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A Human-Centered Computing-Based Artificial Intelligence Implementation Strategy to Enhance User Interaction in E-Learning

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ABSTRACT

This study aims to analyze an artificial intelligence implementation strategy based on Human-Centered Computing to enhance user interaction in e-learning. The study responds to the growing use of AI in digital learning environments and the need to ensure that AI systems remain transparent, ethical, useful, and aligned with users' learning needs. This research used a qualitative case study design at a higher education institution in Indonesia that had implemented a Learning Management System with AI-based features, including learning chatbots, automated feedback, material recommendations, and learning analytics. Data were collected through semi-structured interviews, limited participatory observation, and documentation. The participants consisted of students, lecturers, e-learning administrators, and information technology staff selected through purposive sampling and expanded through snowball sampling when needed. The data were analyzed using thematic analysis. The findings reveal five main themes: perceived usefulness of AI-assisted interaction, trust and transparency in AI feedback, user control and human supervision, digital readiness and institutional support, and the need for more human-centered AI design. These findings show that AI can improve e-learning interaction when it supports real learning tasks, provides understandable feedback, maintains human oversight, and receives adequate institutional support. The study contributes to Human-Centered Computing literature by showing that AI-supported learning interaction is not only a technical issue but also a pedagogical, ethical, and social process. Future research should examine AI-based e-learning across different institutions and learning contexts.

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1. Introduction

The introduction serves as a crucial opening for the research paper. It should capture the reader's attention and provide essential context for understanding the content of the research. The author(s) must clearly address the research problem, offer relevant background information, and establish their work within the existing body of research. Additionally, the introduction should justify the study's significance and outline the paper's structure and contributions.

The development of artificial intelligence in education has changed the way learners access learning materials, receive feedback, and interact with digital learning systems. E-learning no longer functions only as a space for storing course materials. It has developed into an adaptive, personalized, and data-driven learning ecosystem. Chen et al. (2020) explain that AI in education supports intelligent tutoring systems, automated assessment, learning recommendations, and learning behavior analysis. Crompton and Burke (2023) also found that the use of AI in higher education has increased because educational institutions seek learning models that respond better to students' needs. This change shows that AI has strong potential to strengthen learning experiences. However, this potential has not always been followed by an implementation strategy that places humans at the center of system design.

In e-learning practice, the main problem does not only lie in technology availability. It also lies in the quality of interaction between users and the system. Students often experience fragmented learning, overly general feedback, unintuitive system navigation, and low engagement in online classes. El-Sabagh (2021) shows that adaptive e-learning environments can improve student engagement when systems adjust to users' learning styles and needs. Essel et al. (2022) also found that chatbots as virtual teaching assistants can support learning when the system provides relevant and understandable responses. However, the use of AI does not automatically improve learning interaction. AI systems can fail to support learning when their design focuses only on automation and ignores user needs, control, and experience.

This issue is important because interaction in e-learning directly relates to learning motivation, user trust, academic engagement, and the sustainability of system use. From the perspective of Human-Centered Computing, educational technology needs to place humans at the center of the design process. Shneiderman (2020) emphasizes that human-centered AI must balance computer automation and human control. Yang et al. (2021) extend this idea in education by stressing the importance of examining invisible aspects of digital learning, such as attention, emotion, understanding, and students' cognitive processes. Khosravi et al. (2022) also argue that educational AI needs explainability so users can understand the reasons behind system recommendations, feedback, or decisions. Therefore, AI implementation strategies in e-learning must move beyond feature integration toward transparent, ethical, and user-friendly interaction design.

Previous studies have examined AI in education from various perspectives. Ouyang et al. (2022) show that AI in online higher education is widely used for learning personalization, learning analytics, assessment, and instructional support. Kasneci et al. (2023) explain that large language models can support learning through adaptive explanation, writing assistance, and cognitive support. Chan and Hu (2023) found that students view generative AI as a useful tool, but they remain concerned about accuracy, ethics, privacy, and dependency. Albayati (2024) also shows that perceived usefulness, ease of use, privacy, security, social influence, and trust affect students' acceptance of ChatGPT as a learning support tool. These findings show that the success of AI in e-learning cannot be measured only by system sophistication. It must also be understood through users' direct experiences.

Although research on AI in education has grown rapidly, most studies still focus on technical benefits, learning effectiveness, AI literacy, or general technology acceptance. Wang et al. (2024) show that educational AI research has covered adaptive learning, personal tutors, intelligent assessment, learning behavior prediction, and new AI products, but it still needs stronger studies on design, context, and user experience. Tzirides et al. (2024) argue that AI literacy in higher education needs to combine human intelligence and artificial intelligence so students do not only use AI but also understand its limitations and responsibilities. Kajiwara and Kawabata (2024) show that ethical acceptance of chatbots is influenced by perceived usefulness, fairness, privacy, and data protection. Topali et al. (2025) also emphasize that AI and learning analytics solutions require designs that involve the needs of educational stakeholders. This gap shows the need for qualitative research that explores meanings, experiences, barriers, and AI implementation strategies from the perspective of e-learning users.

Based on this background, this study aims to analyze an artificial intelligence implementation strategy based on Human-Centered Computing to enhance user interaction in e-learning. The study focuses on user experience, forms of interaction generated by AI systems, implementation barriers, design needs, and principles for developing more human-centered systems. Chiu (2024) emphasizes that AI-based transformation in higher education requires a research agenda that views technology not only as a tool but also as part of a pedagogical ecosystem. Le Dinh et al. (2025) also stress the importance of a human-centered approach to ensure that AI continues to involve human supervision, ethical consideration, and responsible decision-making. Theoretically, this study contributes to the development of Human-Centered Computing studies in the context of AI-based educational technology. Practically, this study can guide e-learning developers, lecturers, and educational institution managers in designing AI systems that align with learning needs, trust, and user comfort.

2. Materials and Methods

In the method section, the author(s) should provide a detailed account of the procedures, materials, and equipment used in the research. This includes a comprehensive description of the study design, participants or subjects, materials used, procedures followed, and data analysis techniques employed. The goal is to offer sufficient information for other researchers to replicate the study, thereby ensuring the reproducibility and validity of the findings.

This study uses a qualitative approach with a case study design. This design fits the study because the research focuses on an in-depth understanding of artificial intelligence implementation strategies based on Human-Centered Computing to enhance user interaction in e-learning. A case study design is suitable because the phenomenon relates to a specific context, namely the use of AI features in a digital learning system within a higher education institution. This approach allows the researcher to explore user experiences, interaction patterns, technical barriers, design needs, and the perceptions of students, lecturers, and system managers toward AI use. Hu and Chan (2025) show that a human-centered design approach can connect user needs with more relevant AI solutions in digital learning. Shuhaiber et al. (2025) also confirm that trust, perceived ease of use, perceived usefulness, and risk influence students' attitudes toward the use of AI chatbots in higher education.

The study takes place at one university in Indonesia that has used a Learning Management System and has begun to integrate AI features, such as learning chatbots, material recommendation systems, automated feedback, and learning activity analytics. The research period lasts three months, from March to May 2025, so the researcher can observe e-learning use within one lecture cycle. The research subjects include students, lecturers, e-learning administrators, and information technology staff. The researcher selects participants through purposive sampling because the study requires informants who have direct experience in using or managing AI-based e-learning systems. Campbell et al. (2020) explain that purposive sampling is appropriate when researchers need participants who are relevant to the research objectives. Student informants must have actively used e-learning for at least one semester, interacted with AI features, and agreed to participate in interviews. Lecturer informants must have used e-learning for teaching, assignments, assessment, or academic communication. E-learning administrators and IT staff are selected because they understand system development, integration, and implementation challenges.

The initial number of informants ranges from 20 to 25 people. This number consists of 12 to 15 students, 4 to 6 lecturers, 2 e-learning administrators, and 2 IT staff members. The number may increase through snowball sampling if initial informants recommend other people who have important experience with AI use in e-learning. The final number of informants follows the principle of data saturation, which occurs when information becomes repetitive and no longer produces significant new themes. Hennink and Kaiser (2022) show that many qualitative studies can reach saturation through a relatively limited number of interviews when the research population is homogeneous and the research focus is clear. Wutich et al. (2024) also emphasize that participant estimation in qualitative research needs to consider the type of analysis, depth of data, and saturation target. Therefore, this study does not determine the number of participants rigidly. It adjusts the final number based on data adequacy, variation of informant experiences, and the depth of themes that appear during data collection.

Data collection uses semi-structured interviews, limited participatory observation, documentation, and method triangulation. Semi-structured interviews explore students' and lecturers' experiences when using AI features in e-learning. The interview topics include ease of use, feedback quality, clarity of system recommendations, trust in AI, and barriers to digital interaction. Yu et al. (2024) show that user satisfaction and continued intention to use ChatGPT are influenced by users' interaction experiences with the system. Shahzad et al. (2024) also found that awareness, acceptance, and trust play important roles in ChatGPT adoption in higher education. Each interview lasts about 45 to 60 minutes and is recorded after receiving informant consent. Observation focuses on online learning activities, such as LMS discussions, chatbot use, access to recommended materials, and user response patterns toward AI features. Documentation includes LMS user guides, AI feature displays, learning activity records, academic policies related to AI, and technical notes from system administrators.

Data validation uses source triangulation, method triangulation, member checking, and an audit trail. Source triangulation compares information from students, lecturers, e-learning administrators, and IT staff. Method triangulation compares interview results, observation notes, and documents. Member checking takes place by sending interview summaries or initial interpretations to informants to ensure that the researcher's interpretation matches their experiences. The audit trail records the research process, interview guidelines, transcripts, initial codes, analytic memos, categorization decisions, and theme changes during analysis. Braun and Clarke (2021) explain that the quality of thematic analysis depends on the traceability of the analytical process, the fit between themes and data, and researcher reflexivity. Distefano et al. (2023) also show that saturation can be strengthened through early planning, monitoring during data collection, and confirmation after analysis.

Data analysis uses thematic analysis through the stages of data familiarization, transcription, initial coding, code grouping, theme searching, theme reviewing, theme naming, and narrative writing. The analysis follows an inductive orientation so that the themes emerge from informants' experiences, not only from prior theoretical assumptions. However, the researcher still uses the Human-Centered Computing framework as an interpretive lens to examine the relationship between user needs, system design, human-computer interaction, and learning experience quality. Naeem et al. (2023) explain that thematic analysis can be used systematically to build themes and conceptual models from qualitative data. Ahmed (2025) also emphasizes that data saturation needs to be understood flexibly because every study has different contexts, theme complexity, and data depth. In this study, initial codes focus on ease of interaction, trust in AI, feedback clarity, user control, learning personalization, system limitations, and the need for more human-centered design. The final analysis presents the main themes that explain AI implementation strategies based on Human-Centered Computing to enhance user interaction in e-learning.

3. Results and Discussions

The findings show that the implementation of artificial intelligence in e-learning created new forms of interaction between users and the digital learning system. However, this interaction did not only depend on the availability of AI features. It also depended on how users understood, trusted, controlled, and experienced the system. Based on interviews, observation, and documentation, five main themes emerged from the data analysis: perceived usefulness of AI-

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assisted interaction, trust and transparency in AI feedback, user control and human supervision, digital readiness and institutional support, and the need for more human-centered AI design. These themes show that AI can strengthen e-learning interaction when it supports user needs, respects user autonomy, and remains aligned with the pedagogical context. Current studies on human-centered AI in education also emphasize the need to involve stakeholders, maintain human control, and address trust in AI-supported learning environments.

The first theme relates to the perceived usefulness of AI-assisted interaction. Most student participants stated that AI features helped them access explanations, find relevant learning materials, and receive faster feedback. The chatbot feature was seen as useful because students could ask questions outside lecture hours. One student explained, “I use the chatbot when I do not understand the material at night. It helps me get an initial explanation before asking the lecturer.” This statement shows that AI did not replace the lecturer, but functioned as an early support system. Lecturers also viewed AI as helpful for organizing learning resources and identifying students who needed additional support. Observation of LMS activities showed that students interacted more frequently with AI-based recommendation features when the materials were linked to assignments, quizzes, or lecture discussions. This finding indicates that AI-assisted interaction becomes meaningful when it connects directly with students’ learning tasks.

The second theme concerns trust and transparency in AI feedback. Students appreciated fast feedback, but they did not always trust the accuracy of AI-generated responses. Several participants said they compared AI feedback with lecturer explanations, online references, or peer discussions before accepting it. One student stated, “The feedback is fast, but I still need to check whether it matches what the lecturer explained.” This pattern shows that speed alone does not build trust. Users need clear explanations about how the system generates recommendations or feedback. Some lecturers also expressed concern that students might accept AI responses without critical evaluation. Documentation of LMS guidelines showed that the institution had introduced AI features, but it had not provided detailed guidance on how students should evaluate AI-generated responses. This finding supports the need for explainable AI in education, where users can understand the logic behind system recommendations and decisions. Khosravi et al. (2022) argue that explainability in educational AI has specific importance because students and teachers use AI outputs in learning, assessment, and decision-making contexts.

The third theme focuses on user control and human supervision. Participants did not reject AI use in e-learning, but they expected clear boundaries between AI support and human decision-making. Students preferred AI for simple explanations, material recommendations, and technical assistance. However, they still expected lecturers to provide final clarification, moral guidance, assessment explanation, and contextual interpretation. One lecturer stated, “AI can help with routine responses, but academic judgment must remain with the lecturer.” This statement reflects a shared view that AI should support learning rather than dominate it. Observations also showed that students were more comfortable using AI when lecturers explained when and how the feature should be used. This finding suggests that human supervision plays a key role in shaping user confidence. In this context, Human-Centered Computing becomes important because it positions AI as a tool that extends human capability while keeping users involved in meaningful decisions.

The fourth theme relates to digital readiness and institutional support. The implementation of AI in e-learning did not occur in a neutral environment. Students’ interaction with AI was influenced by internet access, digital literacy, device quality, and familiarity with LMS features. Some students used AI features actively, while others used them only when lecturers required them. One student said, “I know the feature exists, but I do not always understand when I should use it.” This statement shows that technology availability does not guarantee effective use. Lecturers also reported that they needed training to integrate AI into teaching activities. IT staff explained that the main challenge was not only system integration, but also user adaptation, data privacy, and support services. These findings indicate that AI implementation requires institutional readiness, not just technical installation. Studies on AI adoption in higher education also show that trust, perceived usefulness, ease of use, and institutional policy shape students' acceptance of AI-based tools.

The fifth theme concerns the need for more human-centered AI design. Participants expected AI features to be simple, responsive, transparent, and relevant to course content. Students preferred AI responses that used clear language, provided examples, and connected explanations with lecture materials. Lecturers expected AI systems to provide flexible support without reducing academic interaction. One lecturer explained, "The system should help students think, not only give answers." This finding shows that users wanted AI to promote learning engagement, not passive dependence. Documentation analysis showed that the AI features were mostly described in technical terms, while guidance on pedagogical use remained limited. This gap shows that the design of AI-based e-learning needs to consider learning goals, user emotions, cultural communication patterns, and the social role of lecturers. Human-centered learning analytics and AI studies also show that stakeholder involvement, pedagogical context, and trust are key factors in authentic implementation settings.

Overall, the results show that AI implementation in e-learning can enhance user interaction when it fulfills three conditions. First, AI must provide useful support that connects with real learning activities. Second, AI must be transparent enough to help users understand and evaluate its outputs. Third, AI must operate within a learning environment that maintains human control, lecturer involvement, and institutional support. These findings indicate that interaction quality does not come from AI automation alone. It emerges from the relationship between technology design, user readiness, pedagogical practice, and institutional governance. In the context of Indonesian higher education, this issue becomes important because e-learning users often have different levels of digital literacy, access, and confidence in using AI-based systems.

Discussion

The findings confirm that AI can improve user interaction in e-learning when it functions as a learning support system rather than a replacement for human educators. Students valued AI because it provided fast access to explanations and learning resources. This finding aligns with Chen et al. (2020), who explain that AI in education can support intelligent tutoring, automated feedback, and learning recommendations. It also supports Ouyang et al. (2022), who found that AI in online higher education is widely used for personalization, analytics, assessment, and instructional support. However, this study adds a more contextual insight. Users did not judge AI only from its technical function. They assessed AI from how well it responded to learning needs, supported confidence, and connected with lecturer guidance.

The findings also show that trust is a central factor in AI-supported interaction. Students used AI feedback, but they still checked its accuracy through lecturers, peers, or other references. This finding is consistent with Khosravi et al. (2022), who argue that explainable AI is essential in education because users need to understand the reasons behind system feedback and recommendations. It also supports Albayati (2024), who shows that perceived usefulness, ease of use, privacy, security, and trust shape students' acceptance of ChatGPT. This study extends these findings by showing that trust in AI is not formed only through system performance. It is also formed through users' ability to question, compare, and validate AI-generated information.

The role of human supervision appears as another important finding. Students and lecturers accepted AI when it supported routine learning activities, but they still expected lecturers to provide final academic judgment and contextual explanation. This finding supports Shneiderman's (2020) view that human-centered AI must balance automation and human control. Yang et al. (2021) also argue that human-centered AI in education must pay attention to cognitive, emotional, and social dimensions of learning. In this study, users did not see interaction as a purely technical process. They understood interaction as a learning relationship that involves explanation, reassurance, context, and academic responsibility. This perspective offers a critical contribution to e-learning studies because it shows that human presence remains essential in AI-mediated learning environments.

The findings differ from studies that emphasize AI mainly as a tool for efficiency. In this study, efficiency appeared as only one part of user experience. Students appreciated quick responses, but they also wanted clarity, relevance, and control. Lecturers valued automated assistance, but they did not want AI to reduce reflective learning or student-lecturer communication. This finding supports Kasneci et al. (2023), who explain that large language models offer opportunities for education but also raise challenges related to accuracy, dependency, and responsible use. It also aligns with Chan and Hu (2023), who found that students recognize the benefits of generative AI but remain concerned about ethical and practical risks. The present study strengthens these arguments by showing that AI use in e-learning must be designed to encourage critical engagement rather than passive consumption of answers.

The institutional dimension also plays a strong role in shaping AI implementation. Students with better digital literacy used AI features more confidently, while other students needed guidance before using them. Lecturers also needed training to integrate AI into course design. These findings align with Shahzad et al. (2024), who found that awareness, acceptance, and trust influence ChatGPT adoption in higher education. They also relate to Topali et al. (2025), who argue that human-centered AI and learning analytics require stakeholder involvement, pedagogical contextualization, and trust-building. This study adds that institutional support must include not only technical infrastructure, but also user training, ethical guidance, data privacy rules, and pedagogical integration.

From a theoretical perspective, this study strengthens the relevance of Human-Centered Computing in AI-based educational technology. The results show that user interaction improves when AI systems are designed around user needs, transparency, autonomy, and human supervision. This finding supports Le Dinh et al. (2025), who emphasize that human-centered AI in higher education needs ethical awareness, human oversight, and responsible decision-making. It also supports recent human-centered learning analytics literature, which shows that educational stakeholders must contribute to the design and implementation of AI systems. The contribution of this study lies in its qualitative explanation of how users experience AI interaction in e-learning. It shows that interaction quality is not only a system feature, but also a social and pedagogical process.

From a practical perspective, the findings suggest that universities need to develop AI implementation strategies that integrate technology, pedagogy, and user support. First, AI features should be connected with course objectives, assignments, feedback activities, and lecturer explanations. Second, AI systems should provide transparent information about the limits of their responses. Third, lecturers and students need training in ethical and critical AI use. Fourth, institutions need clear policies on data privacy, academic integrity, and responsible AI use. Fifth, developers should involve students, lecturers, and IT staff in the design and evaluation of AI-based e-learning features. These strategies can help ensure that AI improves interaction without reducing human agency in the learning process.

This study also offers implications for future research. Future studies can compare AI-based e-learning interaction across different universities, disciplines, or student groups. Further research can also examine how cultural communication patterns influence trust and comfort in AI-mediated learning. Quantitative studies may test the relationship between explainability, trust, user control, and learning engagement. Mixed-method research can also be used to connect user experience data with learning analytics. In addition, future studies need to explore how AI can support inclusive learning for students with different levels of access, literacy, and learning needs. These directions are important because AI in e-learning will continue to develop, while its success will depend on how well institutions design systems that remain human-centered, ethical, and pedagogically meaningful.

4. Conclusions

This study concludes that artificial intelligence implementation in e-learning can enhance user interaction when it follows a Human-Centered Computing approach. The findings show that AI features such as chatbots, automated feedback, learning recommendations, and learning analytics support students and lecturers when they are useful, transparent, easy to access, and connected with real learning activities. However, the study also shows that AI does not automatically improve learning interaction. Users need clear guidance, human supervision, trust, control, and institutional support to use AI meaningfully. The main contribution of this study lies in its qualitative explanation of how user experience, trust, transparency, digital readiness, and pedagogical relevance shape AI-supported interaction in e-learning.

The findings offer theoretical, practical, and policy implications. Theoretically, this study strengthens Human-Centered Computing as a relevant framework for understanding AI-based educational technology. Practically, universities need to design AI features that support learning goals, protect user autonomy, and strengthen lecturer-student interaction rather than replace it. At the policy level, institutions need clear guidelines on ethical AI use, data privacy, academic integrity, lecturer training, and student digital literacy. Future research can expand this study by comparing AI-supported e-learning practices across institutions, disciplines, and student groups. Further studies can also examine the relationship between explainability, trust, user control, and learning engagement through mixed-method or quantitative approaches.

References

Ahmed, S. K. (2025). Sample size for saturation in qualitative research: Debates, definitions, and strategies. *Journal of Medicine, Surgery, and Public Health, 5*, Article 100171. https://doi.org/10.1016/j.glmedi.2024.100171

Albayati, H. (2024). Investigating undergraduate students' perceptions and awareness of using ChatGPT as a regular assistance tool: A user acceptance perspective study. *Computers and Education: Artificial Intelligence, 6*, Article 100203. https://doi.org/10.1016/j.caeai.2024.100203

Braun, V., & Clarke, V. (2021). One size fits all? What counts as quality practice in reflexive thematic analysis? *Qualitative Research in Psychology, 18*(3), 328–352. https://doi.org/10.1080/14780887.2020.1769238

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing, 25*(8), 652–661. https://doi.org/10.1177/1744987120927206

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*, Article 43. https://doi.org/10.1186/s41239-023-00411-8

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Chiu, T. K. F. (2024). Future research recommendations for transforming higher education with generative AI. *Computers and Education: Artificial Intelligence, 6*, Article 100197. https://doi.org/10.1016/j.caeai.2023.100197

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, Article 22. https://doi.org/10.1186/s41239-023-00392-8

Distefano, M. J., Yang, J. S., & Valliant, J. C. D. (2023). Sample size and saturation: A three-phase method for ethnographic research with multiple qualitative data sources. *Field Methods, 36*(1), 3–17. https://doi.org/10.1177/1525822X231194515

El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education, 18*, Article 53. https://doi.org/10.1186/s41239-021-00289-4

Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. K. (2022). The impact of a virtual teaching assistant chatbot on students' learning in Ghanaian higher education. *International Journal of Educational Technology in Higher Education, 19*, Article 57. https://doi.org/10.1186/s41239-022-00362-6

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine, 292*, Article 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Hu, W., & Chan, C. K. Y. (2025). From user needs to AI solutions: A human-centered design approach for AI-powered virtual teamwork competency training. *International Journal of Educational Technology in Higher Education, 22*, Article 52. https://doi.org/10.1186/s41239-025-00551-z

Kajiwara, Y., & Kawabata, K. (2024). AI literacy for ethical use of chatbot: Will students accept AI ethics? *Computers and Education: Artificial Intelligence, 6*, Article 100251. https://doi.org/10.1016/j.caeai.2024.100251

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., Stadler, M., Weller, J., Kuhn, J., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, Article 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., Martínez-Maldonado, R., Sadiq, S., & Gašević, D. (2022). Explainable artificial intelligence in education. *Computers and Education: Artificial Intelligence, 3*, Article 100074. https://doi.org/10.1016/j.caeai.2022.100074

Le Dinh, T., Le, T. D., Uwizeyemungu, S., & Pelletier, C. (2025). Human-centered artificial intelligence in higher education: A framework for systematic literature reviews. *Information, 16*(3), Article 240. https://doi.org/10.3390/info16030240

Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2023). A step-by-step process of thematic analysis to develop a conceptual model in qualitative research. *International Journal of Qualitative Methods, 22*, 1–18. https://doi.org/10.1177/16094069231205789

Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies, 27*, 7893–7925. https://doi.org/10.1007/s10639-022-10925-9

Shahzad, M. F., Xu, S., Javed, I., Riaz, S., & Malik, A. (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*, Article 46. https://doi.org/10.1186/s41239-024-00478-x

Shneiderman, B. (2020). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human-Computer Interaction, 36*(6), 495–504. https://doi.org/10.1080/10447318.2020.1741118

Shuhaiber, A., Kuhail, M. A., & Salman, S. (2025). ChatGPT in higher education: A student's perspective. *Computers in Human Behavior Reports, 17*, Article 100565. https://doi.org/10.1016/j.chbr.2024.100565

Topali, P., Ortega-Arranz, A., Rodríguez-Triana, M. J., Er, E., Khalil, M., & Akçapınar, G. (2025). Designing human-centered learning analytics and artificial intelligence in education solutions: A systematic literature review. *Behaviour & Information Technology, 44*(3), 1–28. https://doi.org/10.1080/0144929X.2024.2345295

Tzirides, A. O., Zapata, G., Kastania, N. P., Saini, A. K., Castro, V., Ismael, S. A., You, Y., Santos, T. A. D., Searsmith, D., O'Brien, C., Cope, B., & Kalantzis, M. (2024). Combining human and artificial intelligence for enhanced AI literacy in higher education. *Computers and Education Open, 6*, Article 100184. https://doi.org/10.1016/j.caeo.2024.100184

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems with Applications, 252*, Article 124167. https://doi.org/10.1016/j.eswa.2024.124167

Wutich, A., Beresford, M., & Bernard, H. R. (2024). Sample sizes for 10 types of qualitative data analysis: An integrative review, empirical guidance, and next steps. *International Journal of Qualitative Methods, 23*, 1–18. https://doi.org/10.1177/16094069241296206

Yang, S. J. H., Ogata, H., Matsui, T., & Chen, N. S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Computers and Education: Artificial Intelligence, 2*, Article 100008. https://doi.org/10.1016/j.caeai.2021.100008

Yu, C., Yan, C., & Cai, N. (2024). ChatGPT in higher education: Factors influencing ChatGPT user satisfaction and continued use intention. *Frontiers in Education, 9*, Article 1354929. https://doi.org/10.3389/feduc.2024.1354929