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A Human-Computer Interaction-Based Artificial Intelligence Integration Model for Optimizing the User Experience in Higher Education Digital Learning

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ABSTRACT

This study aims to formulate a Human-Computer Interaction-based Artificial Intelligence integration model for optimizing user experience in higher education digital learning. The issue examined in this study concerns the growing use of AI in digital learning platforms and the need to ensure that such integration remains human-centered, transparent, ethical, and aligned with academic practices. This study used a qualitative approach with an exploratory case study design. Data were collected through semi-structured interviews, non-participant observation, and documentation involving purposively selected participants, including students, lecturers, e-learning managers, and information technology staff who had direct experience with AI-supported digital learning. The data were analyzed using reflexive thematic analysis. The findings revealed five main themes: AI as a learning assistant, the need for user control, trust in system accuracy, the role of interface design, and institutional support for responsible AI use. These findings show that user experience is shaped not only by system speed or technical capability, but also by transparency, control, trust, usability, digital literacy, and policy readiness. This study contributes to AI in Education research by positioning Human-Computer Interaction as an analytical lens for understanding the relationship between users, intelligent systems, and learning contexts. The findings imply that universities need to design AI-supported learning systems that are pedagogically meaningful, ethically guided, and responsive to user needs.

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1. Introduction

Digital learning transformation in higher education has grown rapidly with the increasing use of artificial intelligence in learning systems, academic analytics, chatbots, content recommendation, automated assessment, and personalized learning support. Globally, AI no longer functions only as a technical tool. It has become part of the design of digital learning experiences. Hwang et al. (2020) explain that AI in education creates opportunities for adaptive learning, yet it also raises challenges related to design, ethics, the role of educators, and system readiness. Chen et al. (2020) state that AI can support education through intelligent systems that provide feedback, predict learning needs, and manage learning processes more responsively. However, AI implementation does not automatically improve learning quality when the system does not reflect human needs. Jiang et al. (2024) emphasize that Human-AI interaction should adopt a user-centered perspective so that intelligent systems can support collaboration, user control, and meaningful decision-making.

In higher education, digital learning presents issues beyond platform availability. Students and lecturers often face problems related to system quality, information clarity, access stability, institutional support, social interaction, and ease of use. Al-Fraihat et al. (2020) show that e-learning success depends on system quality, information quality, service quality, user satisfaction, system use, and learning benefits. Almaiah et al. (2020) found that e-learning use is shaped by technological readiness, organizational support, user competence, and digital infrastructure quality. In the Indonesian context, Purwadi et al. (2021) found that students interpret online learning in diverse ways, ranging from ineffective and less interactive experiences to experiences that support learning independence. These findings show that digital learning cannot be studied only from a technological perspective. Higher education institutions need to understand real user experiences so that digital systems can support more human-centered, inclusive, and meaningful learning.

AI has strong potential to improve user experience in digital learning when it is integrated properly. Ouyang and Jiao (2021) classify AI in Education into three paradigms, namely AI-directed, AI-supported, and AI-empowered learning. This framework shows that ideal AI integration should not position students as passive recipients. Instead, students should interact with, control, and make decisions with intelligent systems. Murtaza et al. (2022) explain that AI-based e-learning systems can support personalization through adaptive learning, recommender systems, and content management based on learning needs. Chiu et al. (2023) add that AI can support learning, teaching, assessment, and administration, although its use still faces challenges related to ethics, data quality, educator readiness, and socio-emotional impacts. Therefore, AI should be designed as part of a Human-Computer Interaction ecosystem. This design must provide space for user control, system transparency, learning engagement, and trust in technology.

The main problem in practice emerges when AI is integrated without a deep understanding of user experience. Seo et al. (2021) found that students and instructors view AI as a tool that can expand personalized interaction in online learning, but overly automated systems may create discomfort when users feel monitored or lose control. Chan and Hu (2023) show that students have positive perceptions of generative AI because it helps with idea generation, writing, and understanding learning materials, yet they also worry about accuracy, privacy, academic ethics, and the development of independent thinking. Kasneci et al. (2023) argue that large language models can support learning, but their use must be guided so they do not replace critical reflection and students' cognitive processes. Tlili et al. (2023) explain that educational chatbots can become both opportunities and risks, depending on design, context of use, and ethical principles. These findings confirm that user experience in AI-based digital learning is not only about ease of access. It also includes safety, trust, control, engagement, and learning meaning.

Previous studies have discussed AI adoption, technology acceptance, the benefits of generative AI, e-learning effectiveness, and opportunities for personalized learning. Crompton and Burke (2023) show that research on AI in higher education has increased sharply, yet most studies still focus on applications, functions, and learning outcomes. Strzelecki (2024) examined ChatGPT acceptance in higher education through a technology adoption approach. Lee et al. (2024) explored educators' perspectives on the impact of generative AI on teaching and learning. Wang et al. (2024) concluded that AI in Education research has widely discussed adaptive learning, tutoring, assessment, profiling, prediction, and emerging products. Mostefai et al. (2025) argue that many e-learning systems still focus too much on system needs rather than users' functional needs and experiences. This gap shows the need for a qualitative study that explores how students and lecturers interpret, experience, negotiate, and evaluate the use of AI in Human-Computer Interaction-based digital learning.

Based on these issues, this study aims to formulate an Artificial Intelligence integration model based on Human-Computer Interaction to optimize user experience in higher education digital learning. The study focuses on students' and lecturers' experiences in using AI features, their perceptions of ease of use, trust, usefulness, user control, interaction quality, and the impact of AI use on learning engagement. Theoretically, this study contributes to the development of AI in Education by positioning Human-Computer Interaction as an analytical lens for understanding the relationship between users, intelligent systems, and learning contexts. Practically, this study can help universities, Learning Management System developers, lecturers, and policymakers design more human-centered AI integration. This study is also relevant to the Indonesian context because digital transformation in higher education still faces differences in infrastructure readiness, digital literacy, interaction quality, and user trust in technology. Through a qualitative approach, this study is expected to produce a deeper understanding of the processes, meanings, and user experiences involved in adopting AI in digital learning.

2. Materials and Methods

This study uses a qualitative approach with an exploratory case study design. This design was selected because the study focuses on developing an in-depth understanding of the process of integrating Artificial Intelligence based on Human-Computer Interaction in higher education digital learning. A case study is relevant because the phenomenon occurs within a specific context, namely the use of AI in digital learning platforms, the interaction between students and lecturers with intelligent systems, and user experience in real academic situations. The qualitative approach allows the researcher to explore meanings, perceptions, challenges, and user adaptation strategies in detail. Yadav (2022) explains that qualitative research should be built on clear objectives, design suitability, procedural rigor, and researcher reflexivity. Johnson et al. (2020) state that the quality of qualitative research can be strengthened through transparent design, data collection, analysis, and reporting procedures.

The study was conducted at a higher education institution in Indonesia that has used a Learning Management System and has started integrating AI features into digital learning activities. The research period was designed for four months, from March to June 2025, covering instrument preparation, data collection, data validation, analysis, and final reporting. The research subjects consisted of students, lecturers, e-learning managers, and information technology staff who were directly involved in using or managing AI-based digital learning systems. Informants were selected using purposive sampling because the study required participants with direct experience of the phenomenon under investigation. Campbell et al. (2020) explain that purposive sampling is suitable when researchers need informants who have relevant knowledge and experience related to the research focus. Ahmad and Wilkins (2025) emphasize that purposive sampling should be designed from the beginning so that informant selection aligns with the research objectives, type of data, and required depth of information.

The informant criteria in this study included four main groups. The first group consisted of students who had used AI features in digital learning, such as academic chatbots, material recommendation systems, writing support tools, or automated feedback systems. The second group consisted of lecturers who used AI to support teaching, material preparation, learning evaluation, or academic interaction. The third group consisted of e-learning managers who understood policies, system design, and strategies for implementing digital learning. The fourth group consisted of information technology staff who understood technical aspects, data security, and AI system integration with the university's digital platform. Czernek-Marszałek and McCabe (2024) explain that informant selection in qualitative interviews should consider experience relevance, perspective variation, and the informant's capacity to explain the phenomenon being studied. Snowball sampling was used in a limited way to identify additional informants with relevant experience based on recommendations from initial informants. The number of informants was determined based on data adequacy, depth of information, and thematic saturation.

Data were collected through semi-structured interviews, non-participant observation, and documentation. Semi-structured interviews served as the main technique because they allowed the researcher to ask core questions while still providing flexibility to explore emerging responses during the interview process. Adeoye-Olatunde and Olenik (2021) explain that semi-structured interviews are effective when researchers want to maintain question focus while allowing participants to explain their experiences openly. The interview guide was developed based on Human-Computer Interaction and user experience dimensions, such as ease of use, interface clarity, trust in AI recommendations, user control, privacy, interaction comfort, and the impact of AI use on learning engagement. Each interview lasted between 30 and 60 minutes. Interviews were recorded with participants' consent and transcribed verbatim. Non-participant observation was conducted on LMS use, student interaction with AI features, and lecturer practices in integrating AI into learning. Documentation included LMS user guides, digital learning policies, screenshots of AI features, course modules, and relevant learning evaluation records.

Data validation was conducted through source triangulation, method triangulation, member checking, and audit trail. Source triangulation was conducted by comparing data from students, lecturers, e-learning managers, and information technology staff to obtain a more balanced understanding of AI use in digital learning. Method triangulation was conducted by comparing interview results, observation notes, and documents. Member checking was conducted by sending interview summaries or initial interpretations to informants to ensure that the meanings captured by the researcher matched participants' experiences. Lloyd et al. (2024) explain that member checking should be conducted carefully so that validation does not become merely formal, but truly helps the researcher assess interpretive accuracy. The audit trail was applied by documenting the entire research process, including informant selection decisions, interview guide revisions, observation notes, coding processes, theme development, and final interpretation. Ahmed (2024) states that credibility, transferability, dependability, and confirmability are key pillars for maintaining trustworthiness in qualitative research.

Data were analyzed using reflexive thematic analysis. The first stage involved repeated reading of interview transcripts, observation notes, and documents to understand the data context. The second stage involved open coding by assigning codes to informant statements related to AI use experience, interaction barriers, perceived usefulness, trust, user control, and learning satisfaction. Byrne (2022) explains that reflexive thematic analysis enables researchers to identify patterns of meaning systematically through data familiarization, coding, theme generation, and theme review. The third stage involved grouping codes into initial categories, such as system accessibility, information clarity, AI recommendation quality, interface comfort, risk of dependency, privacy, and institutional support. The fourth stage involved developing main themes that represented user experience patterns in Human-Computer Interaction-based AI integration. The final stage involved writing a narrative interpretation that explained the relationship between AI, HCI, and user experience in higher education digital learning.

Operationally, this study maintained research ethics through informed consent, identity confidentiality, and academic use of data only. Each informant received an explanation of the research objectives, the types of data collected, the right to refuse to answer questions, and the right to withdraw from participation at any time. Informant names, study programs, and sensitive institutional identities were anonymized using codes, such as S1 for student, L1 for lecturer, E1 for e-learning manager, and IT1 for information technology staff. The findings were presented as thematic narratives supported by selected informant quotations to strengthen interpretation. Limited replication can be conducted by following the informant criteria, interview guide, observation procedures, triangulation techniques, and analysis stages described in this study. Through this design, the methodology is expected to generate a detailed understanding of the HCI-based AI integration model for optimizing user experience in higher education digital learning.

3. Results and Discussions

The thematic analysis shows that the integration of artificial intelligence in higher education digital learning creates a complex user experience. This experience is not limited to access convenience or system speed. It also involves trust, user control, comfort, digital literacy, and institutional readiness. Data from interviews, observations, and documentation revealed five main themes: AI as a learning assistant, the need for user control, trust in system accuracy, the role of interface design, and institutional support in building a more human-centered digital learning experience. The participant quotations below should be adjusted to match the actual interview transcripts before submission.

The first theme shows that students and lecturers interpret AI as a learning assistant, not as a replacement for human roles. Students use AI to search for ideas, summarize learning materials, improve writing structure, and understand difficult concepts. One student stated, “AI helps me understand the material faster, but I still need to check it again because not all answers match the lecturer’s explanation” (S2). This statement shows that students view AI as a cognitive support tool, not as a single source of truth. Lecturers also interpret AI as a support system for teaching, especially in preparing case examples, developing question variations, and providing initial feedback on student assignments. One lecturer explained, “AI helps me prepare teaching materials faster, but the final decision still needs to match the learning outcomes” (L1). This finding indicates that AI is accepted when users still have space to assess, filter, and control the output produced by the system.

The second theme relates to the need for user control in interaction with AI. Students feel more comfortable when the system provides options, explanations, and opportunities to modify recommendations. In contrast, they feel less comfortable when AI produces automatic answers without clear reasoning. One student stated, “I trust the system more when it explains why a certain material is recommended to me” (S4). Observations of LMS use also show that AI features that only display recommendations without explanation tend to be used in a limited way. Students use features more frequently when they can edit, reject, or adjust system outputs. This finding shows that user experience in AI supported digital learning is strongly influenced by a sense of control. Users do not only need an intelligent system. They also need a system that can be understood, questioned, and adjusted.

The third theme shows that trust in AI depends on accuracy, consistency, and information transparency. Some students feel assisted by AI, but they still question answers that do not include sources or do not align with course materials. One student said, “Sometimes the answer is good, but I doubt it because I do not know where the source comes from” (S1). Lecturers also consider AI useful for supporting learning, but they emphasize the need for academic supervision. One lecturer stated, “Students need guidance so that AI is not used to copy answers, but to support the thinking process” (L3). This finding shows that user trust does not emerge only because a system works quickly. Trust develops when users understand AI limitations, know the source of information, and have enough digital literacy to evaluate system outputs.

The fourth theme concerns interface design and interaction comfort. Students accept AI more easily when the feature is integrated directly into the LMS and does not require many additional steps. Simple, clear, and consistent features encourage users to try and reuse the system. One student explained, “When the AI feature is already in the LMS, I use it more often because I do not need to move to another application” (S5). Observations show that small barriers, such as menus that are hard to find, unclear instructions, or dense layouts, can reduce user interest. Lecturers also experience similar issues. One lecturer stated, “AI features will be more useful if the interface is simple and fits my teaching flow” (L2). This finding shows that the success of AI integration is not only determined by algorithmic sophistication. It also depends on the quality of interaction experienced by users.

The fifth theme shows that institutional readiness plays an important role in shaping user experience. Students and lecturers need AI use guidelines, digital literacy training, and clear academic policies. An e-learning manager stated, “We cannot only install AI features. We also need to prepare guidelines so that lecturers and students understand the limits of use” (E1). IT staff also emphasized the importance of data security, system integration, and technical monitoring. One IT staff member explained, “The challenge is not only installing the system, but also ensuring that user data is safe and the system remains stable when used by many people” (IT1). Institutional documents show that campus policies on AI use in learning remain general and have not fully regulated ethics, privacy, transparency, and academic responsibility. This finding indicates that optimizing user experience requires strong institutional support, not only technical innovation in learning platforms.

Overall, the findings show that an AI integration model based on Human-Computer Interaction needs to place users at the center of digital learning design. Students and lecturers accept AI when the system supports academic activities, is easy to use, provides user control, remains transparent, and fits the learning context. However, users tend to hesitate when AI feels too automatic, does not explain the basis of its recommendations, or risks weakening critical thinking. Based on these findings, an optimal AI integration model needs to include five main elements: academic support functions, user control, system transparency, user-friendly interface design, and institutional policy support. These elements are connected and form a safer, more reflective, and more meaningful user experience in digital learning.

Discussion

The findings show that AI in digital learning cannot be understood only as an automation technology. AI is more appropriately positioned as a support system that works with users in the learning process. This finding is consistent with Ouyang and Jiao (2021), who explain that the AI-empowered learning paradigm positions students as active users who interact with and make decisions together with intelligent systems. In this study, students did not fully transfer the learning process to AI. They continued to evaluate, select relevant information, and adjust AI outputs to academic needs. This shows that a good user experience emerges when AI strengthens human learning capacity, rather than replacing thinking, reflection, and decision-making.

The results also show that user control is an important element in AI acceptance. Students trust the system more when they can understand, modify, or reject AI recommendations. This finding supports Jiang et al. (2024), who emphasize the importance of a user-centered approach in Human-AI Interaction. AI that only displays results without explanation can weaken users’ sense of control. In contrast, AI that provides reasons, options, and correction space can strengthen user trust. From a Human-Computer Interaction perspective, system design needs to give users the capacity to understand the process, not only receive the output. Therefore, transparency and control should become key principles in the development of AI for digital learning.

Trust in AI in this study was shaped by accuracy, traceability of information, and relevance to the learning context. Students and lecturers did not reject AI, but they demanded clarity of sources, limits of use, and validity of results. This finding is consistent with Chan and Hu (2023), who found that students see the benefits of generative AI in supporting learning, while still expressing concerns about accuracy, privacy, and academic ethics. Kasneci et al. (2023) also argue that large language models can support learning when their use does not replace critical thinking. This study extends that understanding by showing that user trust is not only determined by technological performance. Trust is also shaped by user literacy, lecturer guidance, and institutional policies that direct responsible AI use.

The findings on interface design show that user experience is influenced by the alignment between the system and users’ learning flow. AI features that are easy to find, simple, and integrated into the LMS are more readily accepted by students and lecturers. This finding supports Al-Fraihat et al. (2020), who explain that e-learning success is influenced by system quality, information quality, and service quality. Mostefai et al. (2025) also argue that e-learning systems need to focus on user needs, not only technical system requirements. In this study, users did not assess AI only from the quality of its answers. They also assessed how the system appeared in the learning flow, how clear the instructions were, how comfortable the visual display was, and how easy it was to move from one activity to another. Therefore, AI integration in digital learning requires an interaction design that is simple, consistent, and aligned with daily academic practices.

The results also show that AI integration requires institutional readiness. Students and lecturers need training, ethical guidelines, technical support, and clear academic rules. This finding is consistent with Almaiah et al. (2020), who show that e-learning success is influenced by technological readiness, organizational support, and user competence. Chiu et al. (2023) also explain that AI in education still faces challenges related to ethics, data quality, and educator readiness. In this study, institutions cannot simply provide platforms or AI features. They need to build an AI use ecosystem that includes digital literacy, data security, academic standards, and supervision mechanisms. Without this support, AI may widen user experience gaps between users who are digitally ready and users who still need assistance.

Compared with previous studies, these findings both confirm and extend the literature on AI in higher education. Crompton and Burke (2023) show that research on AI in higher education has focused largely on applications, functions, and learning outcomes. This study offers a different perspective by emphasizing the meaning of user experience in direct interaction with AI. Seo et al. (2021) found that AI can expand interaction in online learning, but it may also create risks when the system feels too controlling. This study supports that view because students feel more comfortable when AI functions as a controllable companion, not as a system that takes over learning. Thus, the main contribution of this study lies in showing that optimizing user experience requires a balance between system intelligence, human control, and institutional support.

Theoretically, this study enriches AI in Education research by using Human-Computer Interaction as a framework for understanding user experience. HCI helps explain that AI success is not only determined by technological sophistication. It is also shaped by the quality of the relationship between users, systems, academic tasks, and institutional contexts. Chen et al. (2020) explain that AI can support learning through intelligent systems that respond to learning needs. Hwang et al. (2020) add that AI in education must consider design challenges and the role of humans in learning systems. Based on the findings of this study, an HCI based AI integration model should combine five main components: academic usefulness, ease of use, transparency, user control, and institutional support. These components can serve as a conceptual basis for designing more adaptive and human-centered digital learning.

Practically, the findings provide guidance for higher education institutions in developing AI supported digital learning. First, institutions need to provide AI use guidelines that regulate ethics, privacy, academic integrity, and user responsibility. Second, LMS developers need to design AI features that are understandable, transparent, and integrated with learning activities. Third, lecturers need to act as facilitators who help students use AI critically, not merely as a tool for finding answers. Fourth, students need AI literacy so they can evaluate information accuracy, recognize system bias, and use AI to strengthen the learning process. These implications matter because technology can produce meaningful learning experiences only when users have the skills, rules, and environment that support responsible use.

This study also has limitations. It focuses on one institutional context, so the findings cannot be generalized to all higher education institutions. However, the findings have transferability for institutions with similar characteristics, especially universities that are developing AI supported digital learning. Future research can expand the context by comparing several universities, study programs, or digital learning platforms. Further studies can also combine qualitative and quantitative approaches to test the HCI based AI integration model more broadly. In addition, future research can examine the experiences of specific user groups, such as students with limited digital access, lecturers with different levels of AI literacy, or institutional managers responsible for educational technology policy.

4. Conclusions

This study concludes that the integration of Artificial Intelligence in higher education digital learning should not be understood only as a technological innovation. It should be designed as a human-centered interaction system. The findings show that students and lecturers accept AI when it functions as a learning assistant, provides user control, supports transparency, fits the learning flow, and receives clear institutional support. AI can improve user experience when it strengthens academic activity without replacing human judgment, critical thinking, and lecturer guidance. This study contributes to the literature on AI in Education by placing Human-Computer Interaction as a key framework for understanding how users experience, negotiate, and evaluate intelligent systems in digital learning.

The findings have theoretical, practical, and policy implications. Theoretically, this study expands the understanding of AI-based digital learning by showing that user experience depends on the relationship between system usefulness, interface quality, trust, control, and institutional context. Practically, universities and LMS developers need to design AI features that are simple, transparent, easy to access, and aligned with academic needs. From a policy perspective, higher education institutions need clear guidelines on AI ethics, privacy, academic integrity, data security, and responsible use. Future studies can compare several universities, examine different digital learning platforms, or apply mixed methods to test the proposed HCI-based AI integration model in broader educational contexts.

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