



**Subhani, F., Khan, S.A., Sandhu, M.A. and Shahzad, M.F.
(2025) 'What factors affect the adoption intention and
actual use of ChatGPT in higher education? The moderating
role of academic integrity', *TechTrends*. DOI:
10.1007/s11528-025-01096-8**

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What factors affect the adoption intention and actual use of ChatGPT in higher education?

The moderating role of academic integrity

Abstract

The adoption of generative AI in education has revolutionized science by producing human-like texts through contextual understanding, as OpenAI ChatGPT shows. OpenAI's widely used large language model, such as ChatGPT, has become quite popular, especially in higher education. This study examines different factors influencing the adoption and actual use of the ChatGPT to improve student learning outcomes. The unified theory of acceptance and use of technology 2 (UTAUT2) is applied to support our conceptual framework. This study applies the PLS-SEM method for inspecting collected data from 361 Pakistani university students. The findings reveal that performance expectancy, effort expectancy, ChatGPT self-efficacy, social influence, hedonic motivation, and price value significantly influence ChatGPT adoption intention. Conversely, habit and facilitation conditions negatively influence ChatGPT adoption intention. Furthermore, results show that ChatGPT adoption intention significantly influences the actual use of ChatGPT. Additionally, academic integrity is a significant moderator between adoption intention and influences actual use of ChatGPT. The study findings underscore the need for ethical guidelines and educational policies to ensure the responsible use of generative AI in higher education, promoting a balanced approach that influences technological advancements while maintaining academic integrity.

Keywords: ChatGPT self-efficacy, ChatGPT adoption intention, Actual use of ChatGPT, Hedonic motivation, Academic integrity, Higher education

1. Introduction

The use of ChatGPT (Generative Pre-trained Transformer), developed by OpenAI, to integrate artificial intelligence (AI) into education has significantly changed the academic landscape (Ivanov et al., 2024). The development of AI has made significant progress, particularly in the area of language generation, from its introduction at the 1956 Dartmouth conference to modern transformer-based models such as ChatGPT (B. Zhang et al., 2023). Higher education can benefit greatly from using ChatGPT, but there are also disadvantages, including the spread of misleading information and concerns about data security and privacy. In addition, as a research tool, ChatGPT accelerates the research process by creating preliminary research paper drafts, summarizing scientific texts, and facilitating the retrieval of materials (Maheshwari, 2023).

However, it is necessary to recognize the ethical issues and limitations associated with using ChatGPT in education. Educational institutions and trainers must consider factors such as material authenticity, bias in training data, and the promotion of critical thinking related to its implementation (Rahman, 2023). One of the major problems is that over-reliance on ChatGPT and other AI-driven tools can impair students' critical thinking skills and intrinsic motivation, which could impact their success in the classroom and real-world situations. Along with drawbacks, ChatGPT has the potential to renovate education by enabling customized learning experiences, assisting with administrative tasks, supporting research, and developing interactive learning environments (Bernabei et al., 2023). However, ethical considerations and limitations must be considered to optimize its benefits. The best implementation and adoption of ChatGPT in higher education depends on some factors, including technological competence, perceived usefulness,

ease of use, institutional support, individual preferences, and sociocultural influences (Lai et al., 2023).

A prior study (Habibi, Muhaimin, Danibao, et al., 2023) expressed performance expectancy as the perceived usefulness of ChatGPT in achieving desired outcomes, and effort expectancy, which relates to the ease of using the system, is pivotal in determining whether students employ ChatGPT in their academic journey. Moving forward, ChatGPT self-efficacy is the confidence in one's ability to effectively utilize ChatGPT, a crucial psychological construct shaping an individual's willingness to engage with generative AI technology (Yilmaz & Karaoglan Yilmaz, 2023). Socially influenced students are likely to adopt ChatGPT if their peers use it successfully. Positive testimonials and shared experiences can drive wider acceptance and use (Hyun Baek & Kim, 2023; Shahzad, Xu, & Baheer, 2024). Similarly, individuals who integrate ChatGPT into their learnings and openly endorse its benefits can influence adoption. Hedonic motivation is another factor in students that creates pleasure and enjoyment derived from ChatGPT. It can be a potent driver of adoption intention, as it taps into the emotional aspect of technology usage (Hyeon, 2023). On the other hand, the price value, which encompasses considerations of cost and benefits, may either facilitate or hinder adoption among budget-conscious students (Kiryakova & Angelova, 2023). Moreover, the formation of habit, a behavioral pattern of regularly utilizing ChatGPT, can significantly impact its long-term integration into the daily academic routines of students. This factor is particularly relevant as students establish familiarity and comfort with the technology over time (Jan et al., 2023).

Facilitation conditions refer to the support provided to users for utilizing ChatGPT effectively. Reliable internet access, availability of devices, and user-friendly interfaces are essential (Menon & Shilpa, 2023). Students and educators are more likely to adopt and use ChatGPT when these conditions are met. Universities that provide clear guidelines on using ChatGPT appropriately can encourage its use by providing a framework within which students and educators can operate confidently (Qu & Wu, 2024). Academic integrity, ensuring that ChatGPT is used ethically and transparently, is crucial in education. This might involve implementing plagiarism detection software and emphasizing the importance of original thought and proper attribution (Cotton, Cotton, & Shipway, 2024). Developing new strategies using ethical protocols that can help maintain academic standards while incorporating ChatGPT (Bin-Nashwan et al., 2023). Promoting a culture of integrity where students are encouraged to use ChatGPT as a learning aid rather than a shortcut can foster responsible usage. This involves educating students about misuse's ethical implications and potential consequences (Lai et al., 2024). The main objective of the present study is to investigate how factors such as performance expectancy (PE), effort expectancy (EE0, ChatGPT self-efficacy (CGSE), social influence (SI), hedonic motivation (HM), price value (PV), habit (HAB) and facilitation conditions (FC) on the adoption intention (ADI) of ChatGPT. Second, this study examines the influence of adoption intention (ADI) on the actual use (AU) of ChatGPT. Furthermore, academic integrity (ACI) moderates the association between ADI and AU of ChatGPT in university students.

Their technological competence significantly influences the adoption of ChatGPT among university students, their familiarity with generative AI technologies, and their level of digital skills. Students' opinions on adopting ChatGPT are based on assessing its usability and usefulness, focusing on its support for the learning process (Saif et al., 2023; Shahzad, Xu, & Javed, 2024). The effective integration of ChatGPT relies on solid institutional support that includes policies, resources, and educational initiatives that foster an environment conducive to its use. Different

past studies (Menon & Shilpa, 2023; Sahari et al., 2023; Strzelecki, 2023) focused on adoption intention and use of ChatGPT, but no one used factors like self-efficacy and academic integrity in a country like Pakistan. This study used the UTAUT2-based paradigm to investigate ChatGPT usage among Pakistani university students. Filling these research gaps would improve our understanding and guide ChatGPT integration strategies in Pakistani higher education. Therefore, this study considers factors such as PE, EE, SI, CGSE, HM, PV, HAB and FC on ADI and AU of ChatGPT in university students. Furthermore, academic integrity is a significant moderator between ADI and AU of ChatGPT.

The rest of this study is organized as follows. The literature is presented in section 2. The methodology of this study is presented in section 3. The result and analysis are discussed in section 4. The study's key findings and discussion are presented in section 5. The research implications are described in Section 6. Limitations are discussed in section 7.

2. Theoretical Underpinning and Hypotheses Development

2.1. UTAUT2 Theory

The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), originally formulated by researcher Venkatesh that developed in 2003 (Venkatesh et al., 2003) and further refined in 2012 (Venkatesh et al., 2012), represented a widely accepted framework that explains technology adoption in various contexts, including ChatGPT integration. UTAUT2 includes crucial elements such as PE, EE, SI, HM, PV, HAB and FC collectively illuminates individuals' intentions and behaviors related to technology adoption. This study used components such as (PE, EE, SI, HM, PV, HAB and FC of UTAUT2 theory to support the study model. Performance expectancy refers to individuals' perceptions of how incorporating new technology, such as ChatGPT, can increase productivity or performance on specific tasks, particularly in educational environments (Menon & Shilpa, 2023). Effort expectancy, or users' judgments of technology's simplicity and ease of use, has a major impact on students' adoption intentions when evaluating the user-friendliness of ChatGPT (Strzelecki, 2023). The social influence construct looks at how much people think significant others—friends, family, and coworkers, for example—think they should use ChatGPT. Positive recommendations, social norms, and colleague endorsements can significantly impact a user's adoption of ChatGPT (Maheshwari, 2023).

Hedonic motivation measures an individual's perception of the enjoyment or entertainment of using technology and potentially influences students' behavior when adopting ChatGPT (Jan et al., 2023). Price value assesses the perceived costs and benefits of implementing technology and impacts students' adoption decisions when the pros and cons of ChatGPT are considered (Hyeon, 2023). Habit refers to how previous experiences and regular technology use influence current adoption and potentially influence students' decisions based on previous interactions with AI technologies or their habitual use of ChatGPT (Habibi, Muhaimin, Danibao, et al., 2023). Facilitation conditions are the resources and support available to users that facilitate the use of ChatGPT. Access to necessary technology (e.g., internet connectivity), technical support, and user guides can enhance the likelihood of adoption and continued use (Menon & Shilpa, 2023). Applying UTAUT2, it becomes evident that the above factors contribute to the adoption and use of ChatGPT. Therefore, this study used the UTAUT2 theory to support the framework of ChatGPT adoption intention. Eventually, using UTAUT2 multidimensional theory, researchers can better understand the factors that impact technology like ChatGPT in higher education acceptance.

2.2. Performance expectancy and ChatGPT adoption intention

Understanding the elements influencing users' willingness to accept such innovations in integrating cutting-edge technological tools such as ChatGPT into educational environments is ongoing (Ma & Huo, 2023). Performance expectancy is at the heart of technology adoption models, a powerful indicator of consumers' propensity to adopt new technologies (Mensah, 2019). A past study (Strzelecki, 2023) stated that performance expectancy is the expectation of consumers to achieve better performance and results from a ChatGPT technology. This includes students' opinions on how, in the ChatGPT context, an AI-driven tool could improve learning outcomes, academic performance, and overall classroom success. Previous research (Strzelecki & ElArabawy, 2024), indicated that performance expectations significantly impact adopting and using new technologies. In addition, automating tasks such as content creation, quiz preparation, and grading increases performance standards by making the tool easier to use and saving time (Bouteraa et al., 2024). Individuals with higher technological expertise will likely achieve superior outcomes than those less acquainted with AI methods. While performance expectations significantly impact the adoption of ChatGPT, factors such as institutional backing, personal preferences, usability, and sociocultural influences also wield considerable significance (Duong et al., 2023). Finally, students' desire to use ChatGPT in study is largely shaped by how they expect it to enhance their performance. Considering this discussion, the following hypothesis is put forth:

H1: Performance expectancy positively impacts ChatGPT adoption intention.

2.3. Effort expectancy and ChatGPT adoption intention

Students and teachers have high expectations for effort and are likelier to employ ChatGPT in their education. ChatGPT adoption in educational contexts is expected to expand due to factors such as easy usability, time-saving advantages, resource accessibility, supporting training, and positive user experiences (Wang et al., 2022). Students are more at ease integrating communication technology tools and platforms into their lesson plans because of their user-friendly interfaces, clear instructions, and low need for technical knowledge. It is critical to consider the impact of work expectations on people's willingness to adopt and use technology, especially when it comes to students using ChatGPT (Hunde et al., 2023). Effort expectancy is a crucial element of the UTAUT2, which is the perception of how easy it will be to adopt a particular technology. It includes elements such as perceived complexity, ease of use, and simplicity (Ma & Huo, 2023). About ChatGPT, effort expectancy describes how students perceive the usability and simplicity of the platform during the learning phase. Use of ChatGPT to improve research, provide targeted support, and improve learning environments (Strzelecki, 2023). On the other hand, the introduction of generative AI technologies depends heavily on perceived effort expectations. Expectations of the effort involved in adopting ChatGPT among university students are influenced by several factors, such as the usefulness, usability, and accessibility of the platform, which greatly influence students' opinions. This illustrates how crucial the effort expectations are for using ChatGPT in higher education (Strzelecki & ElArabawy, 2024). The following hypothesis is put out in light of above discussion:

H2: Effort expectancy positively impacts ChatGPT adoption intention.

2.4. ChatGPT self-efficacy and ChatGPT adoption intention

Integrating generative AI technologies such as ChatGPT into educational environments is largely replaced by the concept of self-efficacy. According to (Bandura, 1977), self-efficacy is the belief that one can perform a certain task proficiently. Self-efficacy is a crucial factor in determining the propensity of university students to adopt and use ChatGPT, an AI-driven platform, productively. Self-efficacy is a student's confidence in their ability to use, understand, and benefit from the ChatGPT application (Z. Zhang et al., 2023). Multiple studies (Bubou & Job, 2022; Mlambo et al., 2020) have shown a substantial relationship between college students' willingness to use ChatGPT and their trust in this artificial intelligence application. Students who are confident in their abilities are more likely to use ChatGPT for academic purposes. Our study arguments are consistent with the social cognitive theory proposed by Bandura, which postulates that self-efficacy is necessary for performing achievable actions (Bandura, 1977). Students' self-efficacy increases when they are properly trained, coached, and familiarized with the features of ChatGPT. Their sense of self-efficacy greatly influences the willingness of university students to accept and use ChatGPT technology. Successfully incorporating self-efficacy into higher education must be promoted through instruction, support, and positive perspectives regarding its value (Xu et al., 2024). Taking these ideas into account, the study's hypothesis is as follows:

H3: ChatGPT self-efficacy positively impacts ChatGPT adoption intention.

2.5. Social influence and ChatGPT adoption intention

Social influence refers to how others shape individuals' thoughts, feelings, and behaviors. Through social influence, individuals accept information from others as evidence of reality (Shahzad, Xu, & Baheer, 2024). Individuals who observe their peers using and endorsing ChatGPT may feel compelled to adopt it themselves. This is especially true in environments where peer opinion is highly valued, such as workplaces or academic settings (Strzelecki & ElArabawy, 2024). Students often rely on the experiences and recommendations of others to make informed decisions. When trusted sources or influencers in the tech community endorse ChatGPT, it can significantly boost confidence in the tool and increase adoption rates (Maheshwari, 2023). Personal recommendations from friends, colleagues, and family members can be highly persuasive. Hearing positive experiences and success stories about ChatGPT can motivate others to try it. Platforms like Twitter, LinkedIn, Reddit, and specialized forums can amplify the influence. Positive discussions, shared experiences, and endorsements by influencers can create a favorable environment for adoption (Menon & Shilpa, 2023). Social influence plays a critical role in the adoption intention of ChatGPT by leveraging peer pressure, social proof, normative influence, and informational influence. By understanding and leveraging these social dynamics, promoters of ChatGPT can effectively increase their user base and ensure its successful integration into various professional and personal settings (Ma & Huo, 2023). So, it is hypothesized that:

H4: ChatGPT social influence positively impacts ChatGPT adoption intention.

2.6. Hedonic motivation and ChatGPT adoption intention

The focus on enhancing learning experiences has sparked considerable interest in incorporating AI models like ChatGPT into educational settings (Lai et al., 2023). When evaluating educational institutions' adoption of this technology, it is important to consider the elements influencing students' willingness to use ChatGPT. In particular, hedonic motivation is important in shaping people's willingness to adopt new technologies (Al-Azawei & Alowayr, 2020). To explore the connection between hedonic motivation and the inclination of university students to utilize

ChatGPT, particularly focusing on its implications for technology use in education. Hedonic motivation refers to the pleasure or satisfaction of using a specific technology (Menon & Shilpa, 2023). In the context of educational technology, it refers to the feeling of achievement, joy, or pleasure that comes from using technologies such as ChatGPT. This emotional component significantly influences attitudes and intentions towards adopting new technologies. Furthermore, students' hedonic motivation is enhanced when they will use ChatGPT in academia, such as creating the course content and research support (Kim et al., 2023). ChatGPT's diverse learning styles enhance students' educational performance. Understanding hedonic motivation influences educational technology as ChatGPT emphasizes user experience for engaging, enjoyable learning, balancing utility, pleasure, and ethics in integration for success (Al-Rahmi et al., 2020). Hence, from the above arguments, it is derived that hedonic incentives influence university students' intention to use ChatGPT. It is hypothesized that:

H5: Hedonic motivation positively impacts ChatGPT adoption intention.

2.7. Price value and ChatGPT adoption intention

The price value is important in determining users' intentions to use ChatGPT, a generative AI tool (Hyeon, 2023). It impacts the adoption in both professional and educational settings. The price value of ChatGPT is pivotal in users' adoption decisions, correlating with its utility against the associated cost (Jo, 2024). The numerous applications of OpenAI's ChatGPT in communication, education, research, and content creation have attracted attention. Some emphasize ChatGPT's perceived benefits like improved learning, instant feedback, task automation, research aid, and meeting user needs (Acosta-Enriquez et al., 2024). Clear communication about features, costs, and benefits can lead to a deeper thoughtful of the value proposition of ChatGPT usage. For ChatGPT to seamlessly integrate across multiple domains, it is important to consider these complicated aspects of pricing value (Strzelecki, 2023). This perception can stem from several factors, such as the availability of free or cheaper alternatives, the frequency of use, and the relevance of the service to their academic and personal needs (Raman et al., 2024). University students typically have limited financial resources, as they rely on allowances, part-time jobs, or student loans. When evaluating a service like ChatGPT, they must consider whether the cost fits within their budget (Jo, 2024). High subscription fees or upfront costs can make the service less attractive, as students may prefer to allocate their funds to essential expenses like tuition, textbooks, and living costs (Rahman, 2023). Hence, from above discussion, it is concluded that:

H6: Price value negatively impacts ChatGPT adoption intention.

2.8. Habit and ChatGPT adoption intention

The habituation process influences users' intentions to adopt and use ChatGPT, an advanced generative AI language generation model OpenAI developed for academic purposes (Yang et al., 2022). The consistent and frequent use of ChatGPT in higher education can be attributed to established practices, usability features, and routines (Strzelecki, 2023). In technology adoption, habit formation is about integrating a particular tool into daily routines to establish a consistent usage pattern. This includes unconscious and automatic interactions with technology as individuals engage without conscious consideration or choice (Biloš, 2024). A past researcher (Strzelecki, 2024) argued that the habit loop, comprising three components triggers, routine, and reward—offers a valuable framework for comprehending the development of habits in the context of

technology adoption. Daily use of ChatGPT leads to rewards (technological advantages) and ultimately represents habitual behavior. Similarly, students adopt habits and discover a positive relationship between habit development and continued use of ChatGPT (Strzelecki, 2023). Among educators and university students, several factors influence habit formation regarding ChatGPT use, including perceived ease of use, interaction frequency, task compatibility, perceived benefits, social influence, institutional support, and their impact on both intention and actual use of technology (Shahzad, Xu, & Javed, 2024). In light of these findings, the following hypothesis is presented:

H7: Habit positively impacts ChatGPT adoption intention.

2.9. Facilitation Condition and ChatGPT adoption intention

Facilitation conditions are external factors that make it easier or harder for users to adopt and use technology. Students may have consistent access to laptops, tablets, or smartphones capable of running ChatGPT effectively (Ma & Huo, 2023). Many students lack these devices, and their ability to use ChatGPT is compromised. Reliable and high-speed internet access is crucial for using ChatGPT. Students in areas with poor connectivity or those who cannot afford stable internet services face significant barriers (Menon & Shilpa, 2023). The absence of adequate technical support for troubleshooting and guidance can deter students from using ChatGPT. Students encounter issues, and no help is available; they are less likely to adopt the technology (Elshaer et al., 2024). Universities do not endorse or integrate ChatGPT into their systems and curricula, and students might see less value in using it. Institutional support in the form of official recommendations, integration into coursework, or provision of accounts can encourage use (Qu & Wu, 2024). Concerns about how personal data and usage data are handled can deter students. Students who are unsure about ChatGPT's privacy policies may be reluctant to use it. Students are unaware of ChatGPT or its potential benefits and are unlikely to adopt it. Misconceptions or negative publicity about ChatGPT can also deter students from trying it out. Fears about security breaches or misuse of information can also negatively impact adoption (Elshaer et al., 2024). It is hypothesized that:

H8: Facilitation conditions negatively impact ChatGPT adoption intention.

2.10. Adoption intention and actual use of ChatGPT

Adoption intentions affect the actual use of these technologies, and they have become very popular due to their introduction into educational institutions. In particular, a well-known example in this area that has attracted attention in the education sector is ChatGPT, established by OpenAI (Sohail et al., 2023). According to (Davis, 1989), adoption intention is a measure of a person's willingness to adopt a technology that has a major influence on how the technology is used. This goal encourages students to use ChatGPT in learning environments (Shahzad, Xu, & Javed, 2024). Consequently, students attracted to ChatGPT due to its obvious advantages and ease of use tend to integrate it more into their academic activities. Notably, students' positive opinion of ChatGPT's value in supporting learning or streamlining tasks is positively related to active use of the platform. In addition, positive adoption intention promotes further integration by creating a welcoming climate in educational institutions (Tlili et al., 2023). However, this correlation can be modified by contextual elements such as sociocultural effects, institutional support, and technical competence (Maheshwari, 2023). Students' adoption intentions and future usage correlate significantly with their understanding of AI, institutional backing, and societal views. Adoption

goals heavily impact ChatGPT's classroom usage. Yet, contextual complexities demand deep comprehension for its effective integration into teaching methods (Saif et al., 2023). From the above arguments, it is hypothesized that:

H9: Adoption intention positively impacts the actual use of ChatGPT.

2.11. Moderating role of academic integrity

Academic integrity encompasses the principles of honesty, fairness, trust, and responsibility in academic work. Students with a strong sense of academic integrity may scrutinize the legitimacy and acceptability of using ChatGPT (Bin-Nashwan et al., 2023). They are more likely to use the tool ethically, ensuring it aligns with institutional guidelines and personal moral standards. This means they might use ChatGPT primarily for idea generation, clarifying concepts, or as a supplementary tool rather than relying on it for completing assignments or exams (Cotton, Cotton, & Shipway, 2024). These students are likely to question the reliability and truth of information generated by ChatGPT. They may cross-verify the outputs with credible sources, leading to a more cautious and responsible tool use. Students who value academic integrity are more likely to adhere to institutional policies and guidelines regarding the use of AI tools (Kamoun, 2024). Institution has clear policies on how ChatGPT should be used, these students will follow them, which may moderate their actual use of the tool despite high adoption intentions. Students with strong academic integrity are more self-regulated and hold themselves accountable for their learning. They use ChatGPT to complement their knowledge and skills rather than replace their effort (Lai et al., 2024). This self-regulation ensures that their use of ChatGPT aligns with ethical standards. The actual use of ChatGPT by students with high academic integrity tends to enhance their learning outcomes as they use the tool to support and deepen their understanding (Bin-Nashwan et al., 2023). Students with a high sense of academic integrity are likely to use ChatGPT responsibly and ethically, aligning their actual use with their initial intentions. From the above discussion, it is hypothesized that:

H10: Academic integrity moderates the relationship between adoption intention and actual use of ChatGPT.

Based on the earlier literature evaluation, the study model outlined below is shown in Figure 1.

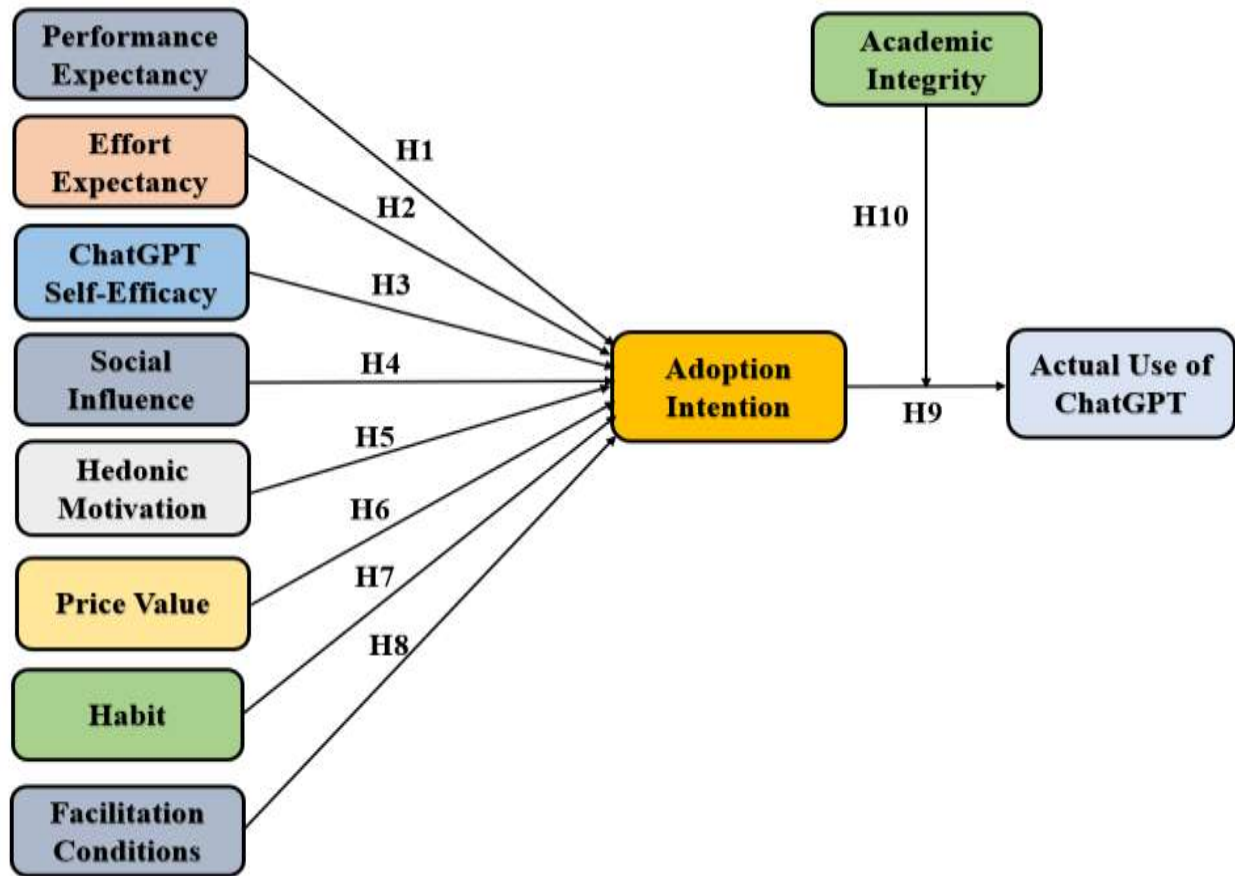


Figure 1: Conceptual framework

3. Research Methodology

3.1. Survey development and measures

The survey instrument utilized in this investigation was derived from the UTAUT2 models, with additional reference to the existing literature on ChatGPT acceptance and usage. The first part of the survey instrument represents respondents' demographic data, while the other part contains information about the variables adopted from prior literature (Strzelecki, 2023; Xu et al., 2024). ChatGPT adoption intention (ADI) and actual use of ChatGPT (AU) are the dependent variables taken into account in this study. Performance expectancy (PE), effort expectancy (EE), ChatGPT self-efficacy (CGSE), social influence (SI), hedonic motivation (HM), price value (PV), habit (HAB), and facilitation conditions (FC) are independent variables in this study. Academic integrity (ACI) is a moderator variable. Every item in the survey had a rating on a Likert scale of 1 to 5, where 1 represented strongly disagree and 5 represented strongly agree. Constructs such as ADI, AU, PE, EE, HM, HAB, CGSE and ACI were composed of a three-item scale, whereas the PV and SI had four-item scales. As shown in Table 2, the survey instrument items were taken from previous studies. All items of constructs are displayed in Table 2 in detail.

3.2. Participants and procedure

For the current study, data is collected from university students located in Lahore, Pakistan. The links to the survey were shared on open social media sites in an effort to attract respondents. The following screening questions are added to the description portion of the questionnaire to validate the current study's authenticity. First, students familiar with and using the ChatGPT for their academic activities are only considered true participants of the study, while the rest of them are excluded. The convenience sample approach is used for data collection since the number of university students is unknown (Correia et al., 2024). Therefore, convenience sampling was used for the questionnaire survey to collect data from three public and three private universities in Pakistan. The Higher Education Commission (HEC) of Pakistan's website was used as a source of data collection to determine the top six public and private universities. The researchers circulated 470 questionnaires and received 401 completed ones. After a rigorous data evaluation, which included correcting outliers and unengaged responses, 361 responses with a 76% response rate, the data remained accessible for analysis. This response rate is consistent with the study (Roscoe et al., 1975), which suggests a sample size of 30 to 500 participants for empirical research is recommended. The final sample of the current study consists of 148 females (41%) and 213 males (59%) responses. Further demographic specifics are provided in Table 1.

Table 1. Respondent information

Demographics	Distribution	n = 361
Gender	Male	213 (59%)
	Female	148 (41%)
Age group	20-28 years	136 (38%)
	28-36 years	151 (42%)
	Above than 36 years	74 (20%)
Education	Bachelor	98 (27%)
	Masters	164 (45%)
	PhD	78 (22%)
	Other	21 (6%)
Year of Study	First	89 (25%)
	Second	74 (20%)
	Third	103 (29%)
	Fourth	95 (26%)
Experience with ChatGPT	Average	51 (14%)
	Good	147 (41%)
	High	163 (45%)

4. Analysis and Results

The ten proposed hypotheses were examined using structural equation modelling (SEM) analysis of the data obtained for this study. Because SEM combines multiple regression analysis and confirmatory factor analysis (CFA), so it was a suitable analysis method for examining causal links between variables (Henseler et al., 2016). As mentioned in the findings and analysis section, a number of experiments were run before the hypothesis testing using SEM. Using the statistical software Smart PLS 4.0, we have examined the suggested theoretical model of ChatGPT adoption and actual use. We determined that PLS-SEM was the best method for the following research to take into account the intricate model of moderation and mediation analysis (Hair et al., 2017; Hamdollah & Baghaei, 2016). The measurement mode and the structural model were evaluated in two stages of the study using the SmartPLS software.

4.1. Common method bias

In order to minimize potential bias, the survey items were examined for the presence of common method bias (CMB) using the Harman single-factor analysis technique (Podsakoff et al., 2003). After factors were eliminated, loadings were looked at, and it was discovered that none of the components explained the majority of the variation, proving the lack of bias in the data. Herman's single-factor analysis shows that a single factor accounts for less than 50% of the variance (Farrukh et al., 2024). Our analysis revealed that a single component only accounted for 34% of the fluctuation, which is far less than the 50% CBM bias criterion. Furthermore, CMB is calculated using the variance inflation factor (VIF). This study demonstrates that the VIF value of each variable is less than 5. Thus, Herman's single-factor and VIF are satisfied, and the CMB with actual data is not a problem.

4.2. Measurement model

PLS-SEM is best suited for exploratory research that thoroughly assesses both the measurement and the structural model (Henseler et al., 2016). Regardless of sample size or data distribution, this method is flexible enough to handle simultaneous connection models and uses bootstrapping techniques and estimate methods, making it appropriate for new and exploratory studies (Hair et al., 2017). We examined the discriminant validity, convergent validity, and reliability of the measurement model. Cronbach's alpha (α), composite reliability (CR) and extracted average variance (AVE) were used to assess reliability. All of the constructs showed good construct reliability, with Cronbach's alpha values (0.779–0.992) and CR values (0.821–0.994) over the suggested criterion of 0.70 and AVE values (0.604–0.984) above the suggested threshold of 0.50 (Bagozzi & Yi, 1989). Convergent validity was evaluated by verifying the factor loading on each of their individual constructs (Shahzad et al., 2021). All factor loadings (0.731–0.995) for the items in Table 2 were higher than 0.70, demonstrating adequate convergent validity.

When inter-construct correlations were less than the square root of the constructs' AVE, discriminant validity was demonstrated. The constructs have sufficient discriminant validity, as Table 3 shows. Discriminant validity was verified by applying the criteria established by Fornell and Larcker. The discriminant validity analysis constitutes an evaluative process aimed at assessing the degree to which discrete constructs within a research framework manifest genuine distinctiveness from one another (Fornell & Larcker, 1981). As seen in Table 3, the square roots of AVE exceeded the associated correlations, satisfying the requirement for discriminant validity. The method used was the Heterotrait-Monotrait (HTMT) ratio, which is commonly used to evaluate discriminant validity (Hair et al., 2017). All of the HTMT values of this study constructs fell below (Bagozzi & Yi, 1989). suggested threshold of 0.90. As a result, discriminant validity was proved.

Table 2: Confirmatory factor analysis

Constructs	Items		FL	α	CR	AVE	Source
Performance expectancy (PE)	PE1	I believe ChatGPT will help me with my learning.	0.907	0.839	0.904	0.758	(Ma & Huo, 2023)
	PE2	ChatGPT increases motivation that I will succeed in areas of my learning.	0.811				
	PE3	Your academic productivity rises when you use ChatGPT.	0.891				
Effort expectancy (EE)	EE1	In learning, the use of ChatGPT gives benefit to me.	0.802	0.779	0.821	0.604	(Ma & Huo, 2023)
	EE2	My interactions with ChatGPT are understandable and transparent.	0.771				
	EE3	It is easy for me to become skillful at using ChatGPT.	0.758				
ChatGPT self-efficacy (CGSE)	CGSE1	I have access to the ChatGPT, which I can operate to achieve my studies goals.	0.994	0.992	0.994	0.984	(Compeau & Higgins, 2017)
	CGSE2	I can put my personal effort into learning, such as ChatGPT tools.	0.995				
	CGSE3	I'm inspired to study about ChatGPT-based technologies.	0.986				
Habit (HAB)	HAB1	I now use ChatGPT on a regular basis.	0.949	0.908	0.942	0.846	(Wang et al., 2022)
	HAB2	I can't stop using ChatGPT on a daily base.	0.956				
	HAB3	I now use ChatGPT without thinking about it.	0.849				
Social influence (SI)	SI1	Many people in my life believe that I ought to use ChatGPT.	0.889	0.889	0.920	0.743	(Menon & Shilpa, 2023)
	SI2	Those that shape my behavior think I ought to use ChatGPT.	0.805				
	SI3	People who I respect in my life would rather that I use ChatGPT.	0.897				
	SI4	People I respect believe automating insurance procedures is a positive development.	0.854				
Hedonic motivation (HM)	HM1	I enjoy using ChatGPT in education.	0.928	0.823	0.898	0.747	(Maheshwari, 2023)
	HM2	ChatGPT is fun to use.	0.919				
	HM3	ChatGPT is a lot of entertaining to use.	0.731				
Facilitation conditions (FC)	FC1	I possess the expertise required to utilize ChatGPT.	0.969	0.966	0.978	0.936	(Menon & Shilpa, 2023)
	FC2	ChatGPT is comparable to the technologies that I have already used.	0.972				
	FC3	When utilizing ChatGPT, I can ask for assistance from other users.	0.961				
Price value (PV)	PV1	The cost of ChatGPT is affordable.	0.918	0.889	0.923	0.750	(Strzelecki, 2023)
	PV2	Considering the price, ChatGPT provides good value.	0.776				
	PV3	In general, ChatGPT applications are worthwhile, as I pay for them.	0.857				
	PV4	I pay for ChatGPT technology for my study with some degree of attention.	0.906				
Academic integrity (ACI)	ACI1	To be really honest, I use ChatGPT to start the process.	0.977	0.956	0.972	0.920	(Bin-Nashwan et al., 2023)
	ACI2	Collaboration is based on a foundation of mutual trust when friends use ChatGPT.	0.961				
	ACI3	Preparing the material before the lecture using ChatGPT comes naturally to me.	0.938				
Adoption intention (ADI)	ADI1	I am excited to adopt ChatGPT.	0.977	0.950	0.968	0.910	(Shahzad, Xu, & Javed, 2024)
	ADI2	I will inform my other colleagues about the use of ChatGPT.	0.915				
	ADI3	I have access to ChatGPT and can adopt it effectively.	0.969				
Actual use of ChatGPT (AU)	AU1	In the future, I intend to continue using ChatGPT.	0.893	0.844	0.905	0.760	(Strzelecki & ElArabawy, 2024)
	AU2	I will make an effort to use ChatGPT for my education.	0.892				
	AU3	I'll continue to keep using ChatGPT frequently.	0.829				

Note: FL = Factor loadings, CR = Composite reliability, AVE = Average variance extracted, α = Cronbach's alpha.

Table 3: Discriminant validity

Constructs	1	2	3	4	5	6	7	8	9	10	11
1. AU	0.872										
2. ADI	0.652	0.954									
3. ACI	0.483	0.449	0.959								
4. CGSE	0.073	0.036	0.100	0.992							
5. EE	0.580	0.506	0.412	0.121	0.777						
6. FC	0.503	0.436	0.946	0.104	0.427	0.967					
7. HAB	0.597	0.324	0.218	0.006	0.538	0.248	0.920				
8. HM	0.132	0.218	0.143	0.052	0.158	0.124	0.028	0.864			
9. PE	0.532	0.849	0.370	0.072	0.355	0.391	0.321	0.089	0.871		
10. PV	0.770	0.492	0.560	0.035	0.509	0.567	0.531	0.072	0.447	0.866	
11. SI	0.147	0.187	0.237	0.110	0.118	0.215	0.062	0.254	0.065	0.167	0.862

4.3. Structural model

After assessing the validity of the data using the measurement model, the hypotheses were tested using the structural model analysis. The statistical significance of the model coefficients was ascertained using the bootstrapping resampling approach, employing a repeated sampling value of 5000 (Henseler et al., 2016). Table 4 displays the t-statistics, empirical path coefficients, and hypothesis results. According to (Hair et al., 2017), the t-value threshold for strong construct associations is 1.96 or higher, meaning that the t-values offer the most precise assessments of the state of the link between the constructs. Similarly, p-values and beta (β) values show the model significance. The predictive significance of the exogenous variables was evaluated using the coefficients of determination (R^2) of the endogenous latent variables. Additionally, the structural model used the SRMR threshold value of 0.080 to evaluate the quality of model fit. The results show that the SRMR score fell below the 0.064 threshold, indicating excellent overall model fit and satisfactory completion of the prediction study's objectives. In order to assess the relative impact of independent constructs on dependent constructs, we additionally computed the f-squared values (Shahzad, Xu, & Baheer, 2024).

Moving forward, (Q^2) was used to evaluate the predictive relevance of the model. (Q^2) was assessed using the blindfolding method, as endorsed by (Anderson & Gerbing, 1988). The (Q^2) result of model 0.334 illustrates the high prediction accuracy of the model and it is helping the particular adoption of ChatGPT in students. The typical values for (f^2) are 0.05, 0.13, and 0.56, indicating moderate, medium, and significant impacts. The value of (f^2) was determined, which shows that effect size varies from moderate to higher (Bagozzi & Edwards, 1998). Whereas the value of (R^2) reflects how much of a latent variable's variance the model can account for the model. According to this study, model explains 79% of the variance in ADI and roughly 49% of the variance in AU. All statistical methods are within range in Table 4.

Table 4: Hypothesis testing

Path	β -values	STDEV	t-values	p-values	Decisions
Panel A. Main effects					
PE $\rightarrow$ ADI (H1)	0.758	0.032	23.971	0.000	Supported
EE $\rightarrow$ ADI (H2)	0.236	0.051	4.606	0.000	Supported
CGSE $\rightarrow$ ADI (H3)	0.062	0.031	2.029	0.043	Supported
SI $\rightarrow$ ADI (H4)	0.089	0.029	3.063	0.002	Supported
HM $\rightarrow$ ADI (H5)	0.092	0.031	2.970	0.003	Supported

PV → ADI (H6)	0.049	0.038	1.286	0.199	Not Supported
HAB → ADI (H7)	0.089	0.042	2.119	0.040	Supported
FC → ADI (H8)	0.008	0.034	0.232	0.817	Not Supported
ADI → AU (H9)	0.593	0.037	16.011	0.000	Supported
Panel B. Moderation effect					
ADI × ACI → AU (H9)	0.167	0.040	4.219	0.000	Supported
Panel C. R²					
ADI R ² = 0.798.					
AU R ² = 0.498.					

Table 4 shows the outcome of our hypothesis. The PE and adoption intention (ADI) in the context of ChatGPT have been exhaustively scrutinized, yielding notable findings. The results, delineated in Table 4, evince a robust positive correlation between PE and ADI (H1: $\beta = 0.758$, $t = 23.971$, $p = 0.000$). Thus, H1 is accepted.

This signifies a substantive impact of EE on the inclination to adopt ChatGPT. The outcomes, elucidated in Table 4, validate the hypothesis (H2) that effort expectancy significantly shapes individuals' intentions to adopt ChatGPT technology. The path analysis revealed a β -value of 0.236 (STDEV = 0.051) with a substantial t-value of 4.604 ($p = 0.000$), providing empirical support for the relationship among effort expectancy and adoption intention.

Results from the analysis (refer to Table 4) underscore the significance of this association. The path coefficient ($\beta = 0.062$) indicates a positive correlation between ChatGPT self-efficacy (CGSE) and adoption intention (ADI), bolstered by a standard deviation of 0.031. The t-value of 2.029 associated with this path emphasizes its statistical significance ($p = 0.043$), suggesting that the observed relationship between ChatGPT self-efficacy and adoption intention is empirically substantial. Consequently, the hypothesis (H3) is supported.

The social influence (SI) and adoption intention (ADI) in the context of ChatGPT have been exhaustively scrutinized, yielding notable findings. The results, delineated in Table 4, evince a robust positive correlation between SI and ADI (H4: $\beta = 0.089$, $t = 3.063$, $p = 0.002$). Thus, H4 is accepted.

A prior study (Strzelecki, 2023) yielded significant findings supporting the positive effect of hedonic motivation (HM) on adopt ChatGPT, aligning with the results presented in Table 4. The β -value of 0.092 (STDEV = 0.031) underscores a statistically significant relationship between HM and ChatGPT adoption intention (ADI) ($t = 2.970$, $p = 0.003$). These findings fortify the earlier hypothesis (H5) and affirm that individuals' hedonic motivations significantly contribute to their inclination toward adopting ChatGPT technology.

In light of prior evidence, it is apparent that perceived price value (PV) negatively influences the adoption intention (ADI) of ChatGPT. The results from hypothesis testing (Table 4) further reinforce this association. The path analysis unveiled a β -value of 0.049 with a standard deviation of 0.038, indicating a negative impact of price value on ChatGPT adoption intention. The corresponding t-value of 1.286 is statistically insignificant at a p-value of 0.199, surpassing conventional insignificance thresholds. Thus, H6 is not supported.

Recent findings affirm the positive influence of habit on the intention to adopt ChatGPT, aligning with earlier research in this domain. As per the empirical results presented in Table 4, the beta coefficient (β) for the path from habit (HAB) to adoption intention (ADI) is estimated at 0.089

with a standard deviation of 0.042. The t-value associated with this path is calculated to be 2.119, yielding a significant p-value of 0.040. Therefore, H7 is accepted.

Moving forward, results show that the facilitation conditions (FC) negatively influence the adoption intention of ChatGPT (ADI) as indicated ($\beta = 0.008$, $t = 0.232$, $p = 0.817$). These findings didn't support adoption intention, as students sometimes heavily rely on ChatGPT and lose their actual output in education. In light of these values, H8 is not supported.

The influence of adoption intention (ADI) on the actual use of ChatGPT (AU) was investigated, revealing a significant and positive impact ($\beta = 0.593$, $t = 16.011$, $p = 0.000$). This finding supports the premise that a user's intention to adopt the technology strongly correlates with their subsequent use of ChatGPT. It aligns with prior studies suggesting that embracing a technological innovation influences utilization. Finally, H9 is accepted.

Lastly, this study's results display the moderating effect of academic integrity on adoption intention (ADI) and the actual use of ChatGPT (AU). As per the empirical results in Table 4, academic integrity significantly moderates the association between ADI and the AU ($\beta = 0.167$, $t = 4.219$, $p = 0.00$). Therefore, H10 is accepted. Figure 2 represents the structural model results.

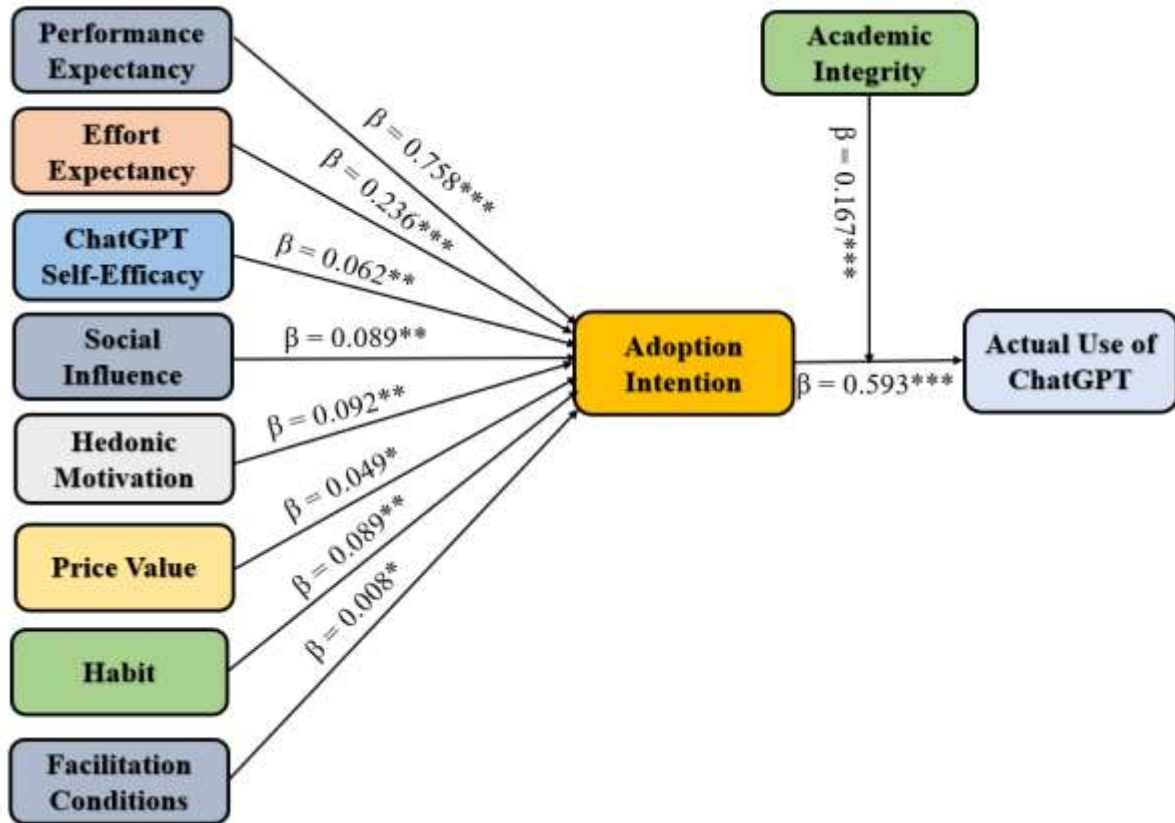


Figure 2: Structural model test results (* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$)

5. Discussion and conclusions

The study's primary goal was to use the UTAUT2 model to evaluate different factors influencing ChatGPT adoption and actual use in Pakistani universities. With the aid of UTAUT2 components, a conceptual framework was created to achieve this goal and evaluate ChatGPT adoption and its

actual impact on the education sector of Pakistan. We employed Pakistani university students who utilized OpenAI, such as ChatGPT, for academic purposes to validate the suggested conceptual model statistically. This study also examines how factors PE, EE, CGSE, SI, HM, PV, HAB, and FC affect the ChatGPT adoption and actual use in the education sector of Pakistan. Additional academic integrity significantly moderates the association between adoption and actual ChatGPT use. The study's findings are categorized into ten primary sections:

First, the study substantiates that performance expectancy (PE) significantly influences the adoption intention of ChatGPT. The findings corroborate prior research (Strzelecki & ElArabawy, 2024), highlighting the indispensable role of users' expectations regarding ChatGPT's performance in shaping their intentions to adopt this ChatGPT technology. Specifically, emphasizing the importance of performance expectations in shaping adoption intentions within the domain of ChatGPT enhances this premise (Duong et al., 2023).

Second, the investigation highlights that effort expectancy positively impacts ChatGPT adoption intention. This finding aligns with prior studies (Hunde et al., 2023; Strzelecki, 2024) emphasizing the significance of effort expectancy in determining users' intentions to adopt ChatGPT technologies. Effort expectancy comprises elements such as ease of learning, and cognitive efforts required to utilize technology. Moreover, the strong constructive affiliation between effort expectancy (EE) and adoption intention highlights the importance of user perceptions and experiences in the design and implementation of ChatGPT (Ma & Huo, 2023).

Third, the investigation further reveals that ChatGPT self-efficacy positively impacts adoption intention. This finding aligns with assertions that an individual's trust in their capabilities to effectively engage with and utilize new technologies strongly influences their willingness to adopt them (Z. Zhang et al., 2023). As per (Bandura, 1977), self-efficacy serves as a pivotal determinant in shaping behaviors and intentions, resonating with the current study's outcomes. These findings provide guidelines for students aiming to enhance ChatGPT adoption rates, emphasizing the pivotal role of self-efficacy beliefs in this process.

Fourth, social influence positively impacts ChatGPT adoption intention. According to a past study (Maheshwari, 2023), social influence suggests that when students perceive that their peers and educators value and use ChatGPT, they are more likely to consider adopting the technology themselves. This effect is likely amplified in a university setting where collaboration and peer opinions are highly valued. Peer usage and academic endorsement create a conducive environment for technology adoption, suggesting that universities can enhance ChatGPT integration by leveraging these social dynamics (Menon & Shilpa, 2023). By incorporating ChatGPT into academic activities, universities can promote widespread adoption and maximize the educational benefits of this innovative tool (Shahzad, Xu, & Javed, 2024).

Fifth, hedonic motivation positively impacts ChatGPT adoption intention. These results echo the importance of considering pleasure and enjoyment derived from ChatGPT as a motivational factor influencing users' intentions. This hedonic aspect is crucial in shaping individuals' perceptions and preferences regarding adopting innovative technologies like ChatGPT (Ma & Huo, 2023).

Sixth, the investigation highlights that price value negatively impacts ChatGPT adoption intention. Following prior research (Strzelecki, 2023), financial constraints are a well-known characteristic of university students. Many students have limited resources and are cognizant of

any extra costs (Raman et al., 2024). Students may weigh the direct expenses of usage or subscription fees for ChatGPT, the indirect costs of data usage, and the possible need for extra tools or resources to properly incorporate the technology into their academic routines (Jo, 2024).

Seventh, moving forward, the investigation unveils that habit positively impacts ChatGPT adoption intention. These results validate the positive relationship between habit and the intention to adopt ChatGPT. The habitual use indicates that indeed shapes individuals' inclination towards embracing ChatGPT technology (Yang et al., 2022). This outcome corroborates previous findings suggesting habituation is a significant factor affecting the adoption of technological innovations (Biloš, 2024; Strzelecki, 2023).

Eighth, facilitation conditions negatively impact ChatGPT adoption intention. The negative impact observed in this study suggests that, despite the availability of these resources, students may perceive them as inadequate, overly complex, or misaligned with their needs (Menon & Shilpa, 2023). This misalignment could lead to frustration and reluctance to adopt ChatGPT, emphasizing the importance of the presence and the quality and relevance of facilitation conditions. Previous studies (Habibi, Muhaimin, Kopong, et al., 2023; Jo, 2023) have often highlighted facilitation conditions' positive role in technology adoption. However, the negative impact found in this study aligns with some emerging research (Elshaer et al., 2024) that suggests a more nuanced relationship.

Ninth, the investigation reveals that adoption intention positively impacts the actual use of ChatGPT. The relationship between adoption intention and actual use underscores the relevance of user attitudes and motivations in shaping the practical implementation of ChatGPT. It implies that users who intend to adopt these generative AI technologies are more likely to actively engage with it (Maheshwari, 2023). Consequently, organizations and developers aiming to enhance the adoption and utilization of ChatGPT should focus on cultivating and reinforcing positive attitudes and intentions among potential users (Shahzad, Xu, & Javed, 2024).

Tenth, academic integrity moderates the relationship between adoption intention and actual use of ChatGPT. Students who place high importance on academic honesty are likely to carefully consider the ramifications of utilizing ChatGPT. They might use the technology more sparingly and carefully, making sure it complies with institutional guidelines and moral principles (Cotton, Cotton, Shipway, et al., 2024). The results of this study have significant ramifications for how colleges handle integrating ChatGPT and other AI techniques to maintain integrity. Establishing a culture of academic integrity inside institutions is crucial in assisting students in ethically using these tools (Bin-Nashwan et al., 2023). To increase knowledge of the possible risks and proper applications of AI tools, educational programs and workshops on digital literacy and ethical usage of generative AI should be implemented (Lai et al., 2024).

This study's results provide technology developers, organizations, and academic institutions with practical tactics and insights to improve the adoption, use, and advancement of AI-driven chat systems such as ChatGPT. By addressing these variables, students may greatly affect users' perceptions and intentions, which will encourage more people to accept and use this advanced technology like ChatGPT.

6. Study implications

The culmination of empirical evidence derived from the comprehensive analysis of factors influencing ChatGPT adoption has far-reaching implications for academia, industry, and technology developers. These implications take various forms, providing insightful information and practical solutions to promote the adoption, use, and advancement of AI-powered chat platforms such as ChatGPT. The study underscores the pivotal role of performance expectations (PE) in shaping users' intentions to adopt ChatGPT. The robust relationship between users' perceptions of ChatGPT's performance and adoption intention highlights the significance of continuously improving and emphasizing the system's performance. Technology developers and providers must prioritize enhancing user experience by meeting or exceeding performance expectations. This necessitates a focus on refining the system's capabilities, ensuring reliability, and maintaining high standards to influence users' adoption inclinations positively.

Effort expectancy emerges as users' perceptions of ease of use, simplicity, and the cognitive effort required to interact with ChatGPT significantly shape their adoption decisions. Simplifying interfaces, improving usability, and reducing the perceived effort necessary for engagement are imperative strategies. By streamlining user interaction, developers can elevate user experiences, thereby augmenting adoption rates across diverse user segments. The study accentuates the role of users' self-efficacy beliefs in influencing ChatGPT adoption intentions. It is essential to bolster users' confidence in utilizing the technology effectively. Strategies to foster self-efficacy beliefs among potential users could significantly impact adoption rates. Comprehensive guidance, training, and support mechanisms could instill greater user confidence, enhancing their willingness to adopt ChatGPT. Highlighting the role of social influence, the influential figures within the academic environment endorse ChatGPT, and its adoption is likely to increase. Similarly, the availability of necessary resources, such as technical support, infrastructure, and training, can influence the actual use of ChatGPT.

The incorporation of hedonic motivations emerges as a notable factor influencing adoption intention. The study affirms the role of habituation in shaping adoption intention. Encouraging habitual usage among users through consistent and engaging experiences could foster stronger inclinations toward adopting ChatGPT. Developing features that encourage habitual engagement and seamlessly integrate ChatGPT into users' daily routines can significantly enhance adoption rates. The strong relationship among adoption intention and actual use of ChatGPT emphasizes the importance of cultivating positive attitudes among potential users. To maintain academic integrity, institutions that effectively communicate policies and provide guidelines for the ethical use of ChatGPT can mitigate negative perceptions and encourage responsible usage. Developers and organizations should reinforce favorable perceptions, highlight system benefits, and ensure ease of use to bolster adoption intentions. This entails strategic efforts to enhance user attitudes and motivations, subsequently driving increased utilization of ChatGPT.

7. Limitations and areas for future research

Despite the robustness of the findings, the study acknowledges certain limitations. First, future research endeavors could delve deeper into exploring nuanced dimensions within each factor influencing ChatGPT adoption. Understanding the intricacies and interplay of these factors could provide a more comprehensive understanding of adoption dynamics. Second, as this study focused on different parameters that affect ChatGPT using questionnaires, longitudinal user behavior tracking was conducted for future studies. Third, it is essential to acknowledge the limitations of this study as it focuses on specific factors influencing adoption intentions. Future research could

explore additional variables like user experience and external influences for a more comprehensive understanding. Fourth, the findings might be context-specific; hence, caution should be exercised while generalizing them across different settings or user groups. Further exploration into the nuanced dimensions of the identified factors could yield deeper insights. Last, this study used single-country Pakistan university students; for future perspectives, the researchers would use different countries or draw a comparison to expand the findings.

Acknowledgment: All authors contributed equally to this work.

Conflicts of Interest: The authors declare no conflict of interest.

Data availability statement: Data will be made available on request.

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