

# Exploring the Moderating Role of Information Security in College Students' Adoption of AI Chatbots

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**Abstract:** As the application of artificial intelligence (AI) in higher education becomes increasingly widespread, AI chatbots have gradually been adopted for routine learning tasks. While previous studies have linked user intention to actual adoption behaviour, the role of contextual factors such as information security (IS) remains under-explored. This study examines the direct impact of the intention to use AI chatbots (ITUAIC) on students' adoption of AI chatbots (SAAIC) and investigates the moderating role of perceived information security. Using SPSS and Amos to analyse survey data from college students, the results indicate that intention significantly predicts adoption behaviour, while IS has a positive moderating effect on this relationship. These findings advance research on the acceptance of AI chatbots and provide practical implications for the implementation of secure chatbots in the education sector.

**Keywords:** AI Chatbots, Intention to Use, Adoption, Information Security, Moderating Effect.

## 1. Introduction

AI applications are rapidly changing the educational landscape, with AI chatbots becoming common tools for enhancing student engagement, providing instant academic support, and improving learning efficiency [1]. As universities explore the advantages of chatbot systems, it is becoming increasingly important to understand the factors that influence student adoption of these technologies [2].

The Technology Acceptance Model (TAM) and its extended models have long emphasised the role of intention as a predictor of technology use [3-4]. Numerous studies have confirmed that intention subsequently influences actual usage behaviour [5-6]. However, recent developments in digital technology, especially those involving artificial intelligence, have raised growing concerns about information security, including data privacy, misuse of personal information, and system vulnerabilities [7].

In this case, students may have the intention to use AI chatbots, but if they perceive the technology to be unsafe, they may not adopt it [8]. Therefore, perceived information security may act as a moderating factor that could either strengthen or weaken the relationship between intention and adoption. Despite its relevance, the moderating role of IS has not received sufficient attention in the educational technology literature.

This study fills this research gap by proposing and validating a conceptual model with a moderating effect. The model posits that ITUAIC can predict SAAIC, with IS serving as a moderating variable in this relationship. By exploring this interaction, this study aims to reveal the psychological and contextual mechanisms behind AI adoption in educational settings.

## 2. Review of Literature

### (1) Theoretical Foundation

The Technology Acceptance Model (TAM) was proposed

by Davis (1989) [9] and is one of the most widely applied theoretical frameworks for explaining user acceptance of new technologies [10]. The model posits that factors influencing an individual's intention to use a specific system determine actual usage behaviour. Over the years, TAM has been expanded and refined to incorporate additional constructs such as trust and perceived risk, enhancing its explanatory power across diverse contexts [11-13]. In the context of AI chatbots in education, TAM provides a solid foundation for exploring how students form intentions to use AI technology and how these intentions translate into actual adoption behaviour. Specifically, the model supports the examination of both psychological and external factors that shape user behaviour.

### (2) Intention to Use AI Chatbots and the Adoption Behaviour

In an educational context, the intention to use AI chatbots refers to the extent to which students are willing to utilise AI chatbots to complete academic tasks. Actual adoption refers to the extent to which students integrate AI chatbots into their daily learning [14]. The adoption of AI chatbots may manifest itself in frequent use for querying academic information, completing learning tasks, etc [1]. Extensive research in the field of technology adoption has consistently emphasised behavioural intention as a direct precursor to actual usage behaviour [15-17]. Recent studies have shown that whether students are willing to use AI chatbots for academic purposes significantly influences their actual interaction with these tools [18-19]. Given the above theoretical and empirical support, we have reason to propose Hypothesis H1.

*H1: Students' ITUAIC positively influences SAAIC.*

### (3) Moderating Role of Information Security

Empirical research on the adoption of AI in higher education indicates that students' adoption behavior is influenced not only by internal attitudes but also by external facilitating factors or barriers, such as technological infrastructure and perceived security [20]. Perceived information security refers to the extent to which users

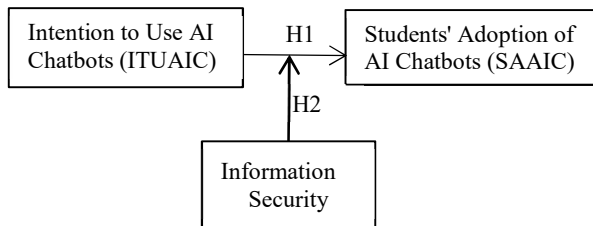
believe a system can ensure confidentiality, data integrity, and prevent unauthorized access [21]. In an educational setting, If students perceive potential risks such as data breaches or misuse of information, they may adopt a cautious attitude toward fully embracing AI chatbots [22].

Although the intention to use is a powerful predictor of behavior, there is a gap between intention and behavior. That is, even though users have the intention to adopt, certain factors may prevent them from taking action or promoting the occurrence of adoption behavior, which remains a key issue in behavioral research [23]. Previous research indicates that perceived security can either reinforce or weaken behavioral responses depending on its level [7,24]. When students perceive the chatbot system as secure, they are more likely to convert their intention to use into sustained usage behavior [25-26]. These findings highlight the need to investigate moderating factors that may influence the strength of the relationship between intention and adoption.

*H2: IS moderates the relationship between ITUAIC and SAAIC.*

### 3. Methodology

This study employed a quantitative, cross-sectional survey design to examine the influence of students' intention to use AI chatbots on their actual adoption behavior, as well as the moderating effect of perceived information security. The research model and hypotheses were tested using SEM and moderation analysis, supported by the statistical software packages SPSS 27.0 and AMOS 28.0. Figure 1 shows the conceptual framework of this study.



**Figure 1.** Conceptual framework of this study

Participants were students from nine colleges in Nantong City, Jiangsu Province, China. Due to the diversity of the student population, the study was categorised by college name and employed a stratified random sampling method. The final dataset included 586 valid responses, a sample size exceeding the minimum recommended by Hair (2011) for data analysis [27]. Prior to analysis, the data were cleaned to remove inconsistent or patterned responses. Student participation in the survey was voluntary, and anonymity and confidentiality were guaranteed.

The survey questionnaire was adapted from existing validated scales to ensure content validity and internal consistency. The questionnaire comprises three main constructs: ITUAIC, SAAIC, and IS. All items are scored using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Data was collected through an online questionnaire, which was distributed via college mailing lists, online learning platforms, and student chat groups. Digital dissemination ensured wide accessibility and enabled real-time data monitoring. The collected data underwent multiple stages of analysis to ensure reliability, including descriptive statistics, reliability testing, validity assessment, and so on.

## 4. Results

### (1) Descriptive Statistics

Descriptive statistical analysis was used to examine the overall distribution and central tendency of the measurement items. This analysis included 586 valid responses, with mean values ranging from 3.55 to 4.11 across all items, indicating that the constructs overall exhibit a positive cognitive bias. The standard deviations of the measured items ranged from 0.816 to 0.977, indicating a moderate level of variability among participants' responses. This suggests that while responses showed some individual differences, they were generally concentrated around the mean, reflecting consistency in students' perceptions and attitudes. Additionally, most kurtosis values were positive, indicating that the distribution has a sharper peak compared to a normal distribution. These results confirm that the data is suitable for subsequent reliability analysis and structural equation modelling analysis.

### (2) Reliability and validity of the data

To assess the measurement quality of the constructs, reliability and convergent validity tests were conducted using Cronbach's alpha coefficient (CA), composite reliability (CR), and average variance extracted (AVE). As shown in Table 1, both constructs demonstrated good internal consistency. The Cronbach's alpha coefficients for ITUAIC and SAAIC were 0.927 and 0.905, respectively, both exceeding the widely accepted threshold of 0.70 [28], indicating high internal reliability. The overall Cronbach's alpha coefficient for the nine-item scale was 0.921, further confirming the strong reliability of the entire scale. In terms of convergent validity, CR values for ITUAIC and SAAIC were 0.846 and 0.800, respectively, both exceeding the recommended minimum value of 0.70 [29]. Additionally, the AVE values were 0.527 (ITUAIC) and 0.501 (SAAIC), both exceeding the 0.50 threshold [30], indicating that these constructs explain over 50% of the variance in their corresponding observed variables.

These results collectively indicate that the measurement model exhibits high reliability and satisfactory convergent validity, supporting the use of these latent constructs in further structural modelling analyses.

**Table 1.** Reliability and Validity for Constructs

Variables	N. of Items	Cronbach's Alpha	AVE	CR
ITUAIC	5	0.927	0.527	0.846
SAAIC	4	0.905	0.501	0.800
Overall	9	0.921	/	/

### (3) Moderation Analysis

To explore whether perceived information security moderates the relationship between ITUAIC and SAAIC, this study adopted a structural equation model incorporating moderating factors. The interaction term (IS×ITUAIC) was calculated by centring the means of ITUAIC and IS and then multiplying them to reduce multicollinearity, consistent with the standard procedure for moderation effect testing [31].

The moderation model was estimated using the maximum likelihood estimation method in AMOS. All variances and covariances were statistically significant, and the model fit well overall, as shown in the regression weight table. The main effect of ITUAIC on SAAIC was statistically significant

( $\beta = 0.528$ , SE = 0.040, C.R. = 13.266,  $p < 0.001$ ), indicating that students' ITUAIC have a strong positive influence on SAAIC. The main effect of IS on SAAIC is also significant ( $\beta = 0.243$ , SE = 0.041, C.R. = 5.874,  $p < 0.001$ ), indicating that students with higher perceived information security are more likely to adopt AI chatbots. Crucially, the interaction term (IS  $\times$  ITUAIC) was statistically significant ( $\beta = 0.123$ , SE = 0.036, C.R. = 3.380,  $p < 0.001$ ), confirming the moderating role of IS.

**Table 2.** Results of Moderating Effect of IS

	Path	Estimate	S.E.	C.R.	P
SAAIC	← IS	0.243	0.041	5.874	***
SAAIC	← ITUAIC	0.528	0.040	13.266	***
SAAIC	← IS $\times$ ITUAIC	0.123	0.036	3.380	***

These findings indicate that perceived information security significantly strengthens the relationship between intention and actual adoption. In other words, when students perceive AI chatbots to be more secure, the positive impact of intention on adoption becomes more pronounced. Based on the above results, H1 and H2 are supported. IS has a positive moderating effect on the relationship between ITUAIC and SAAIC.

## 5. Discussion

This study aims to explore the relationship between students' intentions to use artificial intelligence chatbots and their actual adoption behaviour, while examining the moderating role of perceived information security. The findings further expand on existing research on technology acceptance in educational settings.

First, the findings align with the Technology Acceptance Model and prior literature, confirming that intention is an important and positive predictor of actual adoption behaviour. This further supports the notion that students who form strong behavioural intentions to use AI tools are more likely to integrate them into their academic practices.

Second, the moderating role of IS adds new contributions to the literature. The significant interaction between ITUAIC and IS indicates that even if students intend to use AI chatbots, their actual adoption behaviour still depends on their perception of the system's security and reliability. This finding aligns with the emphasis on the critical role of security-related issues in shaping user trust and subsequent sustained use in digital environments. Therefore, educational institutions and developers should prioritise secure data practices and transparency in AI systems to encourage sustained use.

Additionally, the main effect of IS on SAAIC indicates that security is not only a moderating variable but also a direct influencing factor. Students with higher perceived security levels are more likely to adopt AI tools, even exceeding their initial intentions.

## 6. Conclusion

This study investigates the determinants of college students' adoption of AI chatbots, with a focus on the mediating role of perceived information security. Through structural equation modelling and moderation analysis, the findings confirm that behavioural intention has a strong predictive effect on actual adoption, and this relationship is significantly enhanced when users perceive a higher level of

information security.

The findings hold both theoretical and practical significance. Theoretically, this study enriches the Technology Acceptance Model (TAM) framework by introducing critical contextual factors (IS) as moderating variables. Practically, the research indicates that enhancing users' perceptions of security can promote the adoption and integration of AI chatbots in the education sector.

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## References

- [1] Davar, N. F., Dewan, M. A. A., & Zhang, X. (2025). AI chatbots in education: challenges and opportunities. *Information*, 16(3), 235. <https://doi.org/10.3390/info16030235>.
- [2] Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI Chatbots in Chinese higher education: adoption, perception, and influence among graduate students-an integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology*, 15, 1268549. <https://doi.org/10.3389/fpsyg.2024.1268549>.
- [3] Ma, J., Wang, P., Li, B., Wang, T., Pang, X. S., & Wang, D. (2025). Exploring user adoption of ChatGPT: A technology acceptance model perspective. *International Journal of Human-Computer Interaction*, 41(2), 1431-1445. <https://doi.org/10.1080/10447318.2024.2314358>.
- [4] Mukred, M., Asma'Mokhtar, U., Hawash, B., AlSalman, H., & Zohaib, M. (2024). The adoption and use of learning analytics tools to improve decision making in higher learning institutions: An extension of technology acceptance model. *Heliyon*, 10(4), e26315. <https://doi.org/10.1016/j.heliyon.2024.e26315>.
- [5] Maheshwari, G. (2024). Factors influencing students' intention to adopt and use ChatGPT in higher education: A study in the Vietnamese context. *Education and Information Technologies*, 29(10), 12167-12195. <https://doi.org/10.1007/s10639-023-12333-z>.
- [6] Alkhwalid, A. F., Alidarous, M. M., & Alharasis, E. E. (2024). Antecedents and outcomes of innovative blockchain usage in accounting and auditing profession: an extended UTAUT model. *Journal of Organizational Change Management*, 37(5), 1102-1132. <https://doi.org/10.1108/JOCM-03-2023-0070>.
- [7] Yang, J., Chen, Y.-L., Por, L. Y., & Ku, C. S. (2023). A Systematic Literature Review of Information Security in Chatbots. *Applied Sciences*, 13(11), 6355. <https://doi.org/10.3390/app13116355>.
- [8] Tao, W., Yang, J., & Qu, X. (2024). Utilization of, perceptions on, and intention to use AI chatbots among medical students in China: National Cross-sectional Study. *JMIR medical education*, 10(1), e57132. <https://doi.org/10.2196/57132>.
- [9] Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, 205(219), 5.

- [10] Ursavaş, Ö.F. (2022). Technology Acceptance Model: History, Theory, and Application. In: *Conducting Technology Acceptance Research in Education*. Springer, Cham, 57-91. [https://doi.org/10.1007/978-3-031-10846-4\\_4](https://doi.org/10.1007/978-3-031-10846-4_4).
- [11] Wang, M., Chen, Z., Liu, Q., Peng, X., Long, T., & Shi, Y. (2025). Understanding teachers' willingness to use artificial intelligence-based teaching analysis system: Extending TAM model with teaching efficacy, goal orientation, anxiety, and trust. *Interactive Learning Environments*, 33(2), 1180-1197. <https://doi.org/10.1080/10494820.2024.2365345>.
- [12] Mustofa, R. H., Kuncoro, T. G., Atmono, D., & Hermawan, H. D. (2025). Extending the technology acceptance model: The role of subjective norms, ethics, and trust in AI tool adoption among students. *Computers and Education: Artificial Intelligence*, 8, 100379. <https://doi.org/10.1016/j.caeai.2025.100379>.
- [13] Balaskas, S., Tsiantos, V., Chatzifotou, S., & Rigou, M. (2025). Determinants of ChatGPT Adoption Intention in Higher Education: Expanding on TAM with the Mediating Roles of Trust and Risk. *Information*, 16(2), 82. <https://doi.org/10.3390/info16020082>.
- [14] Huang, Y., & Fung, D. (2024). Impact of AI chatbots on EFL learners' technology adoption: An extension of the UTAUT2 model. *Interaction Studies*, 25(3), 340-368. <https://doi.org/10.1075/is.24019.hua>.
- [15] Choudhury, A., & Shamszare, H. (2023). Investigating the impact of user trust on the adoption and use of ChatGPT: survey analysis. *Journal of Medical Internet Research*, 25, e47184. <https://doi.org/10.2196/47184>.
- [16] Yang, M., Mamun, A. A., Mohiuddin, M., Nawari, N. C., & Zainol, N. R. (2021). Cashless transactions: A study on intention and adoption of e-wallets. *Sustainability*, 13(2), 831. <https://doi.org/10.3390/su13020831>.
- [17] Strzelecki, A. (2024). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive learning environments*, 32(9), 5142-5155. <https://doi.org/10.1080/10494820.2023.2209881>.
- [18] Stöhr, C., Ou, A. W., & Malmström, H. (2024). Perceptions and usage of AI chatbots among students in higher education across genders, academic levels and fields of study. *Computers and Education: Artificial Intelligence*, 7, 100259. <https://doi.org/10.1016/j.caeai.2024.100259>.
- [19] Roca, M. D. L., Chan, M. M., Garcia-Cabot, A., Garcia-Lopez, E., & Amado-Salvatierra, H. (2024). The impact of a chatbot working as an assistant in a course for supporting student learning and engagement. *Computer Applications in Engineering Education*, 32(5), e22750. <https://doi.org/10.1002/cae.22750>.
- [20] Al-kfairy, M. (2024). Factors impacting the adoption and acceptance of ChatGPT in educational settings: A narrative review of empirical studies. *Applied System Innovation*, 7(6), 110. <https://doi.org/10.3390/asi7060110>.
- [21] Palanisamy, R., & Wu, Y. (2021). Users' attitude on perceived security of enterprise systems mobility: an empirical study. *Information & Computer Security*, 29(1), 159-186. <https://doi.org/10.1108/ICS-05-2020-0069>.
- [22] Famaye, T., Adisa, I.O., Irgens, G.A. (2023). To Ban or Embrace: Students' Perceptions Towards Adopting Advanced AI Chatbots in Schools. In: Arastoopour Irgens, G., Knight, S. (eds) *Advances in Quantitative Ethnography*. ICQE 2023. *Communications in Computer and Information Science*, vol. 1895. Springer, Cham. [https://doi.org/10.1007/978-3-031-47014-1\\_10](https://doi.org/10.1007/978-3-031-47014-1_10).
- [23] Hasan, S., Godhuli, E. R., Rahman, M. S., & Al Mamun, M. A. (2023). The adoption of conversational assistants in the banking industry: is the perceived risk a moderator?. *Heliyon*, 9(9), e20220. <https://doi.org/10.1016/j.heliyon.2023.e20220>.
- [24] Lim, S. H., Kim, D. J., Hur, Y., & Park, K. (2019). An empirical study of the impacts of perceived security and knowledge on continuous intention to use mobile fintech payment services. *International Journal of Human-Computer Interaction*, 35(10), 886-898. <https://doi.org/10.1080/10447318.2018.1507132>.
- [25] Acosta-Enriquez, B. G., Arbulú Ballesteros, M. A., Huamani Jordan, O., López Roca, C., & Saavedra Tirado, K. (2024). Analysis of college students' attitudes toward the use of ChatGPT in their academic activities: effect of intent to use, verification of information and responsible use. *BMC psychology*, 12(1), 255. <https://doi.org/10.1186/s40359-024-01764-z>.
- [26] Arpaci, I. (2023). A multianalytical SEM-ANN approach to investigate the social sustainability of AI chatbots based on cybersecurity and protection motivation theory. *IEEE Transactions on Engineering Management*, 71, 1714-1725. <https://doi.org/10.1109/TEM.2023.3339578>.
- [27] Hair, J. F. (2011). Multivariate data analysis: An overview. *International encyclopedia of statistical science*, 904-907. [https://doi.org/10.1007/978-3-642-04898-2\\_395](https://doi.org/10.1007/978-3-642-04898-2_395).
- [28] Taber, K. S. (2018). The use of Cronbach's alpha when developing and reporting research instruments in science education. *Research in science education*, 48(6), 1273-1296. <https://doi.org/10.1007/s11165-016-9602-2>.
- [29] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, 18(1), 39-50. <https://doi.org/10.1177/002224378101800104>.
- [30] Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia pacific journal of management*, 41(2), 745-783. <https://doi.org/10.1007/s10490-023-09871-y>.
- [31] Aiken, L. S. (1991). *Multiple regression: Testing and interpreting interactions*. sage.