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An AI-Based Adaptive Learning Framework for Strengthening Civic Competence and Digital Literacy among University Students

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Abstract

This study developed and evaluated an AI-based adaptive learning framework intended to strengthen civic competence and digital literacy among university students at Universitas Muhammadiyah Sumatera Utara. The study responded to a limitation found in many adaptive learning systems, namely their dominant emphasis on academic achievement while rarely operationalizing civic-digital indicators as triggers for personalization. Using Design Science Research combined with mixed methods, the study was conducted through six iterative stages: needs assessment, co-design of indicators, instrument development and validation, prototype development, quasi-experimental implementation, and evaluation of usability, explainability, and fairness. The final framework consisted of five interconnected layers: diagnostic profiling, civic-digital analytics, adaptive recommendation engine, explainability and reflection, and governance and fairness control. The intervention involved 124 students in four classes, with two classes assigned to the intervention group and two to the control group. The results showed that the intervention group achieved stronger gains in civic competence and digital literacy than the control group. The prototype also obtained an acceptable usability score (SUS = 81.4; UMUX-Lite = 84.7) and its recommendation explanations were considered understandable by both students and lecturers. The study contributes a localized measurement instrument, a practical ethical-AI implementation blueprint, and an adaptive learning design that integrates academic support with responsible digital citizenship.

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1. Introduction

Digital transformation in higher education has increased the demand for learning environments that are not only flexible and data-informed, but also ethically grounded and socially meaningful (Selwyn, 2016; UNESCO, 2023). The adoption of learning analytics and AI-assisted instruction has enabled universities to personalize learning paths, provide timely feedback, and monitor engagement more effectively. However, this rapid development also raises an important question: what kinds of learning outcomes should adaptive systems prioritize?

Most adaptive learning systems are still primarily oriented toward improving academic performance. While this focus is important, it does not fully reflect the broader mission of higher education. Universities are also expected to develop students' civic competence, including their ability to think critically about public issues, engage responsibly in discussions, and respect diverse perspectives (Westheimer & Kahne, 2004). These competencies are increasingly relevant in digitally mediated environments.

In parallel, students are required to develop strong digital literacy. This includes the ability to evaluate information, use data responsibly, and participate ethically in online spaces (Fraillon et al., 2019; Vuorikari et al., 2022). These skills are essential for navigating complex information ecosystems and for preventing the misuse of technology. Therefore, higher education must integrate both civic and digital dimensions into its learning design.

Previous studies have demonstrated that adaptive learning can improve student outcomes and engagement (Khosravi et al., 2022; Pane et al., 2015). However, several limitations remain. First, most adaptive systems rely heavily on academic indicators and rarely incorporate civic or digital competencies into their personalization logic. Second, learning analytics often focuses on prediction and monitoring, with limited attention to how users understand system recommendations. Third, ethical considerations such as fairness and accountability are often discussed conceptually, but are not consistently implemented in practical system design.

This study addresses these gaps by proposing an AI-based adaptive learning framework that integrates civic competence and digital literacy into the personalization process. The framework incorporates indicators such as civic reasoning, responsible participation, and information evaluation. It also embeds explainability features so that users can understand the rationale behind recommendations. In addition, a fairness mechanism is included to monitor potential bias in system outputs.

This study contributes a framework that operationalizes civic-digital indicators within adaptive learning systems. In doing so, it extends the role of adaptive learning from a tool focused on academic remediation to a system that supports responsible and reflective learner development.

1. The study was conducted at Universitas Muhammadiyah Sumatera Utara, where the integration of technological innovation and ethical learning is highly relevant. Within this context, educational practices are expected to align with values of social responsibility and meaningful knowledge use. Accordingly, the study is guided by three research questions:

   (1) how civic and digital competencies can be systematically integrated into adaptive learning,

   (2) what indicators are suitable for triggering such adaptation, and

   (3) how explainability, usability, and fairness can be maintained in the system.

2. Method

Research Design

This study employed Design Science Research (DSR) combined with a mixed-methods approach. The purpose of using DSR was to design, develop, and evaluate an adaptive learning artifact rather than merely analyze an educational problem. The artifact developed in this study was an AI-based adaptive learning framework equipped with a recommendation module and a lecturer-facing dashboard. The research followed an iterative cycle in which each phase informed subsequent refinement.

The study was implemented in an iterative cycle in which each phase informed the next refinement step. The study was conducted at Universitas Muhammadiyah Sumatera Utara (UMSU) in courses related to civic education and selected cross-disciplinary learning contexts that allowed the integration of civic and digital learning indicators. The participants were recruited through purposive selection and consisted of three groups. The first group involved experts in civic education, educational measurement, and information systems who participated in the co-design and validation stages. The second group consisted of lecturers who implemented the framework in classroom practice. The third group involved undergraduate students who participated in the pilot testing and quasi-experimental phases. In the effectiveness stage, the study used at least two comparable classes, namely an intervention class that used the adaptive learning framework and a control class that followed regular instruction. This design was intended to test whether the intervention generated stronger improvements in civic competence and digital literacy than conventional teaching (Hevner et al., 2004; Wieringa, 2014)..

The first phase involved needs assessment, scope clarification, and ethical preparation. Data were collected from lecturers, students, and curriculum documents to identify gaps in current digital learning practice (Hoskins & Mascherini, 2009; Ribble, 2015; Vuorikari et al., 2022; Westheimer & Kahne, 2004). The second phase consisted of co-design activities with experts in civic education, educational practice, and information systems. These sessions were used to define

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the construct dimensions, derive measurable indicators, and formulate the initial adaptation rules. The third phase focused on instrument development and validation. Content validity was checked through expert judgment, while internal consistency and construct quality were examined in pilot testing (Freeman et al., 2014; Khosravi et al., 2022; Pane et al., 2015).

The fourth phase was minimum viable prototype development. The prototype contained five major functions: diagnostic profiling, civic-digital analytics, adaptive recommendations, explanation messages, and lecturer monitoring. The fifth phase involved quasi-experimental implementation in four classes. Two classes were assigned as intervention groups and two as control groups. The intervention classes received adaptive recommendations, reflective activities, short civic case analyses, discussion prompts, and digital ethics exercises. The control classes followed regular LMS-supported instruction without AI-based personalization.

The sixth stage addressed the evaluation of effectiveness, usability, explainability, and fairness. To examine instructional effectiveness, the researchers compared pretest and posttest performance across groups using ANCOVA or General Linear Model (GLM) procedures while controlling for baseline differences. Effect sizes were calculated using Cohen's d to determine the practical magnitude of the intervention. To evaluate the usability of the prototype, the study employed standardized instruments such as the System Usability Scale (SUS) or UMUX, complemented by structured interviews with students and lecturers. To assess explainability, participants were asked whether they understood why certain recommendations were generated and whether those recommendations were perceived as reasonable and supportive. To examine fairness, the researchers conducted an initial audit by checking whether recommendations or outcomes appeared disproportionately favorable or unfavorable across student subgroups. These steps were necessary because the framework explicitly positioned AI not merely as a technical tool, but as a pedagogical system that had to remain transparent, accountable, and educationally just (Doshi-Velez & Kim, 2017; Floridi & Cowls, 2019; Jobin et al., 2019; UNESCO, 2023).

The data analysis combined quantitative and qualitative techniques. Quantitative data from questionnaires, test scores, and usability scales were analyzed using descriptive statistics and inferential procedures. Instrument validation relied on validity and reliability testing, while intervention effectiveness relied on pretest–posttest comparisons, covariance analysis, and effect size estimation. Qualitative data from interviews, observation notes, and reflective responses were analyzed thematically to identify patterns related to student engagement, lecturer acceptance, recommendation clarity, and perceived instructional value. The qualitative findings were used to explain and deepen the interpretation of the quantitative results. This integration of data sources strengthened the study's internal logic and provided a more comprehensive evaluation of the framework.

Table 1. Summary of needs analysis and system responses

Need Analysis Result	Observed Issue	System Response
Lecturers required concise monitoring of civic-digital weaknesses	Current LMS reports were too general and did not reveal who needed civic or digital-literacy support	A dashboard summarized weak dimensions, priority students, and suggested lecturer interventions
Students expected immediate and individualized feedback	Feedback was delayed, generic, and mostly limited to academic correction	The system generated recommendation messages linked to specific civic-digital indicators
Low visibility of ethical digital behavior	Participation data existed, but responsible information use and reflective engagement were not tracked	Rule-based analytics mapped forum behavior, quiz results, and reflective tasks into civic-digital profiles
Unclear reason behind recommendations	Students were reluctant to follow suggestions they did not understand	Each recommendation included a short explanation and the indicator that triggered it
Need for fairer personalization	Students with low activity risked receiving weak or noisy recommendations	A governance layer flagged low-signal cases and encouraged lecturer review before high-stakes intervention

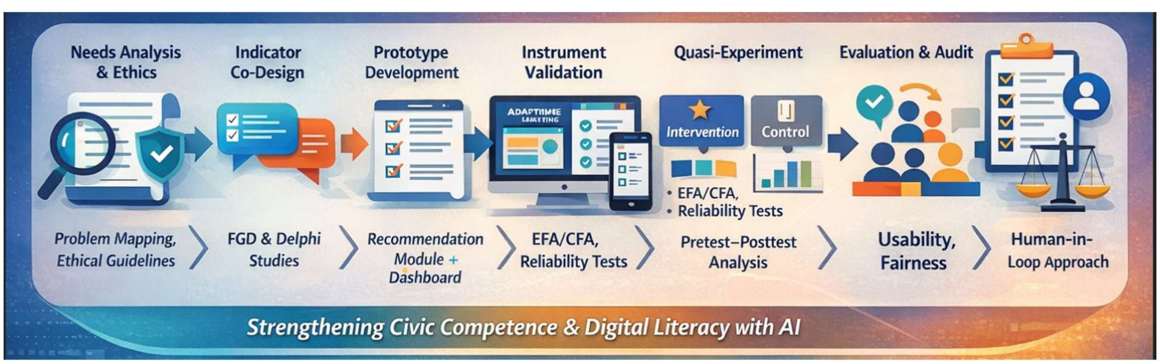

Figure 1. *Sequential mixed-method Design Science Research process used to design, validate, implement, and refine the AI-based adaptive learning framework for strengthening civic competence and digital literacy.*

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3. Result and Discussion

Findings

The needs analysis showed that the main weakness of current digital learning practice was not merely limited access to content, but the absence of a structured mechanism that could translate student behavior into meaningful intervention. Lecturers needed a system that could identify civic-digital weaknesses with sufficient precision, while students wanted feedback that was immediate, individualized, and understandable. These findings confirmed that the problem to be solved was both pedagogical and informational: the classes needed a way to connect behavioral traces, ethical learning goals, and concrete instructional actions (Siemens & Long, 2011; Ferguson, 2012; Ifenthaler & Yau, 2020).

Based on the co-design and validation process, the final framework was structured into five core layers: diagnostic profiling, civic-digital analytics, adaptive recommendation engine, explainability and reflection, and governance and fairness control. The diagnostic layer captured the initial profile of students through pre-test data and early interaction signals. The analytics layer transformed activity traces into interpretable indicators, especially those related to information verification, responsible participation, argument quality, and AI-related literacy. The recommendation layer translated these indicators into specific learning suggestions, while the explainability layer communicated the reasons for those suggestions. The final layer provided safeguards so that recommendations remained transparent, contestable, and open to lecturer judgment (Conati & Kardan, 2013; Luckin et al., 2016)..

The content validation stage indicated that the proposed dimensions were suitable for the university context. The expert panel agreed that civic reasoning, responsible participation, digital information literacy, data literacy, and AI literacy were conceptually coherent and relevant to students at UMSU. Several items were revised for language clarity, contextual relevance, and more balanced wording, but the structure of the instrument was retained. The psychometric results were also satisfactory. The internal consistency values for civic competence and digital literacy were high enough to justify the use of the instrument both for diagnostic profiling and outcome evaluation (Hoskins & Mascherini, 2009; Redecker, 2017; Vuorikari et al., 2022).

The prototype implementation demonstrated that the framework was technically workable within classroom practice. Students in the intervention group received recommendations in the form of short remedial content, case-based prompts, reflective activities, and digital-ethics tasks. Each recommendation was accompanied by a brief message explaining its rationale. Lecturers accessed a dashboard that summarized class risk patterns, weak indicators, and recommended instructional follow-up. This combination reduced the information overload often experienced in LMS environments because lecturers could focus on actionable patterns rather than on raw activity logs (Doshi-Velez & Kim, 2017; Adadi & Berrada, 2018).

The quasi-experimental results showed that the intervention group outperformed the control group across all major variables. The largest gains were observed in digital literacy, particularly in students' ability to identify credible information, interpret data responsibly, and understand the ethical implications of AI use. This result suggests that adaptive support became most effective when the system linked performance information to meaningful ethical and informational cues, rather than merely recommending additional content. The increase in civic competence was also substantial. Students showed improvement in issue-based reasoning, quality of argumentation, reflective participation, and awareness of the social consequences of digital action (Ma et al., 2014; Pane et al., 2015; Freeman et al., 2014; Khosravi et al., 2022)..

Table 2. Measurement quality, usability, and fairness results

Indicator	Final Result	Interpretation
S-CVI/Ave	0.94	Content validity was in the very good category
Civic competence α / CR / AVE	0.89 / 0.91 / 0.57	Internal consistency and convergent quality were acceptable
Digital literacy α / CR / AVE	0.91 / 0.93 / 0.61	The instrument was reliable and stable for diagnostic use
SUS	81.4	The prototype reached the acceptable-to-excellent usability range
UMUX-Lite	84.7	Users perceived the interface as clear and manageable
Explanation clarity	4.23 / 5.00	Students and lecturers generally understood why recommendations were generated
Recommendation parity gap	0.06	No severe imbalance was found in the early fairness audit

Learning engagement data supported these results. Compared with the control group, intervention students accessed remedial materials more frequently, participated more actively in discussion forums, and submitted tasks more punctually. Importantly, the types of activities that received the highest follow-through rates were those that were short, concrete, and clearly justified. This indicates that effective personalization depends not only on matching content to learner needs, but also on presenting the recommendation in a form that users find reasonable and manageable (Viberg et al., 2018; Khosravi et al., 2022).

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Students reported that they were more willing to follow a recommendation when they understood why it appeared. Messages such as 'this task is recommended because your information verification score is below the class average' helped them connect the system's suggestion to their own learning profile. Lecturers also perceived the explanation layer as useful because it supported instructional decisions without requiring them to interpret raw statistical information. In other words, explainability functioned as a bridge between analytics and pedagogical action (Doshi-Velez & Kim, 2017; Floridi & Cowls, 2019).

The preliminary fairness audit produced encouraging, though not definitive, results. No severe imbalance was found in the distribution of recommendations across major user categories. However, a mild cold-start issue appeared among students with very low LMS activity because the limited behavioral signal made it more difficult for the system to produce precise recommendations. This finding is important because it shows that fairness in educational AI is not only a matter of demographic parity, but also of signal quality and participation patterns. For that reason, the framework retained a human-in-the-loop principle in which lecturers could confirm, supplement, or override recommendations when necessary (Selbst et al., 2019; Jobin et al., 2019).

Taken together, the findings indicate that adaptive learning can be expanded beyond academic remediation into a broader educational model that supports reflective citizenship and responsible digital conduct. The contribution of the framework therefore lies not only in its technical design, but in the shift of personalization logic itself. By using civic and digital indicators as adaptation triggers, the framework positioned AI as a medium for value-based educational support rather than as a purely efficiency-oriented tool (UNESCO, 2023; OECD, 2021).

Table 3. Quasi-experimental comparison between intervention and control groups

Variable	InterventionPre-test	Intervention Post-test	Control Pre-test	Control Post-test	p-value	Cohen's d
Civic competence	61.8 ± 7.2	78.6 ± 6.5	62.1 ± 7.1	68.4 ± 7.0	< .001	0.87
Digital literacy	58.9 ± 8.1	80.7 ± 6.2	59.4 ± 7.8	69.5 ± 6.9	< .001	1.02
Learning engagement	65.1 ± 8.5	82.4 ± 6.8	64.7 ± 8.2	71.2 ± 7.5	.002	0.74

4. Discussion

The results of this study demonstrate that adaptive learning becomes more educationally meaningful when personalization is aligned not only with cognitive performance but also with civic and digital-development goals. The findings indicate that the effectiveness of the system lies in its ability to connect behavioral data with actionable pedagogical responses that are understandable and relevant to students.

More importantly, this study brings together civic competence, digital literacy, and AI into a single integrated conceptual framework. Civic competence provides the normative direction for responsible participation, digital literacy ensures the capacity to navigate information ecosystems, and AI functions as the enabling mechanism that operationalizes both domains into adaptive learning processes. This integration suggests that adaptive learning should not be viewed merely as a technical system, but as a pedagogical environment that shapes how students think, act, and interact in digital society.

From a theoretical perspective, the findings can be situated within the concept of learning ecology, where learning is understood as a dynamic interaction between learners, technologies, and social contexts. The adaptive system in this study functions as an ecological mediator that continuously interprets learner behavior and responds with context-sensitive support. At the same time, the framework reflects a sociotechnical systems perspective, in which technological design, human agency, and institutional values are interdependent. The inclusion of explainability, fairness, and lecturer oversight illustrates that educational AI must be designed as a balanced interaction between automated processes and human judgment.

This study extends adaptive learning theory by embedding ethical and civic dimensions into personalization logic. Rather than focusing solely on optimizing academic outcomes, the framework redefines personalization as a process that also supports responsible digital behavior, critical reasoning, and reflective participation.

The role of explainability in this study highlights an important shift in educational AI design. When students understand why a recommendation is generated, they are more likely to engage with it. Explainability therefore acts as a bridge between data-driven analytics and pedagogical meaning. Similarly, the integration of fairness and human-in-the-loop mechanisms demonstrates that adaptive systems should not operate as fully autonomous decision-makers. Instead, they should support educators in making informed and context-sensitive instructional decisions.

Despite these strengths, several critical considerations need to be addressed. One potential risk is the over-reliance on AI systems in educational decision-making. Excessive dependence on automated recommendations may reduce opportunities for human judgment and pedagogical flexibility. In addition, scalability remains a challenge. While the framework performed well in a controlled classroom setting, broader implementation across institutions may face

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constraints related to infrastructure, data quality, and lecturer readiness. These issues highlight the importance of maintaining a balanced integration between technology and human agency.

The findings also have important implications beyond the classroom level. At the policy level, the study supports the need for guidelines that ensure ethical, transparent, and accountable use of AI in education, in line with international frameworks such as UNESCO and OECD. At the curriculum level, the integration of civic competence and digital literacy suggests that these domains should not be treated as separate subjects, but as embedded components within digitally supported learning environments. At the level of AI governance, the study emphasizes the importance of incorporating explainability, fairness auditing, and human oversight into system design to ensure responsible and sustainable implementation.

In summary, this study demonstrates that adaptive learning can evolve into a more holistic educational model when it integrates technological capability with ethical and civic considerations. The framework not only improves learning outcomes, but also contributes to the development of responsible, reflective, and digitally competent learners in contemporary society.

5. Conclusion

The study demonstrates the feasibility of an AI-based adaptive learning framework that integrates civic competence and digital literacy as explicit targets of personalization. The framework extends the common logic of adaptive learning beyond academic correction by embedding ethical participation, information judgment, and responsible technology use into the recommendation process.

The empirical results showed that the framework was pedagogically useful, technically workable, and ethically promising. The instrument quality was adequate, the prototype reached an acceptable usability level, and the intervention classes showed stronger gains than the control classes in civic competence, digital literacy, and learning engagement.

The study contributes a localized measurement instrument, a framework architecture for civic-digital adaptation, and a practical model for incorporating explainability and fairness into classroom-facing AI. Future development should involve wider implementation across disciplines, stronger cold-start handling, and broader fairness auditing with larger samples and longer deployment cycles.

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