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Artificial Intelligence in Learning Design: Acceptance, Perceived Effectiveness, and Barriers

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Abstract

This study mapped perceptions of AI in learning design in the Educational Technology Study Program at Universitas Negeri Surabaya (UNESA). A 25-item, 5-point Likert questionnaire (acceptance, perceived effectiveness, limitations; TAM-informed) was completed by 16 lecturers and 130 students selected purposively (users of, or strongly interested in, AI). Content validity met conventional thresholds (all I-CVI ≥ 0.78; S-CVI > 0.90). Agreement on acceptance (10 items) averaged 82.6% for students (range 80.0–88.5%) and 85.0% for lecturers (range 81.25–87.5%). Agreement on perceived effectiveness (8 items) averaged 85.4% for students (range 80.8–89.2%) and 87.5% for lecturers (range 81.25–93.75%), indicating that respondents believe AI can accelerate material preparation, support adaptive/diagnostic feedback, and enable more personalized learning. Limits were also evident (7 items): difficulty understanding AI (65.4% students; 62.5% lecturers), context relevance of AI outputs (58.5%; 62.5%), curricular alignment (56.9%; 56.3%), feeling safe sharing data (53.9%; 56.3%), and LMS integration (60.8%; 68.8%). Reported training was uneven (61.5% students; 68.8% lecturers), implying roughly 32–38% lacked training. Given the single-site, descriptive design, findings are self-reports—not causal or broadly generalizable. Implications point to pilot-first adoption, targeted capacity building, clearer privacy/ethics governance, and infrastructure alignment before any scale-up.

Keywords: Artificial Intelligence (AI); Learning Design; Technology Acceptance Model (TAM); Higher Education; Indonesia

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INTRODUCTION

Artificial intelligence (AI) is reshaping education end-to-end—from how learning is designed to how it is implemented and assessed—by enabling more adaptive, data-informed decisions. Strategic integration of AI into learning design is therefore central to improving efficiency and effectiveness across educational levels, including higher education, with expected gains for teaching quality and student outcomes (Shah, 2022; Yaccob et al., 2022). In practical terms, progress depends on how institutions plan, design, implement, and evaluate teaching strategies and methods. Current uses already span administrative automation and learning analytics to increase efficiency (Chiu, 2024b; Ullrich et al., 2022), as well as recommendation systems, chatbots, and adaptive learning that help lecturers track learning patterns and provide real-time feedback aligned to student needs—improving engagement and motivation. Integrations with computer simulations, cloud-based smart technologies, and immersive environments further enrich learning experiences (Papadakis et al., 2023). Recent uptake in academia highlights AI's potential to scaffold adaptive learning and to streamline the preparation of teaching resources across face-to-face and online modalities (Chang et al., 2023; Karakose & Tulubas, 2024), with diverse AI approaches designed to meet increasingly complex learning demands (Wu & Yu, 2024).

Despite this momentum, empirical evidence on AI's specific integration into instructional design processes in public universities remains limited, especially for programs oriented to pedagogy rather than engineering or general ICT. In the scholarly literature, research on artificial intelligence in e-learning (AIeL) has primarily emphasized intelligent tutoring systems and assessment tools (Tang et al., 2023). When studies do move beyond tools toward curriculum or program design, they are often concentrated in STEM contexts, where persistent challenges include authentic interdisciplinary integration and the sustainability and scalability of innovations (Deehan et al., 2024; Larkin & Lowrie, 2023). Parallel instructional practice continues, in many settings, to privilege content- or teacher-centered approaches over designs aligned with learner needs, limiting the potential of student-centered pedagogy (Marcelo & Yot-Domínguez, 2019). Within Indonesia specifically, AI implementation in educational practice remains in a development and exploration phase; early initiatives exist, yet adoption is constrained by infrastructure readiness, educator competencies, and user acceptance (Barakina et al., 2021; Kamalov et al., 2023). Against this backdrop, the Educational Technology Program at Universitas Negeri Surabaya (UNESA) offers a pertinent context to examine whether AI presently supports or challenges learning-design practice and to identify the institutional conditions that enable responsible, effective use.

The capabilities of AI map naturally onto core design tasks but also surface questions that must be addressed empirically. Machine Learning can identify learning behaviors and generate predictions that support academic decision-making; Natural Language Processing enables language-based interaction through chatbots and virtual assistants; and Computer Vision analyzes visual inputs, including automatic handwriting recognition for paper-based exams (Kellmeyer, 2019). Cloud and immersive technologies broaden the design space for interactive experiences (Papadakis et al., 2023). Deep Learning has shown strong potential in predicting performance in virtual environments and underpins virtual tutors capable of real-time, complex modeling (Alnasyan et al., 2024). Yet the mere availability of these technologies does not guarantee pedagogical alignment. International findings indicate that adoption intentions are shaped by psychological and experiential determinants—especially performance expectancy, habit, and enjoyment (Lavidas et al., 2024; Nikolopoulou et al., 2021)—suggesting that institutional efforts must pair tool deployment with support for user beliefs and practices. Early assessments of AI use in learning design should therefore jointly consider effectiveness, acceptance among teachers and learners, and concerns about use (AbuSahyon et al., 2023; Hartley et al., 2024). These considerations extend to digital literacy (lecturers' and students' capacity to use AI appropriately), content validity of AI-assisted artefacts, and data-privacy risks—issues that are especially salient as AI is explored for automatic grading and formative assessment, where promise coexists with calls for deeper investigation across educational levels (Aravantinos et al., 2024; González-Calatayud et al., 2021; Shi et al., 2023; Zhao et al., 2022).

To locate where AI may add demonstrable value—and where dependencies or risks are likely—this study treats learning design as a process and uses the ADDIE model as an organizing scaffold: Analysis, Design, Development, Implementation, and Evaluation (Rahman & Duran, 2022; Wahira et al., 2023). In principle, AI can contribute at each phase: diagnosing needs from test data and learning patterns (Analysis), recommending strategies aligned with learner preferences (Design), accelerating the generation of materials such as summaries, presentations, and interactive quizzes (Development), sequencing content adaptively to learners' current understanding (Implementation), and providing real-time analytics of learning outcomes including error-pattern analysis for formative feedback (Evaluation) (Nguyen, 2023). However, effectiveness across this pipeline is conditional on institutional readiness (infrastructure, policy, and integration with learning-management systems), staff capability, and the quality and provenance of data used to power AI systems. These conditions are uneven within and across institutions, underscoring the need for program-level evidence in authentic contexts like UNESA.

In strategic terms, universities worldwide are exploring AI to support personalized learning and strengthen academic support systems, but the drivers of successful integration are as much organizational as they are technical. Capacity building, clear governance, and iterative piloting emerge as central levers for impact (Barrera Castro et al., 2024; Song, 2024). At the same time, heightened expectations around AI's transformative potential (Chiu, 2024a; Holmes & Tuomi, 2022) must be balanced against a commitment to evidence-based teaching—for example, deploying AI to help provide multiple examples, address misconceptions, and enable frequent low-stakes testing, rather than merely accelerating content production (Mollick & Mollick, 2023). Taken together, these considerations motivate a careful empirical assessment of how AI is currently being applied within learning-design practice, how effective and acceptable these uses are to key stakeholders, and what barriers—technical, pedagogical, or ethical—constrain wider adoption.

Accordingly, this study investigates the application of AI in learning design within the Educational Technology Program at UNESA. The purpose is twofold. First, we map the practical roles and perceived benefits of AI across the learning-design workflow in a pedagogically oriented public-university program. Second, we surface barriers—including skills/readiness, content-validity considerations, data-privacy concerns, and process bottlenecks—that must be addressed to ensure effective and ethical implementation. In alignment with international findings on adoption determinants (Lavidas et al., 2024; Nikolopoulou et al., 2021) and early evaluation foci (AbuSahyon et al., 2023; Hartley et al., 2024), our analysis emphasizes acceptance, perceived effectiveness, and concerns, while situating results within Indonesia's current stage of AI adoption (Barakina et al., 2021; Kamalov et al., 2023). Guided by the ADDIE model (Rahman & Duran, 2022; Wahira et al., 2023) and the concrete roles AI can play at each phase (Nguyen, 2023), we provide program-level evidence that can inform targeted professional development, policy and governance, and technology integration strategies at UNESA.

This focus on the learning-design process differentiates the current work from prior studies centered on singular tools (e.g., tutoring or assessment) or STEM-only deployments (Tang et al., 2023; Deehan et al., 2024; Larkin & Lowrie, 2023). By examining where AI is already embedded in design practice, how lecturers and students experience that use, and which conditions facilitate or impede impact, the study offers actionable insights for institutions seeking to move beyond proof-of-concept toward sustainable, pedagogically aligned integration. In sum, our contribution is a contextualized, process-oriented assessment of AI in learning design at UNESA that clarifies value propositions and constraints, balances enthusiasm with measured analysis (Chiu, 2024a; Holmes & Tuomi, 2022), and foregrounds the kinds of evidence-based strategies that AI can realistically support in higher education (Mollick & Mollick, 2023; Barrera Castro et al., 2024; Song, 2024).

METHOD

Research Design

This study employed a descriptive quantitative design to provide a systematic, transparent account of how AI is currently perceived and used in learning-design activities within a single higher-education program. Descriptive approaches are well suited to mapping phenomena, summarizing user preferences, usage rates, and perceived outcomes, and revealing patterns that can ground more analytic follow-ups (Azman et al., 2024; Indrayadi, 2021; Opawole et al., 2022). Prior applications show that descriptive statistics are informative for evaluating adoption and user acceptance of educational technologies such as videoconferencing systems (Ravid et al., 2020) and for diagnosing students' learning difficulties (Indrayadi, 2021). In line with these precedents, our aim here is diagnostic rather than predictive—to characterize acceptance, perceived effectiveness, and barriers in the Educational Technology Program at Universitas Negeri Surabaya (UNESA) without inferring to broader populations.

Although the Technology Acceptance Model (TAM) is often paired with inferential modeling (e.g., regression or SEM), it also provides a useful interpretive frame in descriptive contexts. TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) shape intention and behavior and can illuminate enablers and barriers relevant to AI integration among lecturers and students (Abdekhoda & Dehnad, 2024; Panda et al., 2022; Sackstein et al., 2022). Evidence in educational AI specifically links greater ease of use to stronger motivation to adopt, supporting TAM's relevance to our constructs (Okuonghae & Tunmibi, 2024). Given the exploratory scope and single-program focus, we therefore used TAM to guide instrument construction and to interpret descriptive patterns, not to estimate causal effects.

Consistent with this stance, we followed guidance that descriptive statistics are appropriate when the objective is to summarize sample characteristics and identify salient patterns rather than generalize (Phiri et al., 2022). The research workflow (Figure 1) comprised planning (construct definition and item drafting), implementation (participant recruitment and online administration), and analysis (coding and descriptive summarization). This flowchart clarifies the sequence from participant selection and instrument development to data collection and interpretation using descriptive techniques.

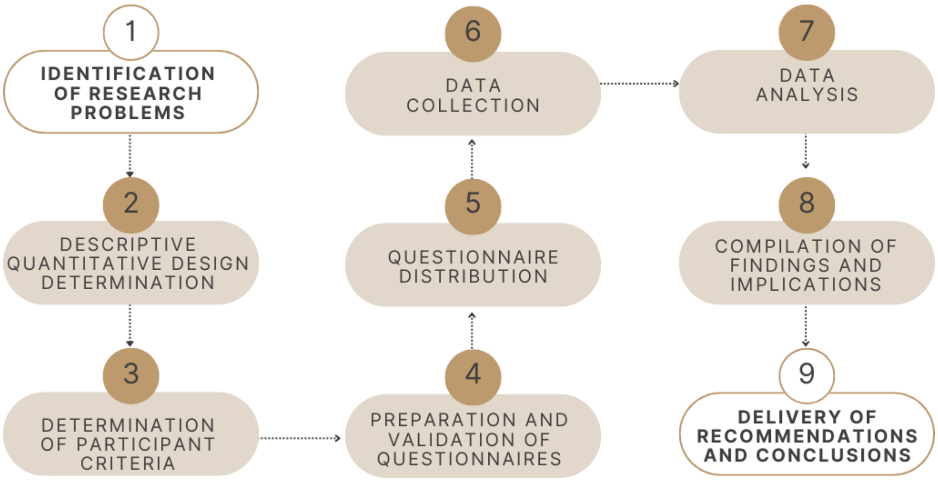

Figure 1. The Flowchart Research Process

Participants, Sampling and Procedures

Participants were 146 members of the Educational Technology Study Program at UNESA: 16 lecturers and 130 students. We used purposive sampling, a non-probability strategy that selects respondents based on characteristics aligned to the study's aims—in this case, experience with or strong interest in AI for educational purposes (Marek & Laumann, 2024; Slater & Hasson, 2024). Clearly articulating such criteria enhances credibility and transparency and helps ensure the sample reflects the target user group for AI in learning design (Slater & Hasson, 2024). Although this is a single-institution study, we sought heterogeneity within the program by including students at varied academic levels and lecturers with diverse teaching responsibilities. Future cross-setting collaborations could strengthen generalizability beyond this context (Reicher et al., 2022).

Regarding sample size, prior work suggests that 100–200 respondents typically afford stable descriptive estimates with acceptable margins of error (Fadhilawati et al., 2024). Our total of 146 falls within this range, with the student subsample exceeding the lower threshold. Interpretation nonetheless prioritizes representativeness over size when considering transferability to other contexts (Maleki et al., 2023; Morales et al., 2025). Because perceptions of AI can vary by demographics and learning modes (e.g., online vs. face-to-face) and by academic level (Alhassan et al., 2023; Were, 2024), we stratified the descriptive summaries by role (lecturer vs. student). Future work may adopt cross-institutional or mixed-methods designs to enrich understanding of AI integration pathways in higher education (Adhikari, 2021; Kyeremeh et al., 2022).

Data were collected via an online questionnaire administered during a regular teaching semester. Invitations described the study purpose, inclusion criteria, and voluntary nature of participation. The form required a response for each item to minimize missing data. No incentives were offered.

Instruments and Validation

We developed a 25-item structured questionnaire spanning three dimensions central to the study aims: acceptance, effectiveness, and barriers to using AI in learning design. Items used a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), a widely adopted format for technology-acceptance research that captures nuanced attitudes while remaining analyzable with clear descriptive summaries (Anderson et al., 2020; González-Zamar et al., 2021). Instrument construction was guided by a targeted literature review and TAM, aligning acceptance with PU/PEOU considerations and operationalizing effectiveness and barriers as perceived value in design tasks and perceived constraints (Beck, 2020).

Three experts—two senior lecturers specializing in instructional design and one practitioner experienced in educational AI—reviewed items for relevance, clarity, and construct alignment using a standardized rubric. A three-to-ten expert panel is typical for balancing coverage and bias in content validation, situating our panel within recommended practice (Afonso et al., 2020; Ansari & Khan, 2023). We quantified agreement using Aiken's V and the Content Validity Index (CVI) (Arsari et al., 2021; Rijal et al., 2024). Aiken's V values approaching 1.0 indicate strong expert consensus at the item level. Item-level CVI (I-CVI) was computed as the proportion of experts rating an item "essential"; all items achieved I-CVI ≥ 0.78, meeting conventional adequacy thresholds (Costa et al., 2025). We also computed the scale-level CVI (S-CVI), which exceeded 0.90, commonly taken as evidence of robust overall content validity (Clarke et al., 2024). These results support the fit of the items to their intended constructs.

Items were coded 1–5 in the direction of agreement; any negatively worded statements (if present) would be reverse-coded prior to analysis. The instrument blueprint mapped items to the three dimensions informed by TAM (acceptance ≈ PU/PEOU; effectiveness ≈ perceived usefulness of AI in specific ADDIE-phase tasks; barriers ≈ perceived constraints and risks). This mapping ensured content coverage across the design workflow while enabling dimension-level summaries.

Data Analysis

Analyses were descriptive and conducted at both aggregate and stratified levels (lecturer vs. student). For each item and dimension we reported frequencies, percentages, and measures of central tendency (means/medians) and dispersion as appropriate (Aksoy, 2023; Nisa et al., 2024). Following common practice with Likert data, "agreement" was operationalized as the percentage selecting Agree or Strongly Agree (response options 4 or 5), allowing straightforward interpretation across items and groups.

Although TAM variables are often examined via inferential techniques (Nugraha et al., 2023), we intentionally did not conduct regression or structural modeling: the goal was to describe current usage and perceptions in one program, not to predict or generalize beyond it (Faqih et al., 2023; Umar & Zakaria, 2022). This decision aligns with recommendations that initial investigations use descriptive statistics to surface immediate responses and practical entry points for institutional action (Tamba & Cendana, 2021). TAM constructs (PU/PEOU) were nevertheless used interpretively to classify and discuss patterns observed in the quantitative summaries (Maryanah, 2022; Soledad et al., 2021).

Because the online form required responses, item-level missingness was negligible. Role-based summaries (lecturer vs. student) were computed side-by-side to highlight convergences and divergences in perceptions. Where applicable, negatively worded items were reverse-coded before aggregation to ensure consistent directionality.

Ethical Statement

Data collection was conducted online via a structured questionnaire. Participants were informed of the study objectives, their right to anonymity, and the confidentiality of responses, and were reminded that participation was voluntary with the option to withdraw at any time without penalty. No incentives were offered, in line with standard ethical research practices. All responses were stored securely and reported only in aggregate form.

RESULTS AND DISCUSSION

The study's results provide specific insights into the application of AI in learning design within the Educational Technology Study Program at Universitas Negeri Surabaya. They result from the analysis of quantitative data collected using questionnaires. Overall, this study presents results that can be broadly categorized into the level of acceptance of AI, the effectiveness of AI in supporting learning design, the challenges faced, and recommendations for future development.

AI Acceptance Findings

To comprehend the degree to which the use of Artificial Intelligence in learning design was accepted, 10 statements were formulated and presented to the student and lecturer respondents. These statements embodied perceptions of AI's usability, its benefits in the teaching and learning process, and comfort and trust in using the technology as part of the learning ecosystem. Table 1 shows the acceptance of AI in learning design.

Table 1. Acceptance of AI in Learning Design

Description	Student (%)	Lecturer (%)
AI helps understand lecture materials	84.62	87.50
AI personalizes learning materials	80.77	81.25
AI improves learning efficiency	88.46	87.50
Optimism towards AI implementation	81.54	81.25
AI provides practical learning recommendations	82.31	87.50
AI supports in designing materials	83.08	87.50
AI improves learning experience	81.54	87.50
AI supports engagement in learning	80.00	81.25
Comfortable using AI for academic tasks	80.77	81.25
AI supports adaptive learning	83.08	87.50

Most students and lecturers highly accept AI use, with average agreement scores above 80% for nearly all items in this respect. The Technology Acceptance Model (TAM) remains a foundational framework for understanding technology adoption, focusing on perceived usefulness and ease of use as key predictors (Greener, 2022). Students feel that there is a need for personalization, time efficiency, and a higher level of engagement with the learning process. Adaptive learning systems using AI-enabled tools are being developed to cater to individual student needs and improve satisfaction (Tan et al., 2024). Lecturers feel that AI would speed up the preparation of teaching materials and introduce them to evidence-based assessment. Lecturers perceive AI as beneficial for content creation, assessment, feedback, and research (Mutanga et al., 2024; Shakib Kotamjani et al., 2023). However, high acceptance does not translate to practical usage without technical training support.

AI Effectiveness Findings

The second aspect considered in this study relates to the effectiveness of using AI to support the learning design process. There are 8 statement items meant to evaluate how much AI contributes to improving the efficiency, quality, and personalization of learning from both the students' and lecturers' perspectives. These include using AI to compile teaching materials, presenting adaptive content, analyzing learning needs, and diagnosing student learning outcomes. Also, perceptions of the accuracy and usefulness of the feedback provided by AI indicate how practical this support is. Table 2 shows the effectiveness of AI in supporting learning design.

Table 2. Effectiveness of AI in Supporting Learning Design

Description	Student (%)	Lecturer (%)
AI materials are easy to understand	85.38	87.50
AI makes it easier to access references	88.46	93.75
AI helps adaptive assessment	84.63	87.50
AI accelerates the preparation of materials	80.77	81.25
AI diagnoses learning difficulties	89.23	93.75
AI enables appropriate learning interventions	81.54	81.25
AI feedback helps learning development	83.87	87.50
AI improves learning and collaboration	89.23	87.50

Respondents consider the AI effective in supporting adaptive assessment, analyzing learning difficulty, and providing personalized feedback. AI-powered systems can analyze student performance data to tailor content, provide targeted interventions, and offer real-time feedback (Akavova et al., 2023). Using data to make the learning process better. For instance, the AI system can automatically identify student error patterns and recommend remedial materials. The lecturers who compile digital content and AI-based assessments also feel efficient. AI enables continuous assessment and personalization of learning paths, creating more effective and inclusive educational environments (T. Gupta, 2024; Halkiopoulos & Gkintoni, 2024). Such effectiveness shall define AI's potential as a co-lecturer within the learning scenario. Meanwhile, such effectiveness still presumes the respective pedagogical support, curriculum alignment, and quality control of AI output.

Identified Barriers and Limitations

Though AI has numerous benefits in the support of the process of learning design, there are several challenges in implementing it within a higher education environment. The third view of this study discusses the constraints hindering the uptake of AI by students and lecturers, covering technical, pedagogical, and ethical barriers. A set of seven statements was drawn up to bring to light issues from low digital literacy to the validity, bias, and transparency of AI systems in an educational setting, due to a lack of training on the use of AI, as well as hesitation on whether AI can assess the context and the curriculum. Table 3 shows the limitations of AI in learning design.

Table 3. Limitations of AI in Learning Design

Description	Student (%)	Lecturer (%)
Difficulty understanding AI systems	65.38	62.50
Received training on using AI	61.53	68.75
AI provides responses that are relevant to the context	58.46	62.50
AI content is in the curriculum	56.92	56.25
Users feel safe in sharing data when using AI systems	53.85	56.25
AI has the potential to encourage academic honesty	55.38	50.00
AI is integrated with LMS	60.77	68.75

The constraint point is the key point in this study. Low scores on these items show there are still significant obstacles. First, digital literacy is inadequate, as more than 60% of students and lecturers say they have not received training. This shows an absence of AI integration with educational standards. AI technologies like machine learning and natural language processing are instrumental in creating adaptive learning systems and inclusive curricula (Iweuno et al., 2024). Although AI is starting to be widely used in learning practices, survey results show that only a portion of respondents (around 56%) consider that the content produced by AI is in accordance with the applicable curriculum. This indicates doubts about the relevance of AI-generated material to competency standards set institutionally or nationally. One of the main reasons for this low perception of suitability is that many AI platforms are generative and global, which do not automatically refer to curriculum. AI can produce content that is conceptually accurate but not necessarily contextual in terms of course structure, learning outcomes, or local learning culture. Therefore, AI must be adjusted within the curriculum framework. Worries about privacy and ethics, such as the potential for plagiarism and assessment manipulation, are the ethical challenges in using AI. These impel the need for a control system to use AI in higher education. However, challenges such as data privacy, ethical considerations, and the need for teacher training must be addressed (Akavova et al., 2023; Joshi, 2023).

Discussion

Interpretation of Key Findings

The findings of this study provide a nuanced understanding of how students and lecturers within the Educational Technology Study Program at Universitas Negeri Surabaya perceive the use of Artificial Intelligence (AI) in instructional design. As AI technologies continue to evolve and permeate educational environments, these insights contribute to the broader discourse on user acceptance, effectiveness, and constraints surrounding AI integration in higher education.

One of the central findings, as presented in Table 1, reveals that both students and lecturers reported high levels of acceptance toward AI use in learning design. Over 80% of respondents across both groups agreed that AI supports personalized learning, enhances material development, and facilitates adaptive learning. This aligns with extensive literature that underscores performance expectancy—a key construct in the Technology Acceptance Model (TAM) and the Unified Theory of

Acceptance and Use of Technology (UTAUT)—as a strong predictor of user intention and satisfaction (Malakul, 2025; Mohsin et al., 2024). The expectation that AI will improve educational efficiency and outcomes contributes to favorable attitudes, which is evident among participants in this study.

Furthermore, the perceived effectiveness of AI, as detailed in Table 2, was also robust. High agreement percentages (above 85%) among both lecturers and students indicate that AI tools are viewed as instrumental in enabling adaptive assessments, diagnosing learning difficulties, and providing targeted feedback. These results support prior research which emphasizes AI's role in enhancing personalized learning and promoting instructional efficiency (Agbong-Coates, 2024; Malakul, 2025). Such capabilities are particularly valued in environments where instructors manage large and diverse classrooms and seek scalable, data-driven interventions.

Nevertheless, Table 3 illustrates a significant set of limitations that must be considered. The most pronounced challenges included inadequate digital literacy, lack of formal training on AI usage, and concerns about data privacy and alignment with institutional curricula. These results reflect findings in recent scholarship, which highlight persistent skepticism among users regarding AI's reliability, ethical implications, and the potential for misuse (Khlaif et al., 2024; Mishra et al., 2024). Additionally, the concern that AI tools might foster academic dishonesty or reduce critical thinking echoes the critiques posited by Khlaif et al. (2025) and Fousiani et al. (2024), who warn of over-reliance on automation at the expense of intellectual engagement.

Importantly, the variation in perceptions across participants suggests the influence of demographic and contextual factors. Research shows that prior exposure to educational technologies, pedagogical orientation, and institutional support significantly affect how users perceive AI tools (Almenara et al., 2024; Deshen & Noa, 2024). In this study, both student and lecturer cohorts came from a technology-focused academic program, potentially explaining the high receptiveness observed. Nonetheless, the absence of widespread AI integration across the university infrastructure—such as full Learning Management System (LMS) integration or clear ethical guidelines—was acknowledged as a barrier to deeper adoption.

These findings reinforce the view that AI's educational value is not solely dependent on its technical capabilities but also on users' readiness, institutional strategies, and the broader ethical landscape in which these technologies operate. As highlighted by Valerio (2024) and Yu and Yu (2023), fostering user trust and reducing anxiety related to surveillance or misuse are critical to sustainable AI adoption. Therefore, a balanced strategy emphasizing both innovation and ethical rigor is essential to maximize AI's benefits in instructional design while addressing its risks.

These results provide a local empirical basis for broader discussions on AI in higher education and echo calls from global literature for continuous support, pedagogical alignment, and inclusive technology implementation strategies (Bharti et al., 2023; Brown et al., 2025; Sharma et al., 2023). The high levels of perceived usefulness and optimism in this study signal a readiness that institutions like UNESA can leverage through informed policy-making and targeted faculty development initiatives.

Comparison with Prior Research

The findings of this study, particularly those related to AI acceptance and limitations as presented in Table 1 and Table 3, align with and diverge from existing research on AI integration in higher education, particularly in the context of Southeast Asia and teacher education programs. Consistent with prior studies, high levels of user acceptance of AI among students and lecturers—evident in the over 80% agreement rates reported in Table 1, echo findings from TAM- and UTAUT-based research that emphasize the significance of perceived usefulness and ease of use in driving technology adoption (L. Lin & Yu, 2023; Yim & Wegerif, 2024). These findings reflect the global trend observed across educational settings where AI tools that are seen as enhancing performance and reducing instructional burden are more readily accepted (Marengo et al., 2024; Nkedishu & Vinella, 2024). However, our study's TAM-based descriptive approach does not extend into inferential modeling, distinguishing it from many studies that use structural equation modeling to quantify these relationships.

In Table 3, limitations such as insufficient training and integration with Learning Management Systems (LMS) resonate with widespread challenges highlighted in research from Southeast Asia and developing regions more broadly. The lack of structured teacher training, which nearly 40% of our participants reported as missing, is a recurring barrier in AI educational implementation (Nkedishu & Vinella, 2024; Patel & Ragolane, 2024). Studies have consistently underscored that educators must develop not only technical skills but also the ability to align AI tools with pedagogical objectives, or risk superficial or ineffective adoption (Alotaibi & Alshehri, 2023). Moreover, resource constraints, an issue frequently cited in regional research, are indirectly reflected in the concerns raised by our participants regarding AI's limited LMS integration and inconsistent curriculum alignment (Gray et al., 2022; M. Gupta & Kaul, 2024). These issues suggest infrastructural and administrative gaps that echo broader findings in Southeast Asia, where disparities in access to digital tools can compromise the efficacy of even well-designed AI interventions (Tarisayi, 2024).

The ethical considerations raised in this study—such as concerns about data privacy and academic honesty—mirror global discussions on the unintended consequences of AI in education. Our findings, showing that over 40% of respondents were unsure about data safety when using AI, reflect trends noted by Alotaibi and Alshehri (2023), who observed that AI-related trust issues can hinder user engagement. Similarly, Fowler (2023) warned of the ethical dilemma posed by students' potential misuse of AI to circumvent learning, which was acknowledged by participants in this study as a risk to academic integrity.

In terms of theoretical alignment, this study's TAM-guided structure fits within a broader pattern of using TAM and UTAUT to assess technology adoption. Yet, as seen in recent literature, there is a growing movement toward expanding TAM to include variables such as ethical implications, trust, and alignment with institutional values (Eslit, 2023; Van et al., 2024). Our study implicitly supports this direction by highlighting the importance of training, curriculum compatibility, and ethical oversight—elements that go beyond the classic TAM constructs of ease of use and usefulness.

Outside the regional context, comparisons with studies from North America and Europe suggest that institutional support plays a more pronounced role in shaping AI readiness and implementation success (Mahligawati et al., 2023; Sharma et al., 2023). While our findings emphasize human and technical limitations, they also suggest that faculty and students at UNESA are willing to engage with AI technologies, provided that adequate systemic and cultural support structures are established. The current study's findings contribute to the growing body of evidence that AI adoption in higher education is influenced by complex, interrelated factors. These include technological competence, training availability, infrastructure readiness, and ethical safeguards—factors that parallel findings in both regional and global studies. To enhance AI integration, future efforts must adopt a holistic strategy that combines infrastructure development, targeted training, and institutional policies grounded in ethical and pedagogical considerations.

Pedagogical and Institutional Implications

The findings of this study, particularly those outlined in Table 2 (Effectiveness of AI in Supporting Learning Design), suggest several critical pedagogical and institutional implications that must be considered for the successful integration of Artificial Intelligence (AI) in higher education. Both students and lecturers reported high agreement (above 85%) on items related to AI's role in facilitating adaptive assessments, diagnosing learning difficulties, and accelerating the preparation of materials. These findings underscore AI's transformative potential in reshaping educational delivery and planning.

Pedagogically, AI is enabling a shift toward personalized and data-informed learning. As reported by Karataş et al. (2024), AI facilitates adaptive instruction by helping educators tailor learning activities to individual student profiles. The evidence from this study supports this observation—respondents affirmed AI's capability to generate personalized content and feedback, which can be used to support differentiated instruction and formative assessment. This aligns with the growing emphasis on student-centered learning, wherein educators use real-time data analytics to refine content delivery and learning pathways (Tolentino et al., 2024).

AI also streamlines instructional planning by automating labor-intensive tasks such as content generation, assessments, and feedback loops, enabling instructors to invest more effort in pedagogical design. This has significant implications for curriculum development. As noted by Li et al. (2024) and Richter et al. (2024), AI tools can support curriculum alignment by mapping learning objectives with outcomes, which is essential for academic programs aiming to stay relevant in evolving fields. Project-based and interdisciplinary learning can also be facilitated by AI's capacity to suggest cross-domain learning materials, reinforcing the findings in this study where AI was perceived to support collaborative learning experiences.

Institutionally, this study reflects the need for targeted professional development in AI. Despite the high perceived effectiveness of AI (Table 2), Table 3 identifies that a significant portion of respondents (over 35%) reported limited training in AI use. This mirrors broader research across Southeast Asia, where institutional readiness often lags behind technology potential (Alotaibi & Alshehri, 2023; Nkedishu & Vinella, 2024). Institutions must therefore prioritize educator training that combines technical skill-building with pedagogical strategies for ethical and effective AI integration (Allam et al., 2023; Zhang et al., 2024).

Infrastructure support is another pressing implication. While AI tools are increasingly sophisticated, their successful adoption hinges on institutional capabilities—such as high-speed internet, integrated learning management systems (LMS), and real-time analytics platforms (Aprianto et al., 2024; Wang et al., 2023). In this study, AI's partial integration with LMS platforms was identified as a limitation (Table 3), which parallels the challenges identified in literature regarding fragmented systems and uneven resource distribution (Gao, 2025). Strategic investments in scalable infrastructure are essential for ensuring equitable access and consistent user experiences.

The integration of AI must also align with institutional policies and strategic planning. Institutions that embed AI competencies into academic policies—such as requiring AI literacy among students or adopting ethical AI usage standards—create a more future-ready academic ecosystem (Alshehri, 2023). Aligning AI tools with LMS also facilitates more transparent and responsive learning environments, where student progress tracking and automated feedback mechanisms support both educators and learners (Destéfano et al., 2024). Furthermore, involving faculty in co-designing AI-enhanced curricula is essential to promote ownership and ensure contextual appropriateness. Faculty engagement in this process not only fosters innovation but also ensures ethical safeguards in AI use, particularly in assessment and data management (Ayeni et al., 2024; P. Lin et al., 2020). As institutions such as UNESA seek to expand their AI capacity, participatory design models and iterative policy development will be key to realizing the full pedagogical potential of AI.

The results from this study suggest that AI can serve as both a pedagogical enhancer and a planning catalyst—provided that it is supported by strong institutional frameworks, faculty development initiatives, and well-aligned policies. The positive perceptions recorded in Tables 2 and Table 3 offer a promising foundation for further institutional reforms that strategically integrate AI into teaching and learning systems.

CONCLUSION

This descriptive, single-site survey of 16 lecturers and 130 students in the Educational Technology Study Program at Universitas Negeri Surabaya mapped perceptions of AI in learning design. Respondents generally reported that AI tools could accelerate preparation of materials, support adaptive/diagnostic feedback, and enable more personalized learning pathways. These are perceived benefits, not measured learning effects. Barriers were also salient: uneven digital literacy, limited formal training, partial LMS integration, and concerns about privacy, ethics, and academic integrity. Viewed through TAM, perceived usefulness is high, while perceived ease of use—and the enabling conditions around it—remain uncertain. Given the scope and design, results are not generalizable and do not establish causality. Institutional uptake should therefore proceed via tightly scoped pilots, targeted capacity building, and clear governance for responsible use, with stronger longitudinal and inferential evaluations required before any scale-up.

RECOMMENDATIONS

Given the small, single-site, descriptive evidence (16 lecturers; 130 students), start with pilots and explicit thresholds before any scale-up. In the next 1–2 years, run tightly scoped AI-literacy modules first within the studied program; cover practical use, disclosure, privacy, and safety. In parallel, adopt enforceable policies (acceptable use, data governance, bias mitigation) and set baselines for outcomes, acceptance (TAM constructs), integrity incidents, and workload, with simple pre/post monitoring. Over years 3–5, form an interdisciplinary AI-Based Adaptive Curriculum Team (pedagogy, data/CS, ethics, psychology, student support) with one external advisor to reduce single-site bias. Align AI materials to standards and run comparative evaluations (A/B or stepped-wedge where feasible). Use mixed methods (performance and usage data plus interviews/observations) across multiple courses/faculties to test transferability. Track risk indicators—fairness of outputs, student well-being, and staff workload—and trigger corrective actions if thresholds are breached.

Beyond 5 years, integrate AI into the Educational Innovation Master Plan only if longitudinal data show sustained learning benefits, stable acceptance, and no disproportionate harms. Institutionalize audits (privacy, bias, security), incident response, transparent reporting, and budget for ongoing PD, model/tool updates, and infrastructure while avoiding lock-in. Across all phases, address current limitations by expanding samples (multi-program/institution), adding inferential and pragmatic experimental designs, running longitudinal cohorts, and testing domain-specific use (e.g., STEM, language). Keep ethics central (bias, privacy, surveillance) and, where possible, preregister evaluations and share instruments. Apply decision gates at each phase—proceed, pause, or pivot—based on outcome gains, equity checks, integrity and well-being indicators, and workload feasibility.

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Conflict of interests

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