e-ISSN 2549-7472
Edumatic: Jurnal Pendidikan Informatika
Volume 10, Issue 1, **190-199.**
https://e-journal.hamzanwadi.ac.id/index.php/edumatic
DOI: 10.29408/edumatic.v10i1.34218

Utilitarian vs Human-Centered AI Acceptance: Explaining Students' Adoption of ChatGPT in Higher Education

Dwi Angesti Dinda Parameswara[1,*], Berlilana [1], Rujianto Eko Saputro [1]

[1] Universitas Amikom Purwokerto, Indonesia
[*] Corresponding author: Dwi Angesti Dinda Parameswara, Universitas Amikom Purwokerto, Indonesia
24MA41D057@students.amikompurwokerto.ac.id

Received: 1 March 2026 | Revised: 15 March 2026 | Accepted: 14 April 2026 | Published: 26 April 2026

Abstract
The growing use of generative artificial intelligence (AI) in higher education raises questions about how students assess and adopt these systems, particularly whether traditional utilitarian models are sufficient to explain their use. This study compares the Technology Acceptance Model (TAM) and the Human-Centered AI Acceptance Model (HCAIAM) in explaining students' behavioral intention to use ChatGPT, while examining how functional and human-centered factors operate within the same framework. A cross-sectional design was used, involving 100 undergraduate students in Indonesia selected through convenience sampling, and the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that TAM provides stronger explanatory power and better model fit ($R^2 = 0.765$; SRMR = 0.073) than HCAIAM ($R^2 = 0.709$; SRMR = 0.136). Perceived usefulness and perceived ease of use emerge as the main drivers of intention, indicating that students tend to use ChatGPT primarily as a tool to support academic tasks. In contrast, human-centered factors such as transparency and ethical alignment influence intention indirectly through trust and attitude. The autonomy construct shows weak reliability and overlaps with other variables, suggesting limitations in its measurement. These findings indicate that utilitarian factors remain central in this context, while human-centered aspects play a more conditional role, and point to a layered pattern of AI acceptance in which different types of factors operate at different levels.

Keywords: behavioral intention; chatgpt; higher education; human-centered AI; technology acceptance model

To cite this article: Parameswara, D. A. D., Berlilana, B., & Saputro, R. E. (2026). Utilitarian vs Human-Centered AI Acceptance: Explaining Students' Adoption of ChatGPT in Higher Education. *Edumatic: Jurnal Pendidikan Informatika*, *10*(1), 190–199. https://doi.org/10.29408/edumatic.v10i1.34218

INTRODUCTION

The widespread diffusion of generative Artificial Intelligence (AI), particularly systems such as ChatGPT, is reshaping how students engage with knowledge, learning processes, and academic work. Unlike earlier digital tools, generative AI systems are capable of producing human-like content, facilitating interactive dialogue, and supporting complex cognitive tasks in real time. These systems are increasingly utilized in higher education to assist with comprehending course materials, generating ideas, and drafting assignments (Dwivedi et al., 2023; Kasneci et al., 2023; Sallam et al., 2023; Zhu et al., 2024). At the same time, AI is expected to support human-centered learning by enhancing understanding and providing personalised assistance (Khosravi et al., 2022). However, its widespread adoption also raises concerns related to academic integrity, reliability, bias, and ethical implications (Cotton et al., 2024; Denecke et al., 2023; Nzenwata et al., 2024; Yan et al., 2024). In particular, generative AI may produce inaccurate or biased information, raising questions about its reliability in academic contexts (Gill et al., 2024). These developments position generative AI not only as a technological innovation but also as a shift in how humans interact with intelligent systems in education.

While this transformation is evident, research on technology acceptance continues to be predominantly rooted in utilitarian perspectives, particularly the Technology Acceptance Model (TAM), which explains user behaviour through perceived usefulness and perceived ease of use (Davis, 1989). Empirical studies on ChatGPT consistently show that perceived usefulness is a strong predictor of students' intention to use AI tools (Zhu et al., 2024), suggesting that students tend to evaluate generative AI primarily in terms of its contribution to task performance. However, this perspective may not fully capture the complexity of generative AI adoption. Unlike conventional technologies, generative AI systems operate autonomously, produce unpredictable outputs, and interact with users in conversational ways. These characteristics introduce additional considerations such as trust, transparency, and ethical alignment, which extend beyond performance-based evaluation (Bouyzourn & Birch, 2025; Shin, 2021). Moreover, limited explainability may reduce user trust and hinder acceptance when users cannot fully understand how AI outputs are generated (Khosravi et al., 2022).

This situation reflects a broader theoretical tension. On one side, utilitarian model such as TAM assume that technology adoption is driven mainly by efficiency and performance considerations. On the other side, human-centered AI perspectives argue that acceptance depends on whether systems align with human values, ensure transparency, and support user agency. Human-centered AI emphasises the design of systems that are interpretable (Bevilacqua et al., 2025; Fetaji et al., 2024), trustworthy, and responsive to user needs (Khosravi et al., 2022), while recent studies highlight that large language models introduce ethical and practical challenges that cannot be fully addressed by traditional adoption frameworks (Yan et al., 2024). The Human-Centered AI Acceptance Model (HCAIAM) reflects this perspective by incorporating constructs such as trust, transparency, ethical alignment, and autonomy (Schmager et al., 2025). However, it remains unclear how these human-centered factors operate in practice and whether they function independently or are embedded within utilitarian evaluations.

A number of limitations in the existing literature remain evident. First, most studies continue to priorities utilitarian factors, implicitly assuming that performance-based evaluation is sufficient to explain AI adoption. This overlooks the possibility that generative AI introduces new forms of interaction that require different theoretical approaches. Second, findings on human-centered constructs, particularly trust, remain inconsistent, with some studies reporting direct effects while others identify only indirect relationships. Third, only a limited number of studies examine utilitarian and human-centered models within a unified framework, thereby constraining understanding of how these perspectives interact. As a result, it remains unclear whether these models represent competing explanations or complementary layers of the same phenomenon.

In response to these limitations, this study undertakes a comparison between TAM and HCAIAM in explaining students' behavioural intention to use ChatGPT. Rather than concentrating solely on which model demonstrates superior performance, the study explores how utilitarian and human-centered factors jointly shape AI acceptance. More specifically, it examines whether performance-based factors continue to play a dominant role or whether human-centered considerations offer additional explanatory power within the context of generative AI.

Building on this perspective, the study proposes a layered acceptance framework in which utilitarian and human-centered factors operate at different levels of evaluation. Utilitarian factors explain baseline, task-oriented adoption, while human-centered factors shape higher-order, experience-based evaluation. This perspective moves beyond a simple model comparison and offers a more integrated understanding of generative AI acceptance.

This study makes three contributions. First, it provides empirical evidence on the relative and combined roles of utilitarian and human-centered factors in generative AI adoption. Second, it contributes to technology adoption theory by clarifying the relationship between these perspectives, suggesting that they operate at different levels rather than as competing models. Third, it situates the findings within broader discussions on human AI interaction and responsible AI use in education, offering insights for both research and practice.

METHOD

A quantitative predictive-explanatory approach was employed to examine and compare the ability of TAM and HCAIAM to explain students' intention to use ChatGPT. Data were collected through a cross-sectional survey involving undergraduate students at Universitas Amikom Purwokerto who had prior experience using ChatGPT. Using convenience sampling, 128 responses were obtained, of which 100 valid responses were retained after data screening. A post hoc power analysis (Cohen, 1988) confirmed that the sample size was sufficient to detect medium effect sizes, although generalizability remains limited.

All variables were treated as reflective constructs, and measurement items were adapted from prior studies and adjusted to the context of generative AI in higher education. TAM includes perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (ATU), and behavioral intention (BI), while HCAIAM includes transparency (ET), trust in AI (TR), ethical alignment (EA), and user autonomy (AC), along with ATU and BI. Each construct was measured using two to four indicators on a five-point Likert scale. The instrument was reviewed by three experts to ensure clarity and content validity, and minor revisions were made accordingly. To reduce common method bias, procedural remedies were applied, including ensuring respondent anonymity and randomizing the order of questionnaire items.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4, as it is suitable for prediction-oriented research, accommodates relatively small sample sizes, and does not require strict normality assumptions (Hair et al., 2017). The analysis followed a two-stage procedure involving measurement and structural model evaluation. Convergent validity was assessed through outer loadings and Average Variance Extracted (AVE), with thresholds of 0.70 and 0.50, respectively, while internal consistency reliability was evaluated using Composite Reliability (CR), with values above 0.70 considered acceptable.

Discriminant validity was assessed using the Heterotrait Monotrait ratio (HTMT), which is considered more reliable than traditional approaches such as the Fornell Larcker criterion. HTMT values below 0.90 indicate that constructs are empirically distinct (Hair et al., 2019). For the structural model, hypothesis testing was conducted using bootstrapping with 5,000 resamples to estimate path coefficients and their significance. Model performance was evaluated using the coefficient of determination (R^2) and effect size (f^2), which indicate explanatory power and the contribution of each predictor.

Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), with values below 0.08 indicating good fit, and the Normed Fit Index (NFI), where values closer to 1 indicate better fit. Multicollinearity was examined using the Variance Inflation Factor (VIF), with values below 5 indicating no critical issues. Common method bias was assessed using Harman's single-factor test, where variance below 50% suggests that bias is not a major concern.

Finally, the two models were compared based on their predictive performance, including differences in R^2, effect sizes, and model fit indices, focusing on relative explanatory power rather than formal statistical comparison. This approach aligns with recent recommendations in PLS-SEM research that emphasize prediction and model comparison.

RESULT AND DISCUSSION

Results

The measurement model results presented in Table 1 show that most constructs meet the recommended criteria for reliability and convergent validity. Indicator loadings range from 0.786 to 0.954, all exceeding the acceptable threshold, while Average Variance Extracted (AVE) values are above 0.50 and Composite Reliability (CR) values are consistently above 0.70. These values indicate that the constructs are measured with adequate consistency and capture sufficient variance from their indicators. One exception is observed in the autonomy (AC) construct, where the Cronbach's alpha value is relatively low ($\alpha = 0.468$), suggesting weaker internal consistency compared to the other constructs.

Table 1. Measurement model evaluation

Construct	Indicator	Loading	AVE	CR	Alpha
PU	PU1–PU4	0.801–0.900	0.748	0.922	0.887
PEOU	PEOU1–4	0.786–0.884	0.728	0.914	0.875
ATU (TAM)	ATU1–2	0.929–0.944	0.876	0.934	0.860
BI (TAM)	BI1–2	0.949–0.954	0.776	0.933	0.904
ET	ET1–2	0.905–0.911	0.825	0.904	0.788
TR	TR1–3	0.891–0.903	0.807	0.926	0.881
EA	EA1–2	0.902–0.950	0.857	0.923	0.838
AC	AC1–2	0.782–0.833	0.652	0.789	0.468

Further evidence is provided by the discriminant validity assessment in Table 2. Most construct pairs fall within acceptable HTMT thresholds, indicating that the constructs are generally distinct. However, several HTMT values involving autonomy exceed the threshold of 0.90, particularly AC–BI (1.068) and AC–ET (1.029). This pattern suggests that autonomy is not clearly differentiated from related constructs and may overlap conceptually with other variables in the model.

Table 2. HTMT matrix

Construct	AC	ATU	BI	EA	ET	TR
AC	-	0.958	1.068	0.976	1.029	0.948
ATU		-	0.820	0.633	0.767	0.736
BI			-	0.806	0.869	0.853
EA				-	0.861	0.839
ET					-	0.969
TR						-

The structural model results are summarized in Table 3 and illustrated in Figure 1 and Figure 2. In the TAM model, the relationships among constructs show strong explanatory power, with R^2 values of 0.751 for attitude (ATU) and 0.765 for behavioral intention (BI), as reported in Table 4. The relationship between perceived ease of use (PEOU) and perceived usefulness (PU) is the strongest ($\beta = 0.655$), followed by the influence of attitude on behavioral intention (β = 0.552). Perceived usefulness also contributes directly to behavioral intention (β = 0.368), and all hypothesized paths are statistically significant ($p < 0.05$).

Table 3. Structural model results

Path	β	t	p	CI (LL)	CI (UL)	f²
PEOU → PU	0.655	6.754	0.000	0.437	0.813	0.750
PU → ATU	0.513	6.507	0.000	0.350	0.659	0.605
PEOU → ATU	0.439	5.509	0.000	0.292	0.604	0.442
PU → BI	0.368	3.340	0.001	0.138	0.570	0.206
ATU → BI (TAM)	0.552	4.756	0.000	0.320	0.777	0.466
ET → TR	0.577	6.325	0.000	0.386	0.736	0.568
EA → TR	0.329	3.652	0.000	0.163	0.514	0.185
TR → ATU	0.431	4.232	0.000	0.232	0.625	0.220
AC → ATU	0.342	3.062	0.002	0.113	0.554	0.138
ATU → BI (HCAIAM)	0.711	9.598	0.000	0.536	0.825	2.440

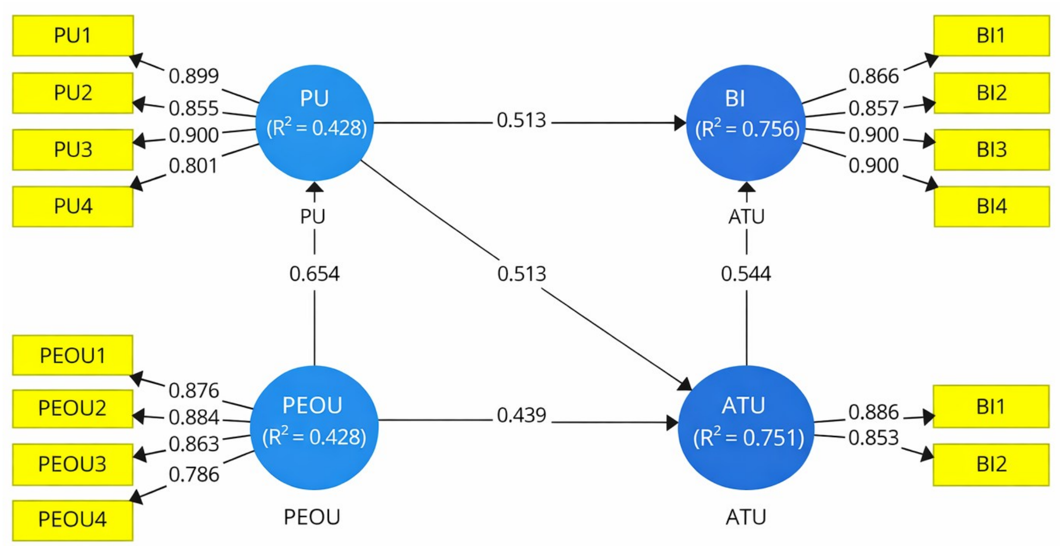

Figure 1. TAM structural model

In the HCAIAM model, the explanatory power is lower, with R^2 values of 0.487 for attitude and 0.505 for behavioral intention. The strongest effect is observed between attitude and behavioral intention (β = 0.711), while transparency shows a strong influence on trust (β = 0.577). Trust (β = 0.431) and autonomy (β = 0.342) both contribute to attitude, although their effects are smaller compared to the main paths observed in the TAM model. All structural relationships remain statistically significant, but their contribution to overall model performance appears more limited.

The comparison of both models is summarized in Table 4. The TAM model shows higher explanatory power for both attitude and behavioral intention, while also demonstrating better model fit, with SRMR = 0.069 and NFI = 0.807. In contrast, the HCAIAM model shows weaker fit indices, with SRMR = 0.148 and NFI = 0.652. These differences indicate that the TAM model aligns more closely with the observed data. Collinearity statistics presented in Table 5 show that all Variance Inflation Factor (VIF) values are below five. This indicates that multicollinearity is not present and does not affect the estimation of the structural relationships in either model.

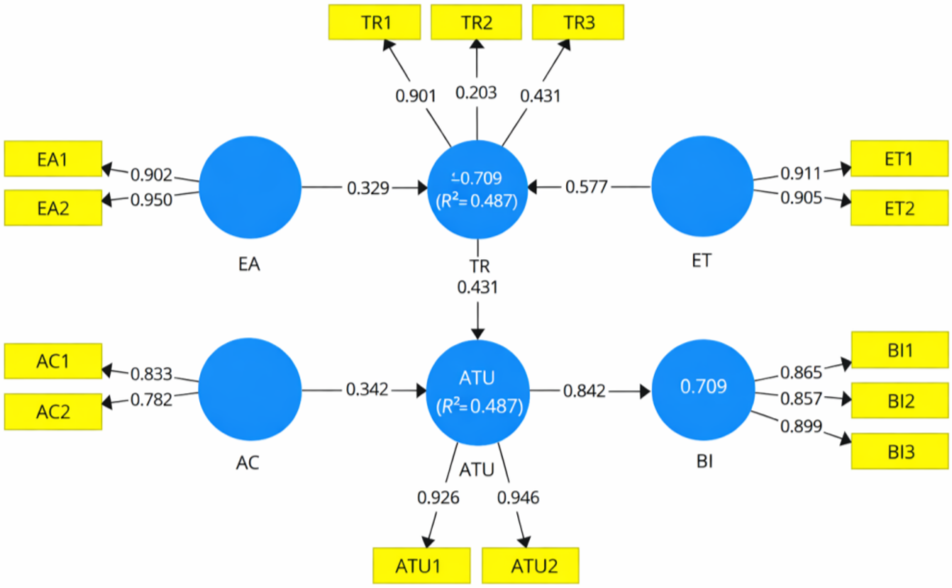

Figure 2. HCAIAM structural model

Table 4. Model evaluation summary

Construct / Model	R^2	Adj. R^2	SRMR	NFI
PU	0.428	0.423	-	-
ATU (TAM)	0.751	0.746	0.069	0.807
BI (TAM)	0.765	0.760	-	-
TR	0.709	0.703	-	-
ATU (HCAIAM)	0.487	0.477	0.148	0.652
BI (HCAIAM)	0.505	0.500	-	-

Table 5. Collinearity statistics

Model	Relationship	VIF
TAM	PEOU → PU	1.000
	PU → ATU	1.750
	PEOU → ATU	1.750
	ATU → BI	2.785
	PU → BI	2.785
HCAIAM	ET → TR	2.009
	EA → TR	2.009
	TR → ATU	1.647
	AC → ATU	1.647
	ATU → BI	1.000

Discussion

The results reveal a clear difference between the two models. TAM demonstrates stronger predictive power and better model fit, while HCAIAM shows weaker performance, particularly in the attitude construct and measurement quality. This suggests that the effectiveness of each model depends on how users interact with the system and what type of evaluation dominates their decision-making. In this study, students primarily use ChatGPT for task completion, which reinforces the dominance of utilitarian evaluation over human-centered considerations, a pattern also noted in recent studies on generative AI use in education (Gill et al., 2024).

This pattern can be understood from how students engage with ChatGPT in academic contexts. The system is mainly used for writing, summarising, and generating ideas, where usefulness and ease of use become central. This aligns with TAM (Davis, 1989) and prior research highlighting the importance of performance-related factors in technology adoption (Venkatesh et al., 2012), as well as recent findings showing that perceived usefulness remains a key predictor in generative AI adoption (Shahzad et al., 2024). At the same time, ChatGPT has been shown to improve learning efficiency and support academic tasks, reinforcing its role as a productivity-oriented tool (Gill et al., 2024). These results indicate that student's approach ChatGPT primarily as a functional system aimed at improving task performance.

This finding helps explain why TAM demonstrates stronger performance in this context. TAM is grounded in instrumental reasoning, whereby users evaluate technology based on its capacity to enhance task performance. In contrast, HCAIAM assumes that users assess AI systems through broader human-centered dimensions, including trust, autonomy, and ethical alignment. However, these dimensions may not fully manifest in task-oriented usage, particularly at early stages of adoption. As indicated by Yan et al. (2024), users tend to prioritise immediate utility when engaging with generative AI, while ethical and experiential considerations become more salient in more reflective forms of use. From a human-centered AI perspective, these factors are expected to gain greater importance as users develop deeper understanding and interaction with AI systems (Khosravi et al., 2022)

The role of trust in this study also differs from earlier findings. Trust does not directly influence behavioural intention but operates through attitude, contrasting with studies that position trust as a primary determinant of AI adoption (Choung et al., 2023). A possible explanation is that trust in this context is closely tied to system performance. Students appear to trust ChatGPT when it produces useful and reliable outputs rather than because it satisfies broader expectations such as transparency or fairness. This interpretation is consistent with research showing that trust in generative AI is often grounded in output quality (Nzenwata et al., 2024), as well as studies emphasising the importance of explainability in building sustainable trust (Khosravi et al., 2022). Differences in AI literacy may also contribute to the indirect role of trust.

The autonomy construct presents a more complex issue. The results show weak reliability and overlap with other variables, indicating that autonomy is not clearly captured. In practice, students may not seek control when using generative AI but instead prefer to delegate tasks to reduce effort, leading to overlap with usefulness and trust. Recent studies suggest that human AI interaction often involves a shift from control to delegation, where users willingly transfer decision-making to the system in exchange for efficiency (Adam et al., 2024; Fuchs et al., 2024; Yan et al., 2024). In addition, generative AI creates interactive learning environments that may blur distinctions between control, assistance, and reliability (Baidoo-Anu & Ansah, 2023), particularly when users have limited understanding of how AI systems operate (Khosravi et al., 2022).

Another key finding is the strong role of attitude in the HCAIAM model. The large effect of attitude on behavioural intention indicates that overall evaluation remains central when multiple human-centered factors are involved, consistent with prior studies on affective responses in technology use (Hasan et al., 2024; Lai et al., 2024). This is also supported by recent findings showing that attitude mediates the relationship between trust and behavioural intention in ChatGPT adoption (Polyportis & Pahos, 2025). However, the unusually high effect size may also indicate structural overlap between constructs or limitations in measurement, suggesting that some human-centered constructs are not yet fully distinct.

Taken together, the findings point to a layered pattern of AI acceptance. Usefulness and ease of use operate as primary drivers, while human-centered factors such as trust, autonomy, and ethical considerations play a supporting role and influence behavioural intention indirectly through attitude. This suggests that human-centered factors are context-dependent and become more relevant as users move beyond purely functional use, particularly as awareness of AI limitations increases (Gill et al., 2024).

This study advances a layered acceptance framework in which TAM accounts for baseline, task-oriented adoption, while HCAIAM captures deeper, experience-based evaluation. This perspective suggests that the two models function at different levels rather than as competing approaches. TAM is more applicable in efficiency-driven contexts, whereas HCAIAM becomes increasingly relevant in more reflective and critical engagement with AI systems. In doing so, the study contributes to technology adoption theory by integrating utilitarian and human-centered perspectives into a unified framework, responding to recent calls for hybrid models (Khosravi et al., 2022).

In practical terms, the findings indicate that system performance and usability should remain the primary focus when integrating generative AI into educational contexts. At the same time, developers and institutions need to progressively incorporate human-centered dimensions, including transparency, explainability, and user control. Overlooking these aspects may constrain long-term adoption (Yan et al., 2024), whereas enhancing AI literacy can support more informed user evaluation and mitigate the risk of overreliance (Gill et al., 2024).

These findings should be interpreted with caution, as the use of convenience sampling and a relatively limited sample size may restrict generalizability. Furthermore, as noted by Khosravi et al. (2022), measurement challenges in constructs such as autonomy highlight the need for further refinement. Future research should therefore consider alternative conceptualizations and examine how these constructs evolve with increased user experience in generative AI, particularly in relation to explainability, trust development, and human AI collaboration.

CONCLUSION

This study shows that TAM has stronger explanatory power than HCAIAM in predicting students' intention to use ChatGPT, with perceived usefulness and ease of use acting as the main drivers of adoption, while human-centered factors such as trust and ethical alignment influence intention indirectly through attitude. The findings support a layered view of AI acceptance in which utilitarian factors function as primary drivers of task-oriented use, whereas human-centered dimensions shape higher-level, experience-based evaluation, indicating that both perspectives are complementary rather than competing. Practically, the results highlight the importance of prioritizing system performance and usability while progressively integrating human centered features such as transparency and explainability to support sustainable adoption. However, the findings should be interpreted with caution due to sampling and measurement limitations, suggesting the need for further validation in future research.

REFERENCES

Adam, M., Diebel, C., Goutier, M., & Benlian, A. (2024). Navigating autonomy and control in human-AI delegation: User responses to technology-versus user-invoked task allocation. *Decision Support Systems*, *180*, 114193. https://doi.org/10.1016/j.dss.2024.114193

Baidoo-Anu, D., & Ansah, L. O. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting Teaching and Learning. *Journal of AI*, *7*(1), 52–62. https://doi.org/10.61969/jai.1337500

Bevilacqua, R., Bailoni, T., Maranesi, E., Amabili, G., Barbarossa, F., Ponzano, M., ... & Sakellariou, G. (2025). Framing the human-centered artificial intelligence concepts and methods: Scoping review. *JMIR Human Factors*, *12*, e67350. https://doi.org/10.2196/67350

Bouyzourn, K., & Birch, A. (2025). What Shapes User Trust in ChatGPT? A Mixed-Methods

Study of User Attributes, Trust Dimensions, Task Context, and Societal Perceptions among University Students. *arXiv preprint arXiv:2507.05046*.
Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. *International Journal of Human-Computer Interaction*, *39*(9), 1727–1739. https://doi.org/10.1080/10447318.2022.2050543
Cohen, J. (1988). *Statistical Power Analysis for the Behavioral Sciences Second Edition* (2nd ed.). Lawrence Erlbaum Associates.
Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*, *61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148
Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly: Management Information Systems*, *13*(3), 319–339. https://doi.org/10.2307/249008
Denecke, K., Glauser, R., & Reichenpfader, D. (2023). Assessing the Potential and Risks of AI-Based Tools in Higher Education: Results from an eSurvey and SWOT Analysis. *Trends in Higher Education*, *2*(4), 667–688. https://doi.org/10.3390/higheredu2040039
Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., … Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, *71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642
Fetaji, B., Fetaji, M., Ebibi, M., & Dimovski, A. (2024). Analyzing and Visualizing AI Decision-Making for Human-Centered Interaction and Trust. *International Symposium on Signal and Image Processing*, 77-89. Singapore: Springer Nature. https://doi.org/10.1007/978-981-97-9515-4_6
Fuchs, A., Passarella, A., & Conti, M. (2024). Optimizing delegation in collaborative human-AI hybrid teams. *ACM Transactions on Autonomous and Adaptive Systems*, *19*(4), 1-33. https://doi.org/10.1145/3687130
Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., Fuller, S., Singh, M., Arora, P., Parlikad, A. K., Stankovski, V., Abraham, A., Ghosh, S. K., Lutfiyya, H., Kanhere, S. S., Bahsoon, R., Rana, O., Dustdar, S., Sakellariou, R., … Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots. *Internet of Things and Cyber-Physical Systems*, *4*, 19–23. https://doi.org/10.1016/j.iotcps.2023.06.002
Hair, J. F., Hult, G. T., Ringle, C., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM). In *Sage* (2nd ed.). SAGE Publications.
Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203
Hasan, R., Ismail, N., Rahman, H., & Bin, A. (2024). Computers in Human Behavior : Artificial Humans Understanding AI Chatbot adoption in education : PLS-SEM analysis of user behavior factors. *Computers in Human Behavior: Artificial Humans*, *2*, 100098. https://doi.org/10.1016/j.chbah.2024.100098
Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., … Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274.

https://doi.org/10.1016/j.lindif.2023.102274

Khosravi, H., Shum, S. B., Chen, G., Conati, C., Tsai, Y. S., Kay, J., Knight, S., Martinez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable Artificial Intelligence in education. *Computers and Education: Artificial Intelligence*, *3*. https://doi.org/10.1016/j.caeai.2022.100074

Lai, C. Y., Cheung, K. Y., Chan, C. S., & Law, K. K. (2024). Integrating the adapted UTAUT model with moral obligation, trust and perceived risk to predict ChatGPT adoption for assessment support: A survey with students. *Computers and Education: Artificial Intelligence*, *6*, 100246. https://doi.org/10.1016/j.caeai.2024.100246

Nzenwata, U. J., Barn-Nzekwe, C. L., Ojelabi, E. O., Oduware, O., Atalor, P. E., Yisau, Y., Adeyela, A. T., Nwanguma, E. C., Emokiniovo, E., & Osisanya, O. A. (2024). A Systematic Review of Generative AI in Education. *Journal of Computer Sciences and Applications*, *12*(1), 25–30. https://doi.org/10.12691/jcsa-12-1-4

Polyportis, A., & Pahos, N. (2025). Understanding students' adoption of the ChatGPT chatbot in higher education: the role of anthropomorphism, trust, design novelty and institutional policy. *Behaviour and Information Technology*, *44*(2), 315–336. https://doi.org/10.1080/0144929X.2024.2317364

Sallam, M., Salim, N. A., Barakat, M., Al-Mahzoum, K., Al-Tammemi, A. B., Malaeb, D., Hallit, R., & Hallit, S. (2023). Assessing Health Students' Attitudes and Usage of ChatGPT in Jordan: Validation Study. *JMIR Medical Education*, *9*(1), 1–15. https://doi.org/10.2196/48254

Schmager, S., Pappas, I. O., & Vassilakopoulou, P. (2025). Understanding Human-Centred AI: a review of its defining elements and a research agenda. *Behaviour & Information Technology*, *44*(15), 3771-3810. https://doi.org/10.1080/0144929X.2024.2448719

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: the role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education*, *21*, 1–23. https://doi.org/10.1186/s41239-024-00478-x

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Venkatesh, V., Walton, S. M., & Thong, J. Y. L. (2012). Quarterly Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology1. *MIS Quarterly*, *36*, 157–178. https://doi.org/10.2307/41410412

Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2024). Practical and ethical challenges of large language models in education: A systematic scoping review. *British Journal of Educational Technology*, *55*(1), 90–112. John Wiley and Sons Inc. https://doi.org/10.1111/bjet.13370

Zhu, C. Z. G., Hall, C. M., Fong, L. H. N., Lin, F., & Naderi Koupaei, S. (2024). Examining the effects of ChatGPT on tourism and hospitality student responses through integrating technology acceptance model. *International Journal of Tourism Research*, *26*(4), e2727. https://doi.org/10.1002/jtr.2727