**A Study of the Key Drivers Behind University Students' Intention to Use and Usage of Generative AI in Academia: Evidence from ChatGPT Use in Saudi Arabia****Saleh Alarifi, Ph.D**

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ABSTRACT

This study aims to identify the determinants affecting the intention of Saudi university students to use generative AI technologies, particularly ChatGPT, in academic contexts. The research incorporates its constructs from TAM, UTAUT2, TPB, and DOI. Data was collected from 213 university students using an online survey, then assessed through Structural Equation Modeling. The results showed that Perceived Behavioral Control, Perceived Credibility, and Social Influence serve as significant predictors of students' intention to use ChatGPT, while Performance Expectancy, Relative Advantage, and Attitude were not significant predictors. Furthermore, intentions strongly predicted actual usage behavior. The results underscore the critical roles of trust, self-efficacy, and social support in facilitating the adoption of AI technologies in Saudi Universities. This study enhances the theoretical framework of AI adoption and provides actionable insights for universities seeking to implement AI tools responsibly and effectively. Subsequent research could explore non-significant variables through qualitative inquiry and assess temporal shifts in usage through longitudinal analysis.

KEYWORDS: generative AI, ChatGPT, higher education, Saudi Arabia, and Intention to Use**1. The Introduction**

Developments in artificial intelligence (AI) are rapidly redefining numerous business fields, with higher education being no exception. Across the aforementioned technologies, generative AI-ChatGPT-has emerged as a powerful resource for academic tasks, enabling students to draft essays, summarize research, and generate ideas quickly and interactively (Rodway & Schepman, 2023). Accordingly, the integration of AI in Academic institutions is anticipated to grow rapidly, reshaping both Pedagogical strategies and practices (Sanabria et al., 2023). These technologies offer promising opportunities to enrich educational experiences and facilitate individualized learning approaches. (Ameen et al., 2023; Aljamaan et al., 2023). However, their adoption at the University level remains an evolving area of research, particularly in non-Western settings such as Saudi Arabia (Alharbi & Drew, 2024; Alshaikh et al., 2024).

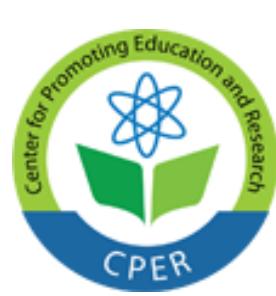
AI technologies are gradually being embedded within educational contexts, where they support customized learning, responsive evaluation methods, and purposeful student interaction in hybrid learning settings (Zhang & Aslan, 2021). Nonetheless, some scholars argue that continued advancements in AI may lead to overreliance on technology for information acquisition and academic tasks, potentially undermining educational integrity and diminishing critical thinking within society (Masa'deh et al., 2024). Moreover, concerns have been raised that AI could eventually replace vital roles traditionally held by administrators, faculty, and academic staff (Keiper et al., 2023).

Although educators recognize the instructional potential of generative AI, they also voice concerns about its ethical implications, the preservation of academic integrity, and the trustworthiness of AI-generated productivity (Alotaibi & Alamri, 2024). These apprehensions are heightened in conservative academic environments where originality and authenticity are strongly emphasized. Recent studies suggest that students exhibit

mixed attitudes toward AI tools, balancing potential academic benefits with fears of overreliance and misinformation (Alhumaid, 2024; Alasmari & Zhang, 2023). In particular, the perceived credibility of ChatGPT has become a crucial factor influencing its adoption, as students require assurance that the content generated is accurate and trustworthy (Ameen et al., 2023; Alsaidi & Al-Rahmi, 2024). Since its introduction, ChatGPT has rapidly garnered attention from scholars and industry professionals within the digital landscape (Masa'deh et al., 2024). Globally, it is primarily employed for research and educational purposes.

The application of ChatGPT in educational environments has garnered substantial scholarly attention in recent years. Contemporary research has explored multiple determinants affecting how students utilize ChatGPT. In their 2024 study, Acosta et al. investigated how university students regard the use of ChatGPT for educational purposes and reported a significant correlation between students' attitudes and their adoption of the tool. Masa'deh et al. (2024) evaluated the forces driving students' adoption of ChatGPT in classroom settings and indicated that perceived enjoyment exerted no significant influence on its use. Acosta et al. (2024) investigated how cognitive and affective attitudes shape behavioral responses toward the use of ChatGPT, concluding that both factors positively influence students' behavioral attitudes.

Existing research in the Middle Eastern context has begun to explore these dynamics; however, an In-depth insight into the aspects driving both behavioral intention to use and usage of ChatGPT among students is still lacking. (Alshaikh et al., 2024; Alturki & Aldraiweesh, 2023). Specifically, there is limited empirical evidence focusing on how constructs such as Performance Expectancy, Perceived Behavioral Control, Relative Advantage, Perceived Credibility, Attitude, and Social Influence affect students' readiness to adopt generative AI for academic purposes in Saudi Arabia (Alzahrani, 2024; Alharbi &



Drew, 2024). Addressing this gap is essential for higher educational organizations aiming to implement AI tools efficiently while upholding academic standards and ethical principles.

This research investigates the predictors of Saudi university students' behavioral intention to use and usage of generative AI, with specific emphasis on ChatGPT, in the context of academic activities. Thus, an exploratory study design is applied as a methodological frame to identify how these constructs influence both intentional and actual usage behavior. The findings are anticipated to guide the progress of strategies for the accountable and effective embedding of AI in higher institutions, enhancing student learning outcomes and offering practical insights for educators and policymakers.

Ultimately, this research adds to the expanding literature on AI technologies' acceptance in education by delivering context-specific understandings and underscoring key factors for successful implementation. Through an examination of the distinct cultural and institutional dynamics in Saudi Arabia, the research offers a foundational framework for future studies and policy initiatives aimed at optimizing the educational benefits of generative AI.

2. The Literature Review

The incorporation of AI technologies into Education at the university level has attracted considerable scholarly interest on a global scale. Technologies based on generative AI (e.g., ChatGPT) have become popular due to their potential to aid academic work, including writing, summarizing, and generating ideas. An extensive insight into the psychological and social forces of students' engagement with these tools is vital for optimizing their integration and impact in academic settings. This review utilizes theoretical frameworks, including TAM, UTAUT2, TPB, and DOI, to analyze the impact of constructs such as Performance Expectancy, Perceived Behavioral Control, Relative Advantage, Perceived Credibility, Attitude, and Social Influence on students' intention to use and usage of ChatGPT at the university level, specifically in Saudi Arabia.

2.1 Performance Expectancy

Performance Expectancy captures students' beliefs regarding the anticipated benefits of generative AI tools, such as ChatGPT, to increase their academic achievements. This construct is a fundamental element of UTAUT2, first introduced to elucidate technology adoption in many situations (Venkatesh et al., 2012). Although the theoretical framework is broad, recent research has concentrated primarily on ChatGPT. Alshaikh et al. (2024) discovered that Saudi students regarded ChatGPT as very useful in raising their writing quality and facilitating comprehension of intricate subjects. Furthermore, Alturki and Aldraiweesh (2023) demonstrated that students had an elevated chance of adopting ChatGPT upon recognizing it as a means for saving time and improving academic performance. The escalating academic competitiveness and pressure to excel amplify the significance of performance advantages (Al-kfairy, 2024). Consequently, when students recognize distinct academic benefits, their intention to

embrace and utilize AI techniques such as ChatGPT markedly intensifies.

H1: Performance Expectancy has a positive impact on the Intention to Use Generative AI

2.2 Perceived Behavioral Control

Perceived Behavioral Control (PBC) denotes students' trust in their capacity to utilize AI tools proficiently, including accessibility, abilities, and resources. Drawing on the Planned Behavior Theory (Ajzen, 1991), PBC is defined by internal capabilities, like self-efficacy, and external constraints or enablers, such as support availability. According to Alhumaid (2024), students who demonstrate strong digital competencies are more inclined to utilize AI technologies, including ChatGPT, in their academic work. In Saudi Arabia, disparities in digital literacy and varying degrees of exposure to AI technology greatly affect PBC. Alasmari and Zhang (2023) discovered that students who received institutional training or peer support had more confidence in utilizing ChatGPT, resulting in a greater propensity to embrace it. Conversely, apprehensions over language hurdles and possible misuse may undermine PBC. Consequently, in ESL-focused studies, control beliefs significantly influenced students' confidence and preparedness to utilize technology (Zou & Huang, 2023; Strzelecki et al., 2024).

H2: Perceived Behavioral Control has a positive impact on the Intention to Use Generative AI

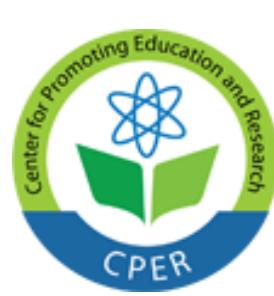
2.3 Relative Advantage

In the context of educational technology, Relative Advantage captures the extent to which students view ChatGPT as offering greater benefits than traditional study methods. Drawing upon Rogers' (2003) Diffusion of Innovations framework, the perceived superiority of an innovation accelerates its adoption. In higher education, students frequently seek technologies that enhance learning efficiency and adaptability. Alharbi and Drew (2024) demonstrated that students valued ChatGPT's immediate response and round-the-clock accessibility, advantages not provided by conventional approaches. Evidence from prior research suggests that the perceived relative advantage of using ChatGPT—particularly in terms of enhanced learning effectiveness—positively influences users' willingness to adopt the technology (Al-Kfairy, 2024). The perceived benefits render generative AI technologies appealing, particularly in competitive academic settings. Consequently, as students increasingly pursue tailored and effective learning assistance, the comparative advantage of ChatGPT will likely remain crucial to its adoption (Abdalla et al., 2024).

H3: Relative Advantage has a positive impact on the Intention to Use Generative AI

2.4 Perceived Credibility

Perceived Credibility denotes the level of students' belief that the information produced by ChatGPT is trustworthy and precise. This notion, initially examined in research on online knowledge sources (Flanagin & Metzger, 2007), has gained particular significance in AI contexts. Ameen et al. (2023) discovered that students' apprehensions regarding disinformation



and the precision of AI outputs significantly impacted their adoption choices. In Saudi Arabia, academic settings prioritize source trustworthiness and compliance with institutional integrity standards, rendering credibility a crucial obstacle or incentive (Alotaibi & Alamri, 2024). Students who regard ChatGPT as a trustworthy resource tend to utilize it more frequently in academic tasks such as essay writing, research synthesis, and language improvement. Consequently, users who perceive the information provided by ChatGPT as trustworthy are inclined to accept and apply the technology (Al-Kfairy, 2024).

H4: Perceived Credibility has a positive impact on the Intention to Use Generative AI

2.5 Attitude

Students' attitudes toward utilizing generative AI encompass their comprehensive assessments, including emotional, cognitive, and behavioral inclinations regarding the tool. As proposed by Davis (1989) in the Technology Acceptance Model, users' attitudes play a pivotal part in facilitating the association between their perceptions and their intention to adopt the technology. Positive opinions indicate students' confidence in the tool's utility and pleasure, whereas negative attitudes frequently stem from ethical apprehensions or anxiety around dependency. Duong et al. (2023) found that in Taiwan and Vietnam, students' observations of ChatGPT's efficacy in contributing to ESL engagement significantly influenced their behavioral intention to adopt the tool. In their 2023 study, Habibi et al. demonstrated that favorable attitudes toward ChatGPT—especially in terms of its perceived academic utility—were strongly associated with students' intention to adopt it for general educational use. Consequently, attitude is crucial for any transformative technology like ChatGPT (Masa'deh et al., 2024).

H5: Attitude toward Generative AI has a positive impact on the Intention to Use Generative AI

2.6 Social Influence

Within the context of technology adoption, Social Influence is defined as students' perception that influential individuals—such as peers, educators, or family—endorse or expect their engagement with ChatGPT. In the UTAUT2 model, Social Influence is crucial in influencing behavioral intention, particularly in collectivist cultures (Venkatesh et al., 2012). Al-Kfairy (2024) found that social influence exerts a considerable effect on students' Intent to engage in adopting ChatGPT. According to Al-Emran et al. (2023), Students tend to adopt ChatGPT in their academic routines when they receive support and observe favorable outcomes from their peers' usage. Alzahrani (2024) discovered that students in Saudi Arabia are more inclined to engage with AI technologies when influenced by positive peer feedback and faculty endorsement. Consequently, when kids observe their peers and educators proficiently utilizing ChatGPT, they are inclined to embrace the technology.

H6: Social Influence has a positive impact on the Intention to use Generative AI

2.7 Intention to Use

This variable captures the students' motivational state to utilize generative AI tools, whereas Actual Use denotes their behavioral engagement in practice. According to Ajzen (1991) and Davis (1989), behavioral intention is the key determinant of whether individuals will use the technology. Foroughi et al. (2024) demonstrated that when students express a favorable behavioral intention towards ChatGPT, they indicate their willingness to integrate it into their routines or assignments. Aljamaan et al. (2023) confirmed that usage intention is a strong predictor of actual engagement with AI technologies, including ChatGPT. Consequently, a greater intention to utilize ChatGPT correlates with an increased likelihood of students employing the platform in their academic endeavors (Ivanov & Soliman, 2023).

H7: Students' intention to use generative AI has a positive impact on actual use of such technologies.

3. Methodology

3.1 Research Framework

A quantitative methodology was implemented to assess the variables affecting Saudi university students' intention to engage with generative AI technologies, with a focus on ChatGPT, for academic use. The quantitative approach is appropriate as it allows for the statistical examination of associations among hypotheses and provides generalizable insights into the student population (Creswell & Creswell, 2018). An online survey form was adopted to accumulate responses from multiple participants and test the linkages outlined in the research model.

3.2 Population and Sampling

The population under investigation includes students attending higher education institutions within the Kingdom of Saudi Arabia. These students embody a variety of academic areas and educational levels (undergraduate and postgraduate). A convenience sampling method was employed for its efficacy in reaching participants via university mailing lists and online educational platforms. While convenience sampling may restrict generalizability, it offers significant preliminary insights, particularly in a nascent study domain such as AI adoption. The expected sample size is a minimum of 200 students, which is enough for structural equation modeling (SEM) analysis and ensures acceptable statistical power (Hair et al., 2019).

3.3 Research Framework and Measures

The study will utilize a structured, web-based questionnaire composed entirely of closed-ended questions to gather responses. The questionnaire items will be derived from validated scales utilized in prior research to ensure reliability and validity (Alharbi & Drew, 2024; Alhumaid, 2024; Ajzen, 1991; Aljamaan et al., 2023; Alsaidi & Al-Rahmi, 2024; Alshaikh et al., 2024; Alzahrani, 2024; Ameen et al., 2023; Davis, 1989; Flanagin & Metzger, 2007; Rogers, 2003; Venkatesh et al., 2012) (illustrated in Figure 1).

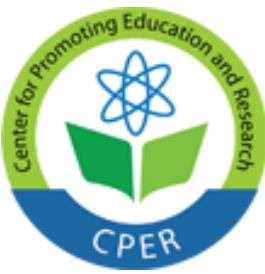
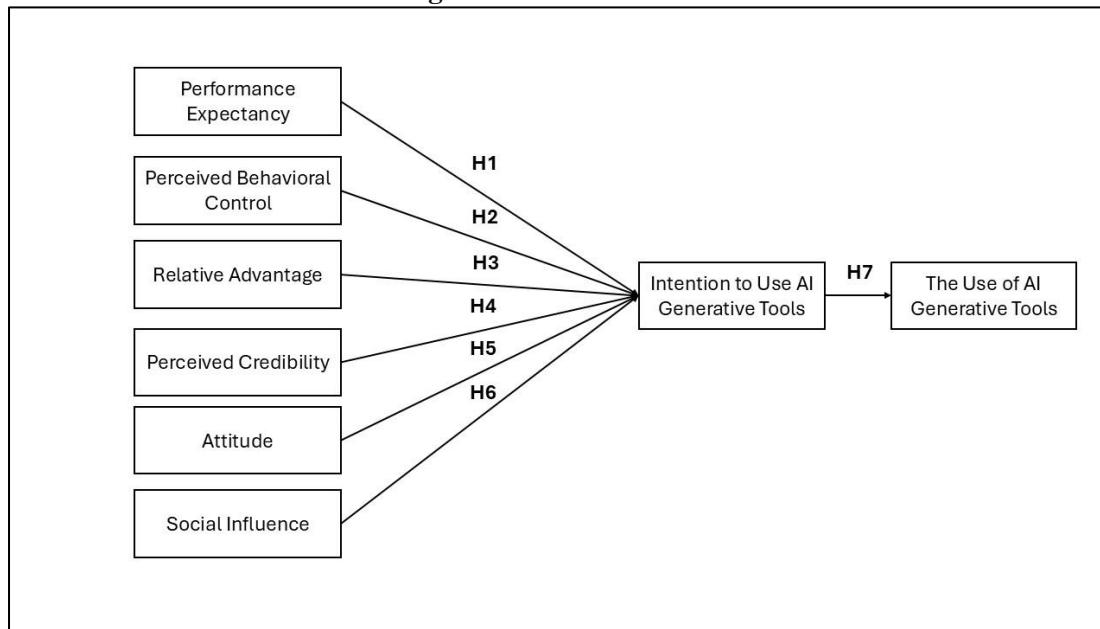


Figure. 1: Research Model



3.4 Data Collection and Analysis Techniques

The survey link is distributed electronically via university communication channels and student networks. The gathered data will undergo analysis through Structural Equation Modeling (SEM), utilizing software like SmartPLS 4.0, selected for its capability to examine intricate relationships among various latent constructs at the same time. The analysis will involve assessing the proposed framework to measure reliability and validity, and examining the structural framework to evaluate theoretical assumptions. Summary statistics will be presented to outline respondent demographics and give an overview of the constructs.

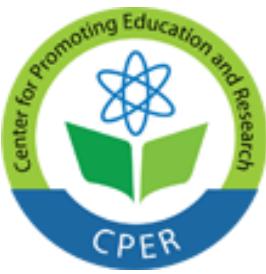
Reliability will be weighed via Cronbach's alpha and composite reliability, whereas validity will be examined over tests of convergent and discriminant validity (DV) (Hair et al., 2019). Path coefficients and their corresponding significance levels (p-values) will be employed to measure the formulated hypotheses.

4. Results

The researcher utilized Google Forms to disseminate the questionnaire, resulting in 224 replies. To ensure data quality, the analysis incorporated several diagnostic checks to identify missing data, response bias, and the presence of outliers. Thus, 11 respondents were excluded, resulting in 213 respondents being available for analysis.

Table 1: Respondents Demographics (N = 213)

| Variable | N | (%) |
|------------------|-----|-------|
| Gender | | |
| Male | 158 | % 72 |
| Female | 60 | % 28 |
| Age | | |
| Under 20 | 54 | % 25 |
| 20 – 25 | 156 | % 73 |
| 26 – 30 | 3 | % 1.4 |
| 31 – 35 | 1 | % 0.6 |
| Older than 35 | 0 | % 0 |
| Education | | |
| First Year | 71 | % 33 |
| Second Year | 26 | % 12 |
| Third Year | 48 | % 23 |
| Fourth Year | 53 | % 25 |
| Graduated | 16 | % 7 |



4.1. The Measurement Model

The (CFA) analysis was implemented to examine the measurement model's suitability and to assess the internal consistency and reliability of the latent constructs. To evaluate construct reliability, CA was applied. Following DeVellis (2016), a threshold of 0.70 or higher is applied to specify adequate internal consistency. In this inquiry, the CA for ATT, IU, PBC, PC, PE,

RA, SI, and TU were 0.851, 0.855, 0.792, 0.871, 0.812, 0.771, 0.876, and 0.923, respectively. These figures demonstrate that all constructs possess a significant level of reliability (Table 2). The CR was calculated to further evaluate the internal consistency of the latent constructs. The findings indicate that the ATT, IU, PBC, PC, PE, RA, SI, and TU constructs are all above the criterion of 0.70, as illustrated in Table 2.

Table 2: A CFA Results for Latent Constructs (N = 213)

| | Cronbach's alpha (CA) | N | Composite reliability (CR) | Average variance extracted (AVE) | R-Square |
|-----|-----------------------|---|----------------------------|----------------------------------|----------|
| ATT | 0.851 | 3 | 0.910 | 0.772 | |
| IU | 0.855 | 3 | 0.912 | 0.776 | 0.589 |
| PBC | 0.792 | 4 | 0.864 | 0.613 | |
| PC | 0.871 | 3 | 0.921 | 0.796 | |
| PE | 0.812 | 4 | 0.876 | 0.640 | |
| RA | 0.771 | 3 | 0.864 | 0.680 | |
| SI | 0.876 | 3 | 0.923 | 0.801 | |
| TU | 0.923 | 5 | 0.942 | 0.766 | 0.704 |

To evaluate the convergent validity, the AVE was quantified, following the guidelines of Hair et al. (2016). All constructs demonstrated AVE scores that surpassed the established benchmark of 0.50. The DV has been assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981), and the findings demonstrated that VD was attained (Table 3).

Table 3: DV Outcomes (N = 213)

| | ATT | IU | PBC | PC | PE | RA | SI | TU |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|
| ATT | 0.878 | | | | | | | |
| IU | 0.649 | 0.881 | | | | | | |
| PBC | 0.557 | 0.531 | 0.783 | | | | | |
| PC | 0.604 | 0.656 | 0.387 | 0.892 | | | | |
| PE | 0.666 | 0.579 | 0.617 | 0.516 | 0.800 | | | |
| RA | 0.663 | 0.544 | 0.682 | 0.427 | 0.682 | 0.825 | | |
| SI | 0.608 | 0.558 | 0.415 | 0.445 | 0.532 | 0.423 | 0.895 | |
| TU | 0.703 | 0.839 | 0.466 | 0.627 | 0.568 | 0.507 | 0.585 | 0.875 |

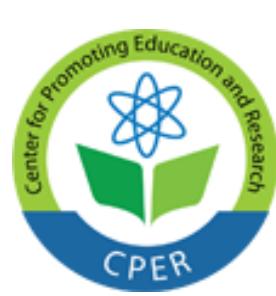
4.2. The Model Estimation

R² signifies the standard deviation of the structural model, and in this analysis, the respective score reflects the aggregated impact of the exogenous latent constructs on the corresponding endogenous variable (ATT, PBC, PC, PE, RA, SI) on the endogenous latent construct (IU), subsequently influencing the endogenous latent construct (TU). As shown in Table 2, the R² score for IU is 0.589, and for TU is 0.704-both

exceeding the recommended threshold of 0.25, thereby supporting the model's validity (Hair et al., 2016). The path coefficient is applied to calculate the intensity and polarity of the inter-construct relationships within the structural model (Hair et al., 2016). The data reveal four pathways displaying substantial correlations (IU → TU, PBC → IU, PC → IU, and SI → IU), in addition to three paths that lack significant relationships.

Table 4: The Hypothesis Results (N = 213)

| Path | path coefficient (β) | Standard deviation (STDEV) | P values | Significance |
|----------|------------------------------|----------------------------|----------|--------------|
| ATT → IU | 0.147 | 0.085 | 0.082 | NS |
| IU → TU | 0.839 | 0.026 | 0.000 | *** |
| PBC → IU | 0.146 | 0.070 | 0.036 | * |
| PC → IU | 0.370 | 0.074 | 0.000 | *** |
| PE → IU | 0.048 | 0.078 | 0.538 | NS |
| RA → IU | 0.079 | 0.072 | 0.275 | NS |
| SI → IU | 0.184 | 0.064 | 0.004 | ** |



The p-value is utilized to designate the statistical significance of the hypotheses. A p-value less than or equal to 0.05 shows a solid indication to reject the insignificant hypothesis, thereby supporting the proposed hypothesis. Consequently, the p-values for four structural paths were below the 0.05 threshold, providing empirical support for Hypotheses H2, H4, H6, and H7.

5. Discussion

This research aimed to examine the determinants prompting Saudi university students' intention to use generative AI technologies—specifically ChatGPT—for academic purposes. The results offer significant insights into the interconnections between Performance Expectancy (PE), Perceived Behavioral Control (PBC), Relative Advantage (RA), Perceived Credibility (PC), Attitude (ATT), Social Influence (SI), Intention to Use (IU), and Usage (TU).

Empirical results demonstrate that PBC, PC, and IS exert a strong effect on IU, with respective standardized path coefficients of $\beta = 0.146$ ($p < 0.05$), $\beta = 0.370$ ($p < 0.001$), and $\beta = 0.184$ ($p < 0.01$). Perceived Credibility showed as the most significant predictor, consistent with Ameen et al. (2023), who identified trust and perceived reliability as crucial factors influencing AI adoption in academic contexts. Alotaibi and Alamri (2024) similarly underscored credibility as a vital element among Saudi students, emphasizing its significance in traditional academic environments.

The substantial influence of PBC verifies previous research indicating that self-efficacy and resource availability are pivotal in technology adoption (Alhumaid, 2024; Alasmari & Zhang, 2023). The results underscore that trust is a crucial element of students' usage intention to adopt ChatGPT, as posited by the Planned Behavior Theory (Ajzen, 1991).

Social Influence demonstrated a considerable beneficial impact on IU, corroborating Alzahrani's (2024) claim that peer and teacher encouragement profoundly influence technology adoption in collectivist settings such as Saudi Arabia. This discovery highlights the significance of cultivating supportive settings via peer-led workshops and academic endorsements to promote AI adoption.

Contrary to expectations, the analysis revealed that Performance Expectancy ($\beta = 0.048$), Relative Advantage ($\beta = 0.079$), and Attitude ($\beta = 0.147$) did not significantly influence students' Intention to Use, as all p-values exceeded the 0.05 threshold. In contrast to the current conclusions, prior research by Alshaikh et al. (2024) and Alturki and Aldraiweesh (2023) reported that Performance Expectancy significantly influenced the adoption of AI technologies. A reasonable justification for this discrepancy is that students, despite acknowledging some performance advantages, are skeptical about the accuracy and ethical ramifications of employing generative AI. Another plausible explanation is that, within this cultural context, students may place greater value on credibility and social endorsement than on purely practical advantages.

The substantial and noteworthy correlation between IU and TU ($\beta = 0.839$, $p < 0.001$) verifies prior research (Aljamaan

et al., 2023), confirming that usage intention is a robust determinant of technology usage. This underscores the necessity of transforming desire into action via institutional support and eliminating obstacles to practical implementation.

6. Academic and Practical Contributions

This research contributes to the conceptual understanding of AI acceptance by extending existing technology acceptance frameworks through the inclusion of constructs such as Perceived Credibility and Social Influence. It emphasizes the cultural specificity of adoption models, especially in non-Western situations where social and trust-related elements may surpass practical considerations.

Universities ought to prioritize reinforcing the legitimacy of AI tools by transparent communication, formal endorsements, and the incorporation of AI literacy into academic courses. Moreover, utilizing social dynamics by engaging peers and teachers as advocates for appropriate AI usage might enhance adoption initiatives.

7. Suggestions for Future Research

Future research should investigate the reasons Performance Expectancy, Relative Advantage, and Attitude did not significantly affect intention in this setting. Qualitative methods, like interviews or focus groups, may yield profound insights into student perspectives and underlying issues.

Furthermore, longitudinal research could investigate how these correlations develop as students get additional experience and as generative AI tools become increasingly integrated into classroom settings. Subsequent studies may additionally juxtapose other cultural or institutional contexts to corroborate and enhance the model further.

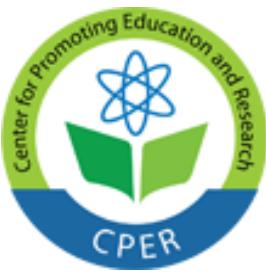
8. Limitations

This study employed convenience sampling, perhaps constraining generalizability. Moreover, self-reported statistics are susceptible to social desirability bias. Notwithstanding these constraints, the findings offer a valuable foundation for future research on the incorporation of generative AI at the university education level.

9. Conclusion

This study analyzed the key determinants shaping Saudi university students' tendency to be involved with generative AI tools—particularly ChatGPT—for educational use. This research utilizes established technology acceptance frameworks (TAM, TPB, DOI, and UTAUT2) and enhances them with constructs like Perceived Credibility and Social Influence, contributing in-depth insight into the contextual drivers shaping AI implementation in Saudi's universities.

The results indicated that PBC, PC, and SI strongly forecasted students' intention to utilize ChatGPT, with Perceived Credibility identified as the most influential factor. In contrast to initial predictions and prior research, Performance Expectancy, Relative Advantage, and Attitude showed no significant impact on intention. This underscores the paramount importance of trust and social validation over mere performance metrics or attitudinal considerations in this situation. The robust correlation



between intention and actual usage highlights the necessity of fostering supportive conditions to convert intention into significant utilization.

Universities should prioritize projects that enhance students' confidence and trust in AI tools, provide explicit standards for safe usage, and engage professors and peers as key advocates. Such strategies can support the effective and ethical integration of generative AI tools like ChatGPT, thereby

enhancing learning outcomes. The study enhances theoretical knowledge by situating AI adoption frameworks within the Saudi educational context and provides a basis for future comparative and longitudinal investigations. Despite the limits of convenience selection and dependence on self-reported data, the insights obtained offer significant guidance for policymakers, educators, and academics, emphasizing the responsible and well-informed integration of AI technologies within higher education settings.

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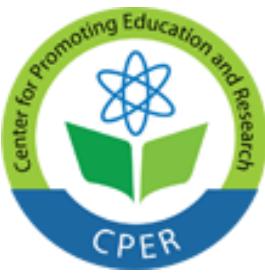
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