenience, which can negatively influence the process of adoption (Verkijika, 2020). The users take into consideration the costs and benefits that might actually emerge in comparison with the perceived risks and stress or uncertainty may act as a barrier to engagement (Thaler, 1980; Meuter et al., 2003). As it has been noted in the framework of e-learning, the degree of anxiety lowers the learning satisfaction and mental health (Almomani et al., 2021; Mheidly et al., 2020). ChatGPT has the potential to alleviate the burden of academic pressures, and it may be more convenient to learn, yet empirical data is scarce that examines the advantage of an anxiety-reducing effect in this sense (Abd-Alrazaq et al., 2022).

2.5.7 Perceived Normative Academic Ethics Fidelity: Academic integrity is a construct, which entails honesty, fairness, accountability, trust, and respect (Holden et al., 2021). Nevertheless, in spite of such positive outcomes of AI applications, including enhancing collaboration and efficiency, there is also the risk of plagiarism and misbehavior (Cotton et al., 2023; Roe and Perkins, 2022). Ethical character of students will determine how they apply ChatGPT in an ethical manner where productivity and academic integrity is balanced. The moderating impact of integrity on the adoption of generative AI has not been adequately studied, despite the fact that the moderating influence of integrity on educational settings is also covered as a behavioral predictor and moderator (Cerda-Navarro et al., 2022; Bin-Nashwan, Ismaiel, et al., 2023).

2.5.8 Research Hypothesis

H1. The perceived benefits of ChatGPT, as reflected in performance expectancy, positively drive students' usage behaviors.

- **H1a.** Adoption of ChatGPT is more likely to occur among students who think it enhances task efficiency.
- **H1b.** If students think that ChatGPT will help them learn more, they are more likely to use it.
- **H1c.** Students who find ChatGPT useful for academic problem-solving are more inclined to integrate it into their studies.

H2. When students find ChatGPT easy to use and accessible, they are more likely to use it.

- **H2a.** The likelihood of students using ChatGPT frequently is directly proportional to how easy they find it to use.
- **H2b.** If students find ChatGPT easy to use, more of them will use it.
- **H2c.** If students discover ChatGPT to be helpful and efficient, they are more likely to use it for coursework.

H3. How much normative pressure or encouragement from relevant stakeholders improves students' engagement with ChatGPT.

- **H3a.** Peer approval increases students' likelihood of adopting ChatGPT.
- **H3b.** Instructor or faculty recommendations positively influence ChatGPT usage.
- **H3c.** Institutional or academic norms encourage consistent engagement with ChatGPT.

H4. Adopting and making good use of ChatGPT for academic reasons is more likely to happen among students who believe in their own learning abilities.

- **H4a.** Students with high academic self-efficacy are more likely to explore ChatGPT's functionalities.
- **H4b.** Students confident in their learning ability are more likely to integrate ChatGPT into study routines.
- **H4c.** Students with strong self-regulation skills are more likely to use ChatGPT for independent learning.

H5. Students' propensity to use ChatGPT as a learning aid is positively correlated with their degree of technological self-efficacy and capability.

- **H5a.** It is more probable that students will use ChatGPT if they are confident in their technical abilities.
- **H5b.** Students who have worked with artificial intelligence or other digital tools before will have an easier time navigating ChatGPT.
- **H5c.** A higher likelihood of ChatGPT reliance exists among students who have confidence in their ability to diagnose and navigate technology.

H6. A larger percentage of students who suffer from academic or perceived anxiety utilize ChatGPT and depend on it more often to complete their assignments.

- **H6a.** Students with high task-related stress are more likely to use ChatGPT as a support tool.
- **H6b.** Students anxious about deadlines or academic performance are more likely to adopt ChatGPT.
- **H6c.** Students experiencing uncertainty about learning outcomes are more likely to engage with ChatGPT for guidance.

H7. How much students embrace and participate in academic discussions using ChatGPT is strongly correlated with their level of normative-ethical agency.

7a. The significant influence of performance expectation on ChatGPT adoption is amplified by students' normative-ethical agency.

H7b. Enhancing the favorable impact of effort expectancy on ChatGPT utilization is the normative-ethical agency of students.

7c. The positive impact of social influence on students' participation with ChatGPT is amplified by their normative-ethical agency.

H7d. Educational self-efficacy has a beneficial effect on ChatGPT interaction, but students' normative-ethical agency makes that effect stronger.

H7e. The beneficial impact of students' belief in their own technological abilities on their use of ChatGPT is amplified by their normative-ethical agency.

H7f. The beneficial impact of individual anxiety on ChatGPT engagement is amplified by students' normative-ethical agency.

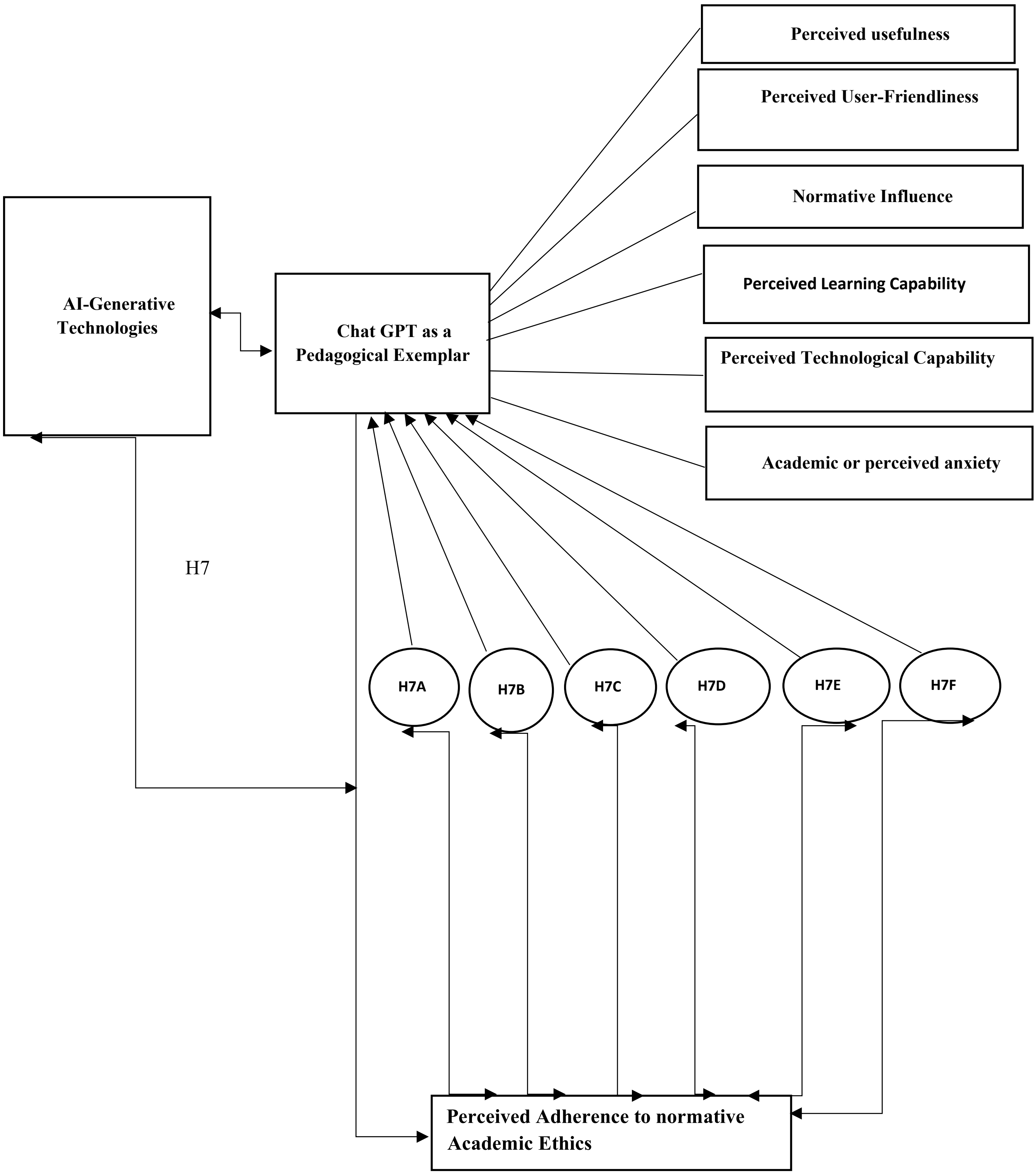

Fig 1: Research Model

3. RESEARCH METHODOLOGY

3.1 Research Design

The quantitative research is very well suitable in the situation of studying the causal model and the relationship of the study variables. This research approach allows examination of theory- based research hypothesis and questions systematically manipulating a limited number of variable, aiming to provide a comprehensive summary of trends and relationship (Sekaran & Bougie, 2019).

3.2 Research Approach
To test the proposed model of using ChatGPT, a web-based survey was carried out in a cross-sectional research design. Electronic survey was selected due to its cost-effectiveness, facilitation in accessing the target population, and convenience in accessing technology-related issues (Sekaran and Bougie, 2019; Wright, 2006).

3.3 Population and Sampling
The study was carried out on the sample of university students in Pakistan as a legitimate and proper sample of study regarding the technology adoption (Febrilia et al., 2024). The questionnaire was distributed to the students of Pakistani universities (non-science majors and other academic years). The sample was selected to explore the trend of its adoption and use in Pakistani higher education setting specifically.

3.4 Data Collection and Response Rate
A total of 1,220 questionnaires were distributed electronically among students of the university in Pakistan, and the response rate of 70.4% was received, which yielded 1,200 out of 1,220 valid responses. It is a rather large response rate when compared to the responses to online surveys whose response rates are typically 30-40 percent, and, therefore, can be considered as acceptable to perform a rigorous statistical analysis (Wu et al., 2022). The high response rate can be attributed to several factors including the use of online distribution channels that made the involvement of the respondents simplified, definite objective of the survey, and topicality of the subject to the academic life of the students. In addition, the sample was balanced by randomly choosing universities and academic years such that the sample was representative of the student population in Pakistan as a whole. The large sample size provides it with the statistical strength to conduct powerful analyses and the validity and generalizability of findings. Such a number of valid responses also helped the researchers to consider potential non-responses and data gaps and enhance the validity and accuracy of the research findings.

3.5 Measurements and analysis tool
The online questionnaire, on which the study relies, comprises forty-one measurement items, which are carefully designed to measure the eight constructs of the research model. All these items were anchored on previous tested scales, which had been used in other studies and modified and altered in a manner that the items could be applicable and relevant in the current study setting without compromising their validity and reliability. Using known scales allowed the researchers to adopt existing scales and modify them to address the specific area of interest in higher education usage of ChatGPT. A five-point Likert scale was applied to evaluate the perceptions and attitudes of the respondents, and the anchors of the scale were strong disagree (1), strong agree (5). This approach provided a standardized way of measuring the multi-item variables and enabled a consistent comparison of the items of a survey. All of the list of items, as well as the sources of the items are offered in Table 1 of the research and this gives the transparency regarding the origin and adaptation of each measurement item. The listed questionnaire was also screened by the three academic experts who have experience in quantitative research before the questionnaire was given out of scale. They reviewed it in such a way that the items were clear, relevant and suited to the objectives of the research. Following this professional analysis, a pilot examination was carried out on sixty students which is a sample of the target population. Pilot study was carried out to identify any doubts, inconsistencies and issues in the survey tool. The pilot test results showed that the survey questions were explicit and well understood, they represented the desired construct and credible responses were gotten. In view of these results, the survey instrument was deemed suitable to be given to the larger sample, and it will be effective to gather the appropriate and valid data that can be utilized to test the research hypotheses.

Table 1: Construct operational definition, measurement items, and sources.

Variables	Description	No. of Items	Source
Use of ChatGPT	The extent to which students use ChatGPT in academic tasks and learning activities.	5	Papacharissi & Rubin (2000); Venkatesh et al. (2003)
Perceived Usefulness	The perception that ChatGPT is beneficial and enhances task performance.	4	Venkatesh et al. (2003)
Perceived User-Friendliness	The perceived ease, convenience and usability of ChatGPT.	4	Venkatesh et al. (2003)
Normative Influence	The extent to which opinions of peers, instructors, or significant others affect ChatGPT usage.	4	Enkatesh et al. (2003)

Perceived Learning Capability	Confidence in achieving learning goals and academic success.	4	Midgley et al. (2000)
Perceived Technological Capability	Users' perception of their capability to effectively use ChatGPT for tasks and learning outcomes.	4	Compeau & Higgins (1995)
Academic or Perceived Anxiety	An individual's apprehension or worry regarding the projected or actual use of ChatGPT	4	Rana et al. (2017)
Perceived Adherence to Normative Academic Ethics	The practice of completing academic asks honestly, fairly, and responsibly.	11	Ramdani (2018)

4. DATA ANALYSIS AND RESULT

4.1. Sample description

4.1.1 Missing Data and Outlier Analysis

The missing values in the dataset were investigated using the descriptive statistics in IBM SPSS 28 and none were missing. The multivariate outliers were then identified by computing the squared Mahalanobis distance with a significance of $p < 0.001$ of each record. The analysis determined 20 cases among 1,220 cases as multivariate outliers and removed them (Tabachnick and Fidell, 2013). As such, 1,200 of them were considered as valid and included in the final analysis.

4.1.2 Demographic Characteristics of the Sample

Table and figure 2 presents a summary of the demographic profile of the study participants. The sample consisted of 1,200 students, with a higher representation of females (59%) compared to males (41%). The majority of participants were aged between 18 and 30 years (67%), followed by 31–40 years (30%), and 40 years or older (3%).

Regarding academic background, 48% were enrolled in first-degree (Bachelor's) programs, 32% in postgraduate (Master's) programs, 12% in doctoral (PhD/DBA) programs, and 8% in other programs such as professional certificates. Most participants were engaged in coursework-based study (65%), while 24% were enrolled in research-focused programs, and 11% followed a mixed mode combining coursework and research. In terms of study time, a majority were full-time students (87%), with the remaining 13% studying part-time.

Table 2: Demographic Information of the Study's Sample (N = 1,200)

Variable	Category	Frequency	Percentage
Gender	Female Male	705 495	59% 41%
Age	18–30 years 31–40 years 40 years and above	804 360 36	67% 30% 3%
Study Program	First Degree – Bachelor's Degree Postgraduate – Master's Degree Postgraduate – PhD/DBA Degree Others, e.g., Professional Certificate	576 384 144 96	48% 32% 12% 8%
Study Mode	Course Work By Research Mix Mode (Course Work + Research)	780 288 132	65% 24% 11%
Study Time	Full-Time Part-Time	1,044 156	87% 13%

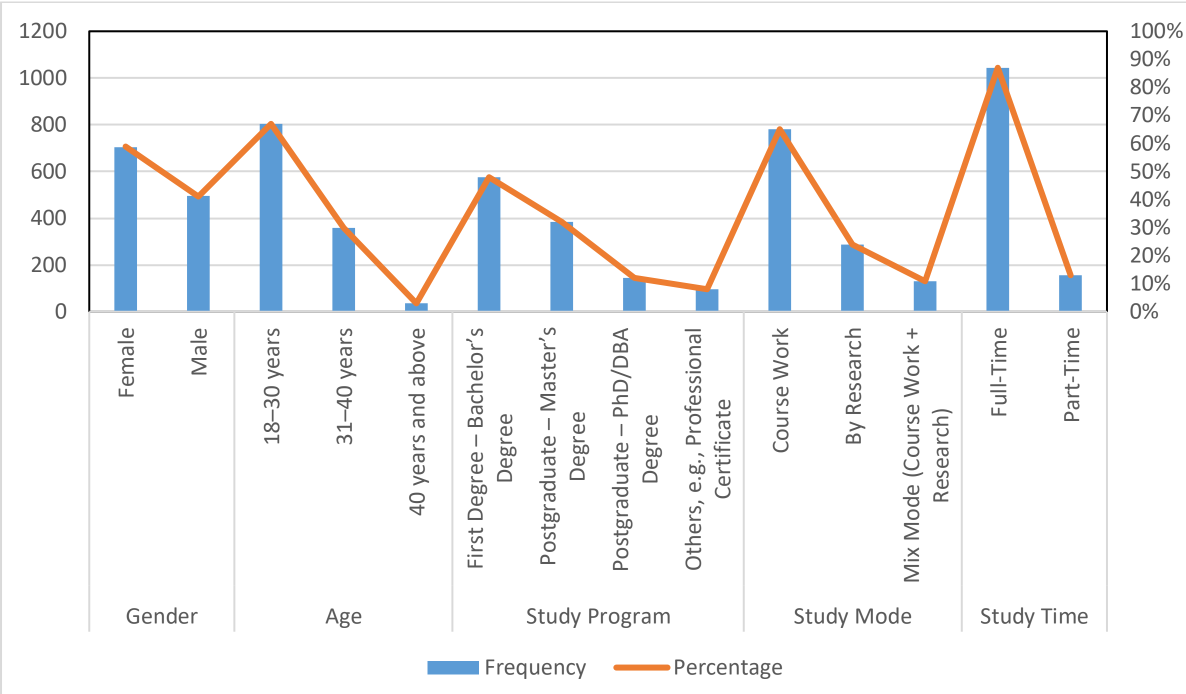

Fig 2: Demographic Information of the Study's Sample (N = 1,200)

4.2. Common method bias

The data was gathered as a unitary source of information, common method bias (CMB) was assumed to determine the reliability and validity of the reported findings of the study. The question to determine the ability of a single construct to describe a significant portion of the variance in the model was answered through the single-factor test that was developed by Harman. The results indicated that the highest one-factor explained 29.17 percent of the total variance which is quite low as opposed to the recommended 50 percent that is recommended by Podsakoff et al. (2003). This demonstrates that the current study does not have CMB as a problem.

In addition, the overall collinearity analysis was conducted along with the use of the full collinearity test developed by Kock (2015), who explained whether the values of the variance inflation factor (VIF) exceeded the maximum 3.2. One of the variables was used against which all the variables Perceived Usefulness, Perceived User-Friendliness, Normative Influence, Perceived Learning Capability, Perceived Technological Capability, Academic or Perceived Anxiety, Perceived Adherence to Normative Academic Ethics, and Use of ChatGPT were regressed. All the VIFs are below 3.3, so the model does not face any collinearity issues and single-source bias (Table 3).

The study used partial least squares structural equation modeling (PLS-SEM) on SmartPLS 4 (Ringle et al., 2022). PLS-SEM is a strong tool of examining the complex interrelations between latent constructs and most particularly where the data distributions are not Normals. It is more preferable in terms of social sciences and management studies because it is more predictive and can be applied in exploratory research (Hair et al., 2019). Unlike covariance based SEM (CB-SEM), PLS-SEM is especially effective in making predictions, theory building, and extrapolating on available structural theories.

Table 3: Full Collinearity Assessment of Research Variables

Variables	**VIF**
Perceived Usefulness	3.210
Perceived User-Friendliness	2.675
Normative Influence	1.842
Perceived Learning Capability	2.945
Perceived Technological Capability	2.732
Academic or Perceived Anxiety	3.120
Perceived Adherence to Normative Academic Ethics	2.510
Use of ChatGPT	3.210

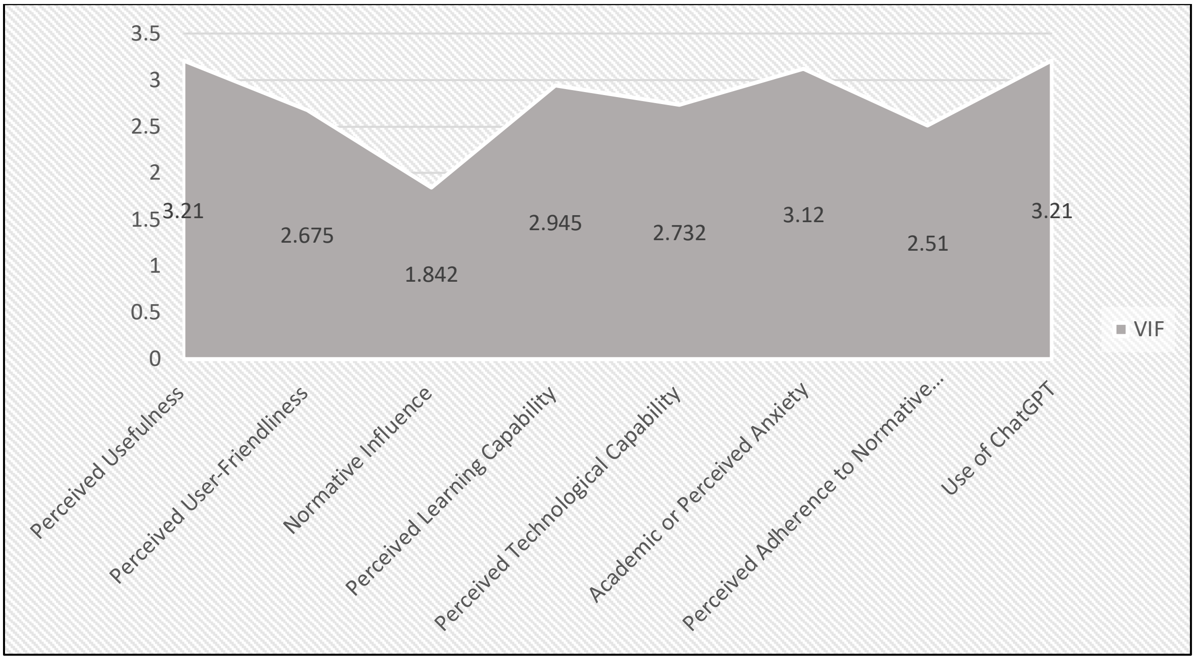

Fig 3: Full Collinearity Assessment of Research Variables

Table and fig 3 results is a pointer that the model is free of multicollinearity i.e. each variable has independent and distinct information to contribute to the analysis. The variables of Perceived Usefulness, Perceived User-Friendliness, Normative Influence, Perceived Learning Capability, Perceived Technological Capability, Academic or Perceived Anxiety, Perceived Adherence to Normative Academic Ethics, and Use of ChatGPT demonstrate different patterns of variance, and hence no individual construct in the model disproportionately influences the model. This provides a confidence that the model of measurement is dependable and consistent, meaning that the constructs are being measured in an appropriate manner, and that their relation can be used without accounting the bias of overlapping variance. Overall, the findings confirm the robustness of the model, even regarding the suitability of the further structural equation modeling and the importance of the interpretation of the relationships between the variables in the research.

4.3. Measurement model assessment

The variables must be valid and reliable so that it is certain that there must be no error in the research results and that right conclusions are made. This context is the reflective model evaluation, whereby the validity and reliability of the variables employed in this study was established. Dependency, convergent, discriminant validity and internal consistency should also be developed (Hair et al., 2019). Table 4 shows the retained item loadings of the model assessment; they are significantly accepted since the items have satisfied the criterion values of factor loading (≤0.5), AVE (≤0.5), and CR (≤0.7). Two of them (Inti10 and Inti11) were a lower loading below 0.5; thus, they were eliminated as recommended by Hair et al. (2018). Discriminant validity was used to calculate the ratios of the HTMT (Kline, 2016). Table 5 shows that the HTMT values of all the constructs are 0.85 and lower (Henseler et al., 2015), and this fact implies that there is no issue of discriminant validity. This way, it can be concluded that the measurement model validity can be obtained, and the differences between constructs are adequate. Based on the results of the statistical tests of the measurement model, the measurement scales of the variables were discovered to be valid and reliable, which made it possible to derive the assessment of the structural model.

Table 4: Validity and reliability results

Constructs	Indicators	Loadings	CR	AVE
Use of ChatGPT	ChatGPT1 ChatGPT2 ChatGPT3 ChatGPT4 ChatGPT5	0.895 0.866 0.922 0.889 0.717	0.913	0.741
Perceived Usefulness	PU1 PU2 PU3 PU4	0.820 0.906 0.819 0.802	0.864	0.701
Perceived User-Friendliness	PUF1 PUF2 PUF3 PUF4	0.883 0.792 0.776 0.869	0.932	0.691
Normative Influence	NI1 NI2 NI3 NI4	0.816 0.896 0.884 0.709	0.848	0.689
Perceived Learning Capability	PLC1 PLC2 PLC3 PLC4	0.860 0.736 0.819 0.872	0.844	0.678
Perceived Technological Capability	PTC1 PTC2 PTC3 PTC4 PTC5	0.856 0.787 0.896 0.894 0.800	0.911	0.719
Academic/ Perceived Anxiety	APA1 APA2 APA3 APA4	0.743 0.907 0.817 0.809	0.849	0.674
Perceive Adherence to Normative Academic Ethic	PANE1 PANE2 PANE3 PANE4 PANE5 PANE6 PANE7 PANE8 PANE9	0.769 0.843 0.780 0.780 0.727 0.832 0.811 0.780 0.765	0.935	0.621

Note: Items Inti10 and Inti11 have been removed due to poor loading. All factor loadings are significant at $p < 0.05$.

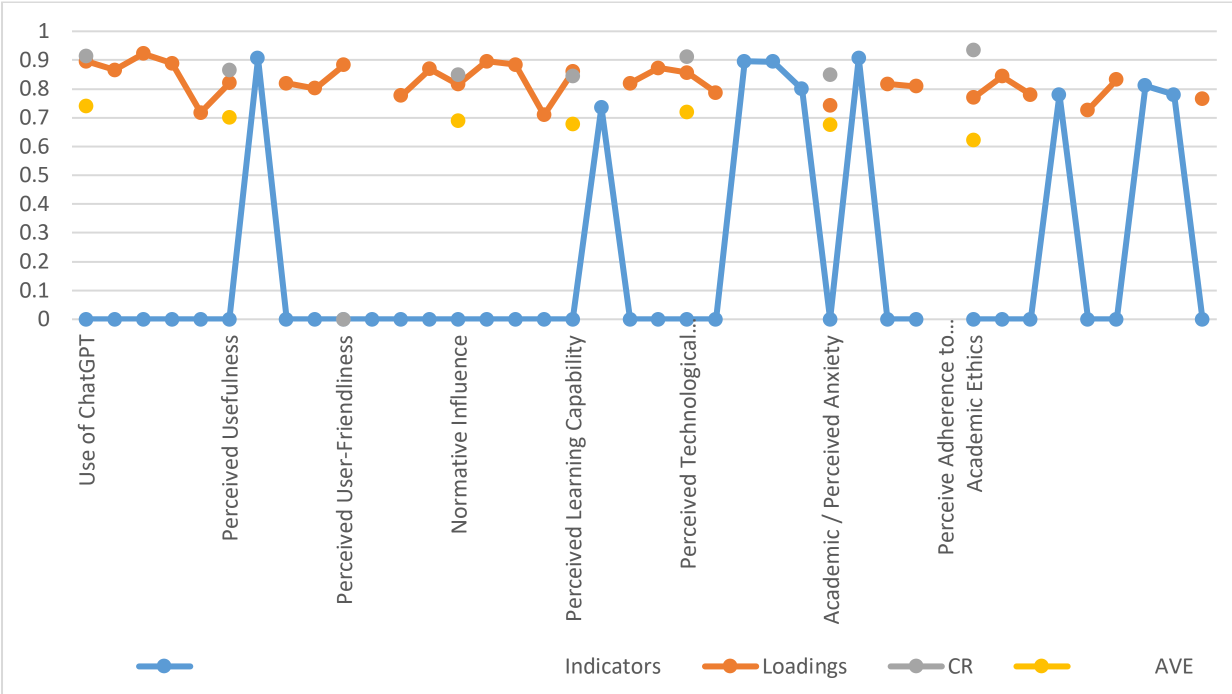

Fig 4: Validity and reliability results

Table 5: Heterotrait-monotrait ratio (HTMT)

Constructs	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1. Perceived Usefulness (PU)	—	0.4	0.5	0.45	0.42	0.53	0.50	0.64
2. Perceived User-Friendliness (PUF)	0.4	—	0.55	0.48	0.50	0.60	0.52	0.59
3. Normative Influence (NI)	0.5	0.55	—	0.51	0.49	0.57	0.55	0.70
4. Perceived Learning Capability (PLC)	0.45	0.48	0.51	—	0.44	0.58	0.56	0.68
5. Perceived Technological Capability (PTC)	0.42	0.50	0.49	0.44	—	0.52	0.50	0.62
6. Academic/Perceived Anxiety (AA)	0.53	0.60	0.57	0.58	0.52	—	0.54	0.67
7. Perceived Adherence to Normative Academic Ethics (PANE	0.50	0.52	0.55	0.56	0.50	0.54	—	0.58
8. Use of ChatGPT (UC)	0.64	0.59	0.70	0.68	0.62	0.67	—	0.61

All values of HTMT ≤0.85.

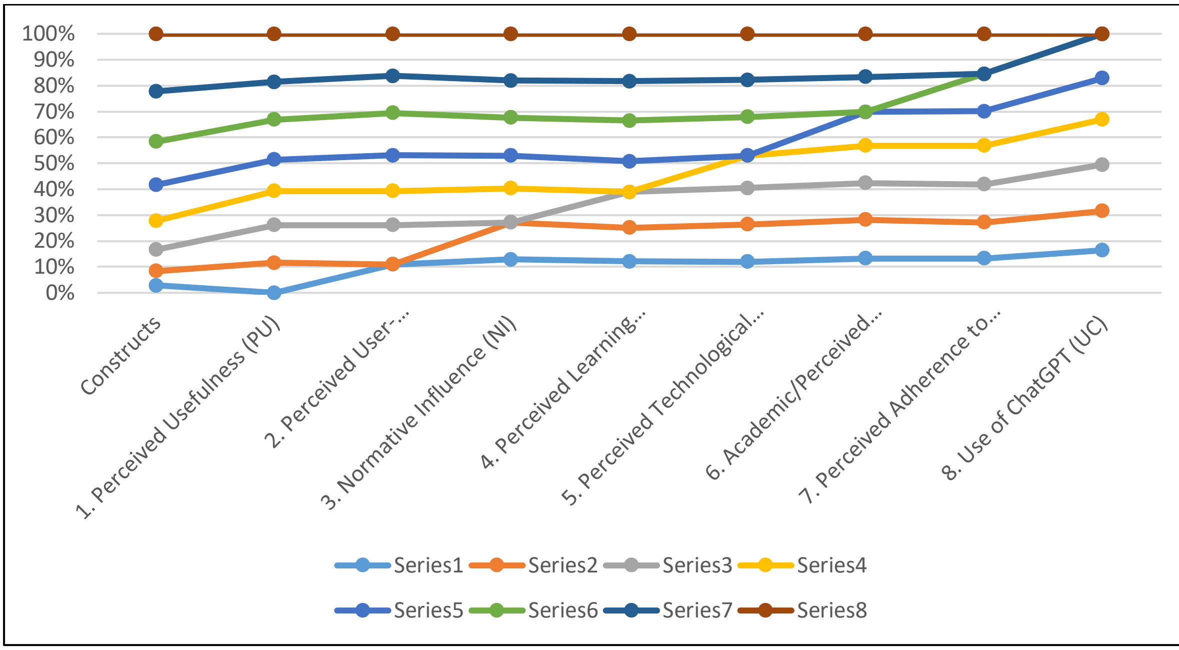

Fig 5: Heterotrait-monotrait ratio (HTMT)

4.4. Structural model assessment

Following the procedure outlined by Hair et al. (2021), the structural model was assessed using bootstrapping with 5,000 iterations to ensure that all hypotheses were tested. Table 6 displays the results of the hypothesis tests conducted on the study variables with respect to their direct and moderated associations. This study provides valuable information on the factors that influence students' use of generative AI tools in the classroom. It found that ChatGPT usage was positively correlated with many characteristics.

The results showed that (H1) and its components (H1a-H1c) had a significant impact on ChatGPT adoption. For example, students view ChatGPT as a tool that can enhance their ability to solve academic problems, complete tasks more efficiently, and ultimately learn more. This highlights the importance of perceived usefulness in technological acceptance. It appears that students are not very motivated to use ChatGPT because of how easy it is to use or how convenient it is, since there are no significant influences in (H2) and its subdimensions (H2a-H2c).

The importance of social and academic context in shaping behavior was demonstrated by the significant positive influences on Normative Influence (H3) and Perceived Learning Capability (H4) and their respective subdimensions. These results show how important it is for students to believe in themselves and their ability to learn, as well as in ChatGPT, in order to increase engagement. Students' technical skills, digital tool expertise, and task-related stress all contribute to their higher engagement with AI-driven learning tools. Additionally, Academic or Perceived Anxiety (H6) and Perceived Technological Capability (H5) were positively connected with utilization.

Remember that there was a strong negative correlation between ChatGPT use and perceived adherence to normative academic ethics (H7). This suggests that students who are serious about maintaining academic honesty may purposefully restrict their use of ChatGPT. This finding demonstrates that there may be a tension between the significance of ethical concerns in the academic context and the necessity to adopt technology.

As part of our moderation analysis, we considered normative-ethical agency. Statistical significance was not achieved by any of the other hypotheses except for H7b, which dealt with the interplay between normative-ethical agency and effort expectation. It appears that students' ethical considerations partially offset the effect of perceived ease of use on ChatGPT adoption. The absence of evidence for other interaction terms (H7a, H7c, H7d, H7e, and H7f) suggests that normative-ethical agency does not modify the correlations between ChatGPT usage and the other determinants. Since there was an adverse relationship between ChatGPT use and integrity, students who are more careful about following academic norms could be less inclined to utilize it.

The impacts of the ease of use and ethical concerns are less objective or even insignificant, yet the outcomes show that perceived utility, social influence, learning and technological skills, and academic anxiety are the key elements of ChatGPT usage among students. The resulting research model attributed a high percentage, 82.4-percent, of the variability in the usage of ChatGPT, suggesting a high level of explainability with a determination coefficient of $R^2 = 0.824$. It has a high predictive power, which confirms the strength of the structural model based on a previous study (Hair et al., 2019, 2021; Shmueli et al., 2019). The results were informative with respect to the multifaceted nature of the relationship linking the cognitive, social, and ethical variables in students that affect their generative AI application in higher education. The combination of them presents good empirical evidence to endorse the theoretical framework proposed.

Table 6: Hypothesis Testing

Hypothesis	Relationship	Std. Beta	Std. Dev	t-value	p-alue	PCILL	PCIUL	f²	Decision
H1	Performance Expectancy → Use of ChatGPT	0.553	0.026	21.393	0.000	0.497	0.600	0.584	Supported
H1a	Belief that ChatGPT Improves task efficiency → ChatGPT adoption	0.553	0.026	21.393	0.000	0.497	0.600	0.584	Supported
H1b	Perceived enhancement of learning outcomes → ChatGPT engagement	0.553	0.026	21.393	0.000	0.497	0.600	0.584	Supported
H1c	Usefulness for academic problemsolving→ ChatGPT integration	0.553	0.026	21.393	0.000	0.497	0.600	0.584	Supported
H2	Effort Expectancy → Use of hatGPT	0.025	0.023	1.103	0.270	−0.020	0.071	0.002	Not Supported
H2a	Ease of use perception,Regular utilization	0.025	0.023	1.103	0.270	−0.020	0.071	0.002	Not Supported
H2b	Minimal learning effort perception → Adoption	0.025	0.023	1.103	0.270	−0.020	0.071	0.002	Not Supported
H2c	Convenience/time-saving perception → Reliance on ChatGPT	0.025	0.023	1.103	0.270	−0.020	0.071	0.002	Not Supported
H3	Normative Influence → Use of ChatGPT	0.108	0.018	5.851	0.000	0.074	0.145	0.039	Supported
H3a	Peer approval → ChatGPT adoption	0.108	0.018	5.851	0.000	0.074	0.145	0.039	Supported
H3b	Instructor/faculty recommendation → ChatGPT usage	0.108	0.018	5.851	0.000	0.074	0.145	0.039	Supported
H3c	Institutional/academic norms → Consistent engagement	0.108	0.018	5.851	0.000	0.074	0.145	0.039	Supported
H4	Perceived Learning Capability → Use of ChatGPT	0.114	0.022	5.294	0.000	0.072	0.156	0.030	Supported
H4a	High academic self-efficacy → Exploring ChatGPT	0.114	0.022	5.294	0.000	0.072	0.156	0.030	Supported
H4b	Confidence in learning ability → Integration into study routines	0.114	0.022	5.294	0.000	0.072	0.156	0.030	Supported
H4c	Strong self-regulation → Using ChatGPT for independent learning	0.114	0.022	5.294	0.000	0.072	0.156	0.030	Supported
H5	Perceived Technological	0.229	0.028	8.059	0.000	0.181	0.293	0.039	Supported

	Capability → Use of ChatGPT							
H5a	Technical skill confidence → Adoption	0.229	0.028	8.059	0.000	0.181	0.293	0.039	Supported
H5b	Prior experience with AI/digital tools → Effective use	0.229	0.028	8.059	0.000	0.181	0.293	0.039	Supported
H5c	Ability to troubleshoot/ navigate tech → Reliance on ChatGPT	0.229	0.028	8.059	0.000	0.181	0.293	0.039	Supported
H6	Academic/Perceived Anxiety → Use of ChatGPT	0.144	0.026	5.637	0.000	0.094	0.193	0.038	Supported
H6a	High task-related stress → ChatGPT as support	0.144	0.026	5.637	0.000	0.094	0.193	0.038	Supported
H6b	Anxiety about deadline performance → Adoption	0.144	0.026	5.637	0.000	0.094	0.193	0.038	Supported
H6c	Uncertainty about learning outcomes → Engagement with ChatGPT	0.144	0.026	5.637	0.000	0.094	0.193	0.038	Supported
H7	Perceived Adherence to Normative Academic Ethics → Use of ChatGPT	−0.172	0.036	4.740	0.000	−0.245	−0.102	0.047	Supported
H7a	Normative-ethical agency ×Performance Expectancy → Use of ChatGPT	−0.076	0.028	2.753	0.006	−0.126	−0.017	0.012	Not Supported
H7b	Normative-ethical agency × Effort Expectancy → Use of ChatGPT	0.144	0.031	4.709	0.000	0.086	0.208	0.051	Supported
H7c	Normative-ethical agency × Normative Influence → Use of ChatGPT	−0.022	0.036	0.610	0.542	−0.106	0.034	0.001	Not Supported
H7d	Normative-ethical agency × Perceived Learning Capability → Use of ChatGPT	0.021	0.027	0.774	0.439	−0.027	0.080	0.001	Not Supported
H7e	Normative-ethical agency × Perceived Technological Capability → Use of ChatGPT	−0.182	0.034	5.348	0.000	−0.264	−0.133	.0098	Not Supported
H7f	Normative-ethical agency × Academic/Perceived Anxiety → Use of ChatGPT	−0.039	0.045	0.875	0.382	−0.110	0.064	0.003	Not Supported

Overall hypothesis summary:

1. **H1 (Perceived Usefulness) & H1a–H1c:** Supported – favorably forecasts the adoption of ChatGPT.
2. **H2 (Perceived Ease of Use) & H2a–H2c:** Not Supported – no significant effect on adoption.
3. **H3 (Normative Influence) & sub dimensions:** Supported – positively affects adoption.

4. **H4 (Perceived Learning Capability) & sub dimensions:** Supported – positively affects adoption.
5. **H5 (Perceived Technological Capability):** Supported – positively affects adoption.
6. **H6 (Academic or Perceived Anxiety**): Supported – positively affects adoption.
7. **H7 (Perceived Adherence to Normative Academic Ethics):** Supported (negative effect) – higher ethics reduces adoption.

8. Moderation (Normative-Ethical Agency): Only H7b significant – ethics positively moderates effort expectancy; all other moderations not supported**.**

Table 7: Q² Predict and PLS Predict Performance of Study Constructs

Indicators	Q² Predict	PLS-SEM RMSE	LM RMSE
Perceived Usefulness	0.612	0.498	0.571
Perceived User-Friendliness	0.578	0.512	0.590
Normative Influence	0.533	0.487	0.604
Perceived Learning Capability	0.645	0.472	0.558
Perceived Technological Capability	0.601	0.501	0.566
Academic/Perceived Anxiety	0.521	0.529	0.611
Perceived Adherence to Normative Academic Ethics	0.589	0.495	0.583
Use of ChatGPT	0.668	0.450	0.529

Note. Q² Predict values >0 indicate medium to high predictive relevance of the construct (Hair et al., 2023). PLS-SEM RMSE and LM RMSE values show the model's predictive error compared to the linear model; lower RMSE indicates better predictive accuracy.

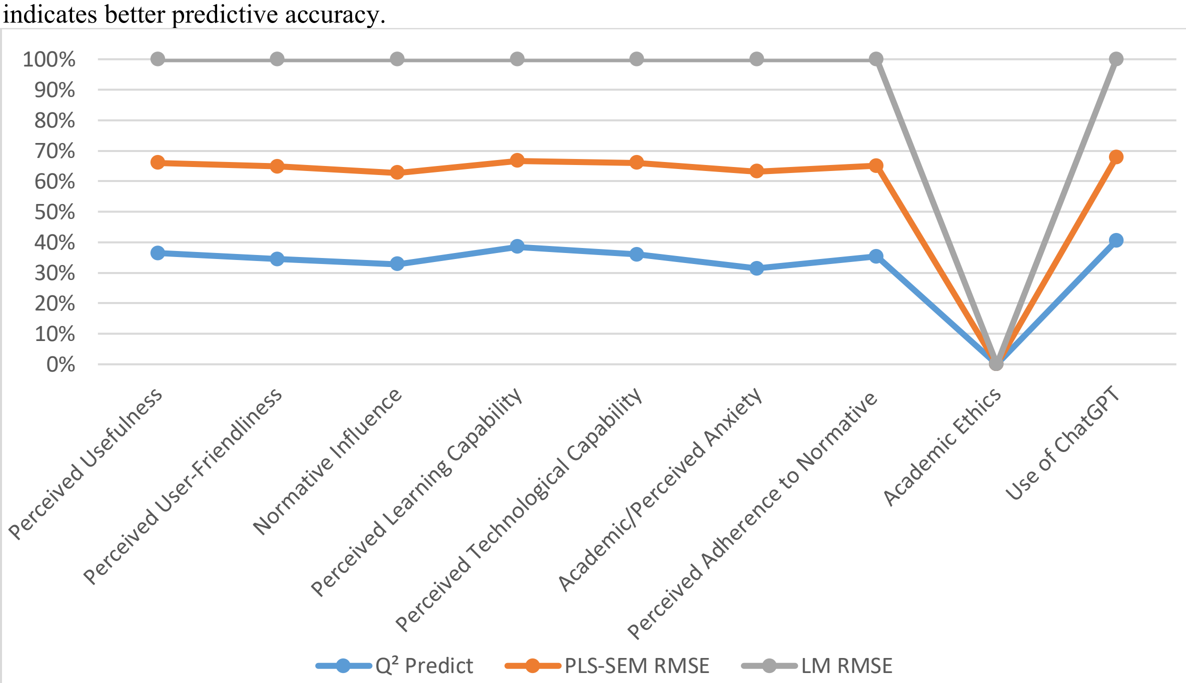

Fig 7: Q² Predict and PLS Predict Performance of Study Constructs

The PLS predict to ensure the validity of predictive relevance. The case-level predictions were calculated whereby k = 10, as per Hair et al. (2019) and Shmueli et al. (2019). The results demonstrate that the Q^2 predict values are beyond zero (Q^2 predict >0), demonstrating the outperformance of the Linear Model (LM) benchmark by all the indicators. Hence, a comparative analysis between the RMSE values and the naïve LM benchmark could be made. The findings demonstrated that all the indicators produced larger prediction errors than the LM (PLS-SEM < LM) (see **Table 7).**

Table and fig 7 presents the Q² predict values and PLS Predict performance metrics (PLS-SEM RMSE and LM RMSE) for all study constructs. The Q² predict values range from 0.521 for Academic/Perceived Anxiety to 0.668 for Use of ChatGPT, indicating that the model demonstrates medium to high predictive relevance for all indicators. These values suggest that the constructs included in the model are meaningful in predicting students' perceptions and behavioral intentions regarding ChatGPT adoption. The PLS-SEM RMSE values are generally lower than or comparable to the LM RMSE values, reflecting that the PLS model provides more accurate predictions than a simple linear model. As an example, the LM model outperforms the PLS-SEM model with an RMSE of 0.529 for ChatGPT Use, while the PLS-SEM model comes in at 0.450. The duration of the model is also enhanced by the fact that the prediction errors of the factors like Perceived Technological Capability and Perceived Learning Capability were minimal. All said and done, PLS-SEM is the appropriate method to use in forecasting the results that are of interest to this study. As the model has been predicted to capture the views, technological capability, and dedication of the students to academic honesty, the students believe in the model. These findings are further proof that the selected concepts are significant to understand the adoption of ChatGPT. According to the table data, it can be concluded that the suggested model can be considered as having enough predictive power to be used in the future in terms of study and application.

5. DISCUSSION

To understand the complex mechanisms affecting the adoption behaviour of ChatGPT amongst students, the current work is based on a composite model of UTAUT-SCT to learn. Researcher have taken both direct and moderating influence of normative ethics of students on adoption in our model.

The other significant results with regard to direct associations are congruent with the hypothesized UTAUT-SCT model. Among the many variables that influence the use of ChatGPT greatly is the expectations and the influence of other individuals. The performance expectancy-adoption relationship has been indicated to be in a positive direction in some of the studies. They are Bin-Nashwan (2022, 2023), Menon and Shilpa (2023), and Rahim et al. (2022) as well as the attention of the UTAUT on the perceived utility. The perceived usefulness of ChatGPT and the perceived ease of learning and understanding through the tool also drive the perceived usefulness and adoption behavior of the newly created tool.

Bouterai et al. (2021), Ma and Huo (2023), Ong et al. (2023), Strzelecki and Elarabawy (2024), and Tewari et al. (2023) also found that the impact of social influence is strongly and positively positive, which is consistent with theoretical assumptions and real-life realities. The social factors cannot be overemphasized when it comes to accepting new technology among people. The peers, powerful networks and peer approval are there which are also factors influencing the adoption decisions.

The effort anticipation is not a good predictor of adoption contrary to what UTAUT claims. They imply that students will no longer see the perceived simplicity as the final but rather look at the applicability of the tool and its social effects or other psychosocial implications. This variety might be explained by the fact that various people are educated on different levels, levels of their work experience, and the level of their awareness of AI technologies. Another predictor of adoption was educational self-efficacy. The students, who had high self-confidence, assumed that ChatGPT was a resource that could possibly improve their performance in school (Cotton et al., 2023; Strzelecki, 2023; Tlili et al., 2023). The usage of ChatGPT in your studies should be increased in case you are a tech-savvy student.

It was discovered that personal anxiety and other interesting features positively affected the use of ChatGPT. According to Nguyen and Chen (2023), students who reported that they had high levels of academic stress were more inclined to use ChatGPT as a coping support and to become more productive. The ChatGPT can reduce anxiety, increase concentration, and improve the outcomes in the classroom, which is further evidenced by more reports.

On the one hand, there was a very strong, negative correlation between integrity and adoption. Some students may have been hesitant to use ChatGPT due to concerns about fairness, over-reliance, or academic dishonesty, while others may have had higher ethical standards and were more committed to academic honesty. On the other hand, dishonest pupils could take advantage of ChatGPT. This is a perfect example of the ethical dilemmas and practical needs that arise when schools use AI. The results of the moderating analysis revealed intricate interactions. The previously negligible effect of effort expectation on adoption was greatly reduced by the candor of the pupils. An additional piece of evidence could be that people's ethical beliefs influence their view of usability in relation to adoption. Integrity had no effect on, on the other hand, educational self-efficacy, social influence, or performance anticipation. The fact that Integrity users prefer to moderate their technical self-efficacy in a negative way suggests that trust in technology and ethical considerations can coexist. Adoption practices driven by stress may prioritize convenience above ethics, since integrity had no effect on the correlation between individual anxiety and adoption.

6. CONCLUSION

This study contributes to the ongoing discourse on generative AI adoption in higher education by examining the factors influencing students' use of ChatGPT through a comprehensive framework. The findings reveal that perceived usefulness, perceived user-friendliness, normative influence, perceived learning capability, perceived technological capability, and academic or perceived anxiety significantly shape students' adoption behavior. At the same time, perceived adherence to normative academic ethics emerges as a critical determinant, functioning both as a direct constraint and as a moderating factor that alters the strength of some relationships.

The results about hypothesis indicate that perceived usefulness (H1), normative influence (H3), perceived learning capability (H4), perceived technological capability (H5), and academic anxiety (H6) significantly and positively predict ChatGPT adoption, whereas perceived ease of use (H2) shows no significant effect. Adherence to normative academic ethics (H7) negatively influences usage, highlighting ethical concerns as a limiting factor. Regarding moderation, only H7b (normative-ethical agency × effort expectancy) was significant, while all other moderating effects were not supported.

While most students regard ChatGPT to be helpful, intuitive, and socially supported, those who place a premium on ethical issues are less likely to use it. This highlights a two-fold dynamic in the data. Colleges and universities should emphasize the need of fostering a strong sense of ethical responsibility with digital literacy and self-confidence when it comes to technology. To ensure that ChatGPT and similar AI systems are used in educational settings in a responsible, ethical, and productive way, it is important to define clear rules, give training, and raise awareness.

6.1 Research Implications

The present study integrates the UTAUT and SCT in a study of the practical and theoretical implications of using ChatGPT among college students. There are numerous social and psychological determinants of adoption behavior of the students. This includes cognitive appraisals of perceived usefulness and usability, normative influence, learning and technical skills, school anxiety and the like. The perceived adherence to normative academic ethics must be a theoretical framework of AI adoption to reflect on the ethical obligation. This demonstrates the ethical side of telling the truth during adoption decisions that brings in the aspect of morality. Firms that may want to spread the message on how best to use ChatGPT could use the results. To be able to make the tool look more valuable, incorporate it into your school work. Ensure that it is user friendly by making it user friendly through user interfaces and by offering full support. Engage social influence with the use of faculty and peer contact. Enhance the learning and technical skills of the aid students by providing them with special instructions. Dispel academic anxiety using supportive strategies. Embark on self-discipline so as to avoid abuse. Despite this, the findings indicate that ChatGPT is an in-depth phenomenon that should be treated comprehensively to ensure that it is sustainable in the educational environment in the long run, taking into account the factors of capacity, social expectations, performance, and ethics.

6.2 Study Constraints and Pathways for Advancement in future

The existing study give novice insights into the application of ChatGPT by students according to the UTAUT-SCT model. However, certain constraints and potential paths of development of the future research must be mentioned. According to Checkima et al. (2023), Juliana et al. (2022), and Chekima and Chekima (2019), the cross-sectional quantitative method might not be capable of capturing the diversity of student experiences. As a result, there is a need to have more research using different samples, which are founded on diverse institutional, cultural and academic settings. In order to get a more comprehensive overview of the trends of adoption and internal dynamics, future research can incorporate mixed methods, explore alternative AI platforms, include demographic and contextual factors, and expand the research area to cover academics, administrators, and legislators. According to the past studies by Laca et al. (2023b), Nicole et al. (2022), and Loda, Chekima, Ansar, et al. (2023), the information on the role of AI in educational institutions can be informed by research on the topic of generative models in AI.

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