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Research Article

AI-Driven Adaptive Online Digital Modules for Communication Courses Using Learning Analytics and Natural Language Processing

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Abstract

Background: The rapid growth of online learning in higher education requires innovative solutions that support independent, scalable, and standardized learning experiences. Artificial Intelligence (AI), particularly Learning Analytics (LA) and Natural Language Processing (NLP), offers opportunities to enhance digital learning through adaptive content delivery, personalized learning pathways, and automated formative feedback.

Aims: This study aimed to develop and evaluate an AI-driven adaptive online digital module for Communication courses that supports personalized learning and standardized instruction across higher education institutions using Gemini.

Methods: This study employed the ADDIE development model, comprising Analysis, Design, Development, Implementation, and Evaluation. Learning Analytics was used to monitor student engagement and learning progress, while NLP analyzed students' written responses to generate automated formative feedback. The module was validated by instructional design, subject matter, and media experts, followed by individual and small-group trials. Its effectiveness was evaluated using normalized gain (N-Gain) analysis.

Results: Expert validation, individual trials, and small-group evaluations indicated that the developed module achieved a "very good" level of feasibility. The effectiveness evaluation produced a high N-Gain score (0.7), indicating a substantial improvement in student learning outcomes. The integration of Learning Analytics and NLP supported adaptive learning, timely feedback, and increased student engagement.

Conclusion: The AI-driven adaptive digital module is feasible and effective for supporting online learning in Communication courses. Integrating Learning Analytics and Natural Language Processing enables personalized instruction and data-informed learning support, making the module a promising approach for improving learning quality in higher education.

Keywords: Artificial Intelligence; Communication Course; Digital Module; Learning Analytics; Natural Language Processing.

1. INTRODUCTION

Higher education institutions, including Universitas Negeri Surabaya (UNESA), have a fundamental responsibility to ensure students' right to high-quality learning experiences. With the rapid advancement of information and communication technology, universities are expected to integrate emerging technologies, particularly Artificial Intelligence (AI), to create more personalized, data-driven, and adaptive learning environments. UNESA has demonstrated this commitment through the implementation of online learning programs; however, these initiatives have not yet been fully adopted across all courses and departments. At the same time, the Educational Technology study program is actively pursuing internationalization through academic collaboration with partner universities both nationally and internationally. This initiative requires digital learning systems that not only provide broad accessibility but also maintain consistent instructional quality, timely feedback, and personalized learning support. Consequently, the development of an AI-driven online learning platform has become an important strategic priority.

The internationalization of the Educational Technology study program also requires learning environments capable of supporting diverse learner needs while

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maintaining comparable learning standards across institutions. In this context, Learning Analytics (LA) and Natural Language Processing (NLP) offer complementary capabilities that extend beyond those of conventional Learning Management Systems (LMS) (Chandler et al., 2024; Emara et al., 2021; Sajja et al., 2025). Learning Analytics enables continuous monitoring of learner engagement, participation, and academic progress, allowing lecturers to identify students who require additional support and to provide timely instructional interventions. Meanwhile, NLP enables automated analysis of students' written communication, facilitating rapid formative feedback and more consistent evaluation of communication performance (Ouyang et al., 2023; Zheng et al., 2023). These capabilities are particularly valuable in collaborative and cross-institutional learning environments where providing individualized feedback manually becomes increasingly difficult as class sizes grow.

Online learning has evolved considerably since the widespread adoption of Learning Management Systems (LMS), which provide core functions such as content delivery, discussion forums, quizzes, gradebooks, and communication tools (Almelhi, 2021; Kumar et al., 2025). Although these functions effectively support course administration, conventional LMS platforms primarily deliver static learning materials and rule-based assessments. They generally lack mechanisms to interpret students' written communication, identify misconceptions from open-ended responses, monitor learning behavior continuously, or personalize instructional pathways according to individual learning needs (Padhy et al., 2025; Singh et al., 2025). As a result, lecturers often rely on manual assessment and delayed feedback, limiting opportunities for timely instructional intervention and individualized support. Recent AI-enhanced LMS environments seek to overcome these limitations through intelligent tutoring, predictive analytics, and automated feedback systems.

These limitations are particularly important in Communication courses because learning outcomes extend beyond factual knowledge acquisition. Students are expected to develop communication competence through written reflection, argument construction, collaborative discussion, interpersonal interaction, and the application of communication strategies in authentic contexts. Such competencies require continuous practice accompanied by immediate, high-quality formative feedback. Conventional LMS quizzes and objective assessments are effective for measuring factual understanding but are less capable of evaluating the quality, coherence, and appropriateness of students' communication or providing individualized guidance for improvement. Consequently, relying solely on traditional LMS functions may limit students' opportunities to refine higher-order communication skills throughout the learning process.

The Communication course is a mandatory four-credit course in the Educational Technology study program at UNESA. It equips prospective educational technologists and teachers with competencies in communication theory, instructional communication, interpersonal and group communication, and communication within digital learning environments. Because communication competence develops through repeated practice and feedback rather than content exposure alone, the course requires learning environments capable of supporting continuous interaction, reflection, and formative assessment. Integrating Learning Analytics and NLP therefore provides a strong pedagogical rationale (Laylo, 2026). Learning Analytics enables lecturers to monitor participation patterns, engagement levels, and learning progress in real time, while NLP supports automated analysis of students' written responses and discussion contributions to generate timely formative feedback. Together, these technologies create adaptive learning experiences that are difficult to achieve using conventional LMS modules alone.

The Communication course also requires learning resources that promote active, independent, and collaborative learning. AI-driven digital modules address these pedagogical requirements by integrating adaptive learning pathways, personalized recommendations, automated formative feedback, and data-driven instructional support (Huriati et al., 2023). Rather than presenting identical learning sequences to all students, the modules respond dynamically to learner performance and engagement, enabling students to progress according to their individual needs. Feedback generated from Learning Analytics and NLP encourages reflection, self-regulated learning, and continuous improvement of communication competence. Previous studies have demonstrated that timely formative feedback enhances learning outcomes (Mandouit & Hattie, 2023), while technology-supported learning environments increase engagement and deepen learning experiences (Chen et al., 2021). The present study extends these findings by demonstrating how AI technologies can support the pedagogical requirements of Communication courses, where continuous interaction, feedback, and communication practice are central to achieving the intended learning outcomes.

Currently, the Communication course has not fully adopted AI-driven digital modules. Existing learning materials are compiled from multiple sources and delivered primarily through conventional LMS features, limiting opportunities for adaptive instruction, automated analysis of students' communication performance, and timely personalized feedback (Barna, 2026; Ragab et al., 2025). Consequently, students receive limited support for developing communication competencies through iterative practice and reflection.

Based on the learning outcomes of the Communication course, student characteristics, and recent developments in educational AI, this study proposes the development of AI-driven adaptive online digital modules integrating Learning Analytics and Natural Language Processing. The proposed system is designed not merely to digitize instructional materials but to provide intelligent learning support through adaptive content delivery, continuous monitoring of learning behavior, and automated formative feedback. By addressing the pedagogical limitations of conventional LMS environments, the developed module is expected to create more meaningful, personalized, and effective learning experiences while preparing students to become educational technology professionals capable of working in increasingly digital and AI-supported educational contexts.

2. MATERIAL AND METHOD

The research approach includes several aspects such as development models, development procedures, and product testing. In addition to conventional instructional design, this study integrates Artificial Intelligence (AI) components, specifically Learning Analytics and Natural Language Processing (NLP), to enhance personalization, automate feedback, and support adaptive learning. The development model applied in this study is the ADDIE model. This model was chosen because it provides a systematic and flexible framework for instructional development while allowing the integration of intelligent systems. The ADDIE process is sequential but also iterative, allowing evaluation at each stage can redirect development to earlier stages. The output of each phase becomes the input for the next phase, including AI model refinement.

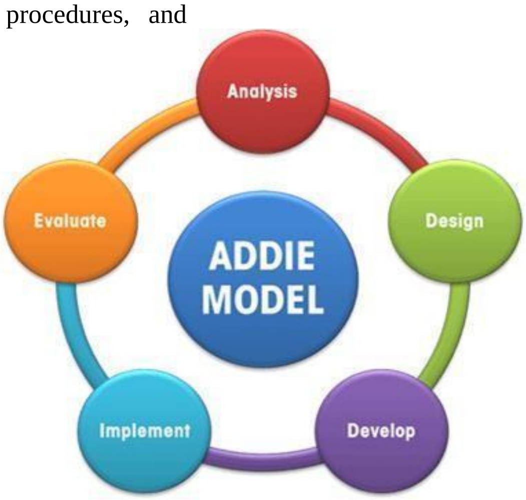

Figure 1. The ADDIE Method

The ADDIE framework is a cyclical and continuous process throughout instructional planning and implementation. This framework consists of five stages, each with specific goals and functions in the development of instructional design (Spatioti & Kazanidis, 2022). The following is a description of the stages of the ADDIE development model according to Branch 2009 (Ussainova et al., 2025):

Analysis (AI-Supported Needs Analysis)

This stage focuses on identifying learning problems and determining system requirements as the foundation for developing the digital module. In addition to conducting interviews, initial data such as student performance, learning behavior, and interaction patterns are examined using Learning Analytics principles. This analysis explores students' competencies and characteristics, including their knowledge, skills, and attitudes, as well as patterns of learning behavior such as engagement levels, participation, and response time. It also considers the alignment between course materials and the intended learning outcomes (Drugova et al., 2022).

The findings from this analysis reveal several gaps in the current learning environment, particularly the absence of adaptive digital modules and intelligent feedback systems in the Communication course (Chai et al., 2025; Yan & Qianjun, 2025). These limitations highlight the need for a more responsive and data-driven approach to learning. Therefore, this study proposes the development of an AI-driven digital module that integrates Learning Analytics and Natural Language Processing (NLP) to address these challenges and support more personalized and effective learning experiences (Naik et al., 2025).

Design (AI-Based Instructional and System Design)

This stage focuses on designing both the instructional content and the AI system architecture in an integrated manner. Beyond conventional instructional design elements, the study incorporates several AI-driven components to enhance the learning experience (Baba et al., 2024; Thajchayapong & Goel, 2025). The Learning Analytics component is designed to determine the types of data to be collected, including quiz scores, activity logs, and students' text-based responses, which are used to monitor learning progress and inform instructional decisions. In parallel, the Natural Language Processing (NLP) component is structured to enable automated analysis of student responses, such as identifying sentiment, extracting key concepts, and generating feedback (Gawade et al., 2025; Khaddar et al., 2026).

Furthermore, the design process includes the development of adaptive learning pathways that allow the system to personalize content delivery based on individual student performance and engagement. Overall, the design is guided by a comprehensive consideration of student characteristics and learning needs, targeted competencies, and appropriate learning strategies, including AI-supported interactions (Bond et al., 2024; Silva et al., 2024). Assessment and evaluation methods are also carefully planned, incorporating automated feedback mechanisms to support continuous learning improvement.

Development (AI System and Module Development)

This stage involves the development of both the digital learning module and its embedded AI components in a cohesive system. The process begins with the creation of digital learning content, including instructional materials, videos, and interactive quizzes designed to support student engagement and understanding (Hadyaoui & Belcadhi, 2026). Alongside content development, AI features are integrated into the system to enhance its functionality (Gligorea et al., 2023; Lim et al., 2026). A Learning Analytics dashboard is developed to monitor and visualize student performance, enabling both learners and lecturers to track progress effectively. In addition, a Natural Language Processing (NLP) module is incorporated to analyze students' textual responses and generate automated, meaningful feedback (Achar et al., 2026).

All components are then systematically integrated into the SIDIA Learning Management System (LMS) to ensure seamless operation within the online learning environment (Ikhsan et al., 2025; Naseer et al., 2024). Following the development process, product trials are conducted in two phases. Initial testing is carried out with a small number of students to identify usability issues and evaluate the accuracy of AI-generated feedback. This is followed by small group testing to assess overall system performance, including its adaptability to different learner behaviors. Through these stages, the development process ensures that both the instructional content and AI functionalities operate effectively and support the intended learning outcomes.

Implementation

At this stage, the developed system is implemented in an actual learning environment, where students engage directly with the AI-driven digital module through the LMS. The implementation process involves continuous monitoring of student learning behavior using Learning Analytics, allowing the system to capture patterns of engagement, participation, and performance. At the same time, the Natural Language Processing (NLP) component provides automated feedback by analyzing students' responses and offering timely, relevant input to support their understanding.

In addition, the system delivers adaptive content tailored to individual student performance, ensuring that learning pathways remain personalized and responsive to learners' needs. Through this implementation, the study evaluates the effectiveness, usability, and attractiveness of AI-supported learning, particularly in enhancing student engagement and the overall learning experience.

To clarify the implementation of Artificial Intelligence within the SIDIA Learning Management System, this study employed a data-driven architecture consisting of four integrated layers: data collection, AI processing, adaptive decision-making, and learning delivery. Student interaction data including login frequency, time-on-task, learning activity logs, quiz scores, discussion participation, and written responses were continuously collected through the SIDIA LMS.

The Learning Analytics component processed behavioral and performance data to identify engagement patterns, monitor learning progress, and detect students requiring additional instructional support. In parallel, the Natural Language Processing (NLP) component analyzed students' written responses submitted through assignments and discussion forums to identify key concepts, evaluate semantic relevance, and generate automated formative feedback.

Outputs from both AI components were integrated within an adaptive decision engine that recommended appropriate learning materials, personalized learning pathways, and targeted feedback according to each student's learning progress. These recommendations were delivered through the SIDIA LMS dashboard, enabling both students and lecturers to monitor learning performance continuously and support timely instructional interventions. The AI System architecture of the SIDIA LMS is shown in Figure 2.

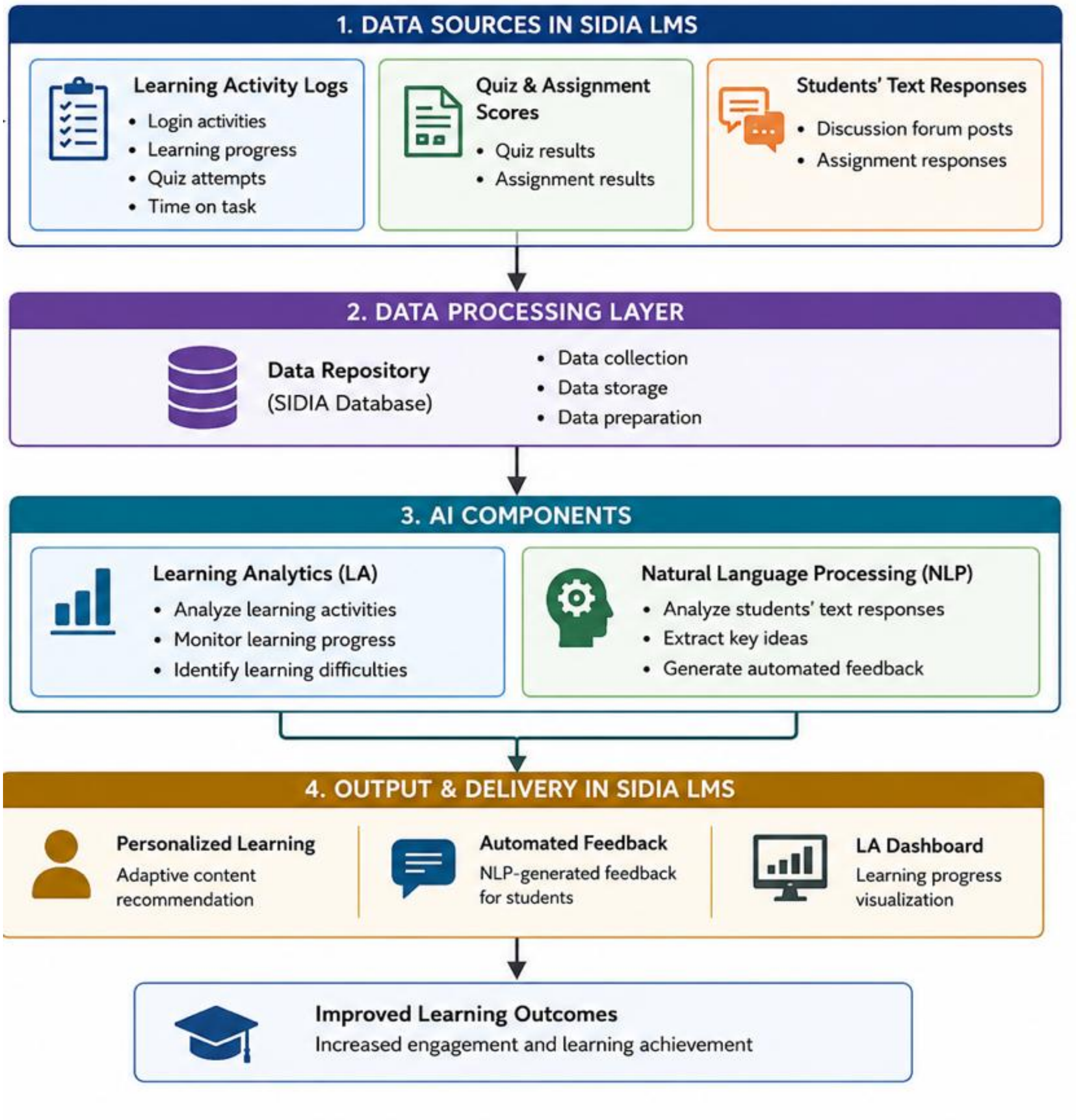

Figure 2. AI System Architecture of the SIDIA LMS

Evaluation

Evaluation in this study was conducted using both formative and summative approaches, with additional support from AI-generated insights derived from Learning Analytics. The evaluation process includes measuring student learning outcomes through pretests and posttests, followed by N-Gain analysis to determine the effectiveness of the intervention (Dafitri et al., 2026). Beyond conventional evaluation methods, AI-based analysis is utilized to examine patterns of student engagement, assess the accuracy of NLP-generated feedback, and identify trends in learning improvement over time.

Expert validation was also carried out to ensure the quality of the developed system. Instructional design experts and content experts evaluate the relevance, accuracy, and pedagogical soundness of the learning materials as well as the integration of AI-based features. Additionally, the performance of the AI system itself is evaluated in terms of its accuracy and usefulness in supporting the learning process, particularly in delivering feedback and adapting content.

The research subjects consisted of individuals directly involved in the development and implementation of the system. These include material experts from the Department of Curriculum and Educational Technology, Universitas Negeri Surabaya, who evaluate the appropriateness and accuracy of the content, as well as instructional design experts from the Educational Technology study program who assess the quality of the instructional design and AI integration.

Furthermore, students enrolled in the Learning Communication course in the same program act as primary users of the AI-driven digital module, providing data on usability, engagement, and learning effectiveness.

The data collection instruments are used to obtain the data required for evaluating both the instructional quality and the AI system performance. In addition to conventional methods such as questionnaires, this study also incorporates Learning Analytics data to capture students' interaction patterns within the system. The instruments used in this study include:

(1) Questionnaires, used to measure the feasibility, usability, and attractiveness of the developed product (Sarun, 2026).

(2) Tests (pre-test and post-test), used to measure students' learning outcomes before and after using the AI-driven online learning system.

(3) Learning Analytics data, including log data, student activity, engagement level, and performance tracking.

(4) NLP-based data analysis, which processes students' textual responses to evaluate communication skills and generate automated feedback.

A questionnaire is a set of written questions used to obtain responses from participants regarding their perceptions of the system. Meanwhile, tests are systematic procedures used to measure student learning outcomes. In this study, pre-test and post-test techniques are used to identify differences or improvements in learning outcomes after the implementation of AI-driven digital modules.

To measure the effectiveness of the learning intervention, the N-Gain test is applied (Dafitri et al., 2026). In addition, Learning Analytics is used to support data-driven evaluation by identifying patterns of student improvement, engagement, and interaction during the learning process.

The N-Gain test was conducted on 30 undergraduate students of the Educational Technology study program in the even semester of the 2023–2024 academic year. This test aims to determine the effectiveness of AI-driven digital modules in improving student learning outcomes using a one-group pretest-posttest design. The results are calculated using the standard N-Gain formula, as shown in Figure 3, and categorized according to the N-Gain criteria as presented in Table 1.

$$\text{N} - \text{Gain} = \frac{\text{Posttest Score} - \text{Pretest Score}}{\text{Ideal Score} - \text{Pretest Score}}$$

Figure 3. The formula of Normalized Gain

Table 1. N-Gain Score based on category

N-Gain Value	Category
$G > 0,7$	Tall
$0,3 \leq g \leq 0,7$	Currently
$G < 0,3$	Low

The expert validation instrument employed a binary Guttman scale (Yes = 1, No = 0). This scale was selected because the primary objective of expert evaluation was to determine whether each instructional design, media, and content criterion had been satisfactorily fulfilled rather than to measure varying degrees of quality. Binary responses reduce ambiguity in expert judgments and facilitate objective assessment of product feasibility by clearly identifying whether each criterion meets the predetermined development standards. Similar approaches have been applied in instructional product validation where compliance with design specifications is the primary focus (Dafitri et al., 2026). The percentage of fulfilled criteria was subsequently calculated to determine the overall feasibility of the developed digital module.

$$P = \frac{F}{N} X\ 100\%$$

Figure 4. The formula of Criteria Eligibility Level

Information:

P = Percentage Number

F = Frequency for which the percentage is being sought

N = Number of respondents times the highest score times the number of questions

To interpret the percentage results, the calculated values were used to determine the level of success of the online learning system. The product feasibility criteria are presented in Table 2.

Table 2. Product Revision Criteria Eligibility Level

Percentage	Criteria	Information
81%-100%	Very Well	No revision
61%-80%	Good	No revision
41%-60%	Pretty Good	Revision
21%-40%	Not Good	Revision
0%-20%	Not Very Good	Revision

3. RESULT AND DISCUSSION

3.1 Results

This study produced an online digital module to support the learning process. The validation results from subject matter and media experts were rated as very good. The subject matter experts assigned a validity score of 100%. Media experts gave a score of 91.67%, stating that the criteria were very good. The results of subject tests for Educational Technology students at the Faculty of Education, Universitas Negeri Surabaya (UNESA), were obtained from individual and small-group trials. Three students participated in the individual trial, while six students participated in the small-group trial, yielding scores of 90% and 95%, respectively. The diagram of the feasibility test results can be seen in Figure 3. This means that students stated that the online digital module based on RPS OBE had very good criteria. The products contained in the SIDIA LMS are digital modules that can be uploaded to SIDIA for online learning.

The digital module cover for online learning is shown in Figure 4. Before the effectiveness test, prerequisite tests were conducted, including a normality test and a homogeneity test, namely a normality test with the results of all data from normally distributed subjects and a homogeneity test with results of all data from homogeneous subjects. The results of the effectiveness test show that the average pretest score was 61 and the average posttest score was 88.5, resulting in an N-Gain score of 0.7 in the high category.

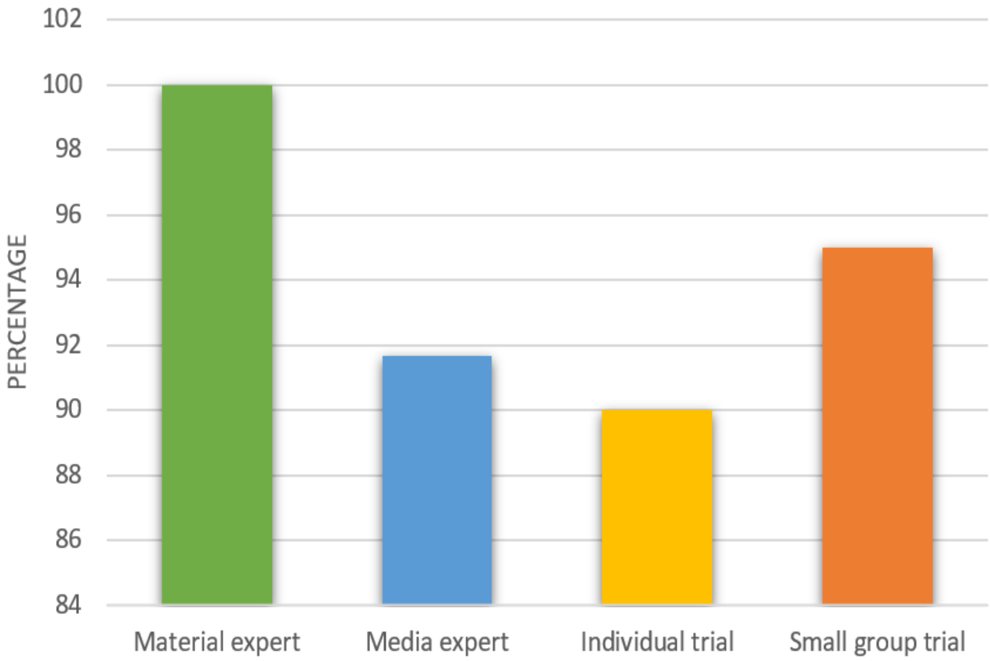

Figure 3. Feasibility Test Results Development Results

3.2 Discussion

The Communication course is inherently practical, requiring learning resources that foster active participation and independent learning (Andrew W. Cole & Weber, 2019). Conceptual understanding is essential not only for achieving learning outcomes but also for supporting meaningful learning processes. In this context, the development of AI-driven online digital modules creates a more adaptive and intelligent learning environment. These modules are both feasible and highly effective, particularly when integrated with Learning Analytics and Natural Language Processing (NLP), which enable personalized learning and automated feedback.

The effectiveness evaluation demonstrated a high N-Gain score of 0.7, indicating that students achieved substantial improvements in learning outcomes after using the AI-driven module. This improvement can be explained by the complementary roles of the embedded AI features. Learning Analytics continuously monitored students' learning progress, quiz performance, participation, and interaction patterns within the LMS. These data enabled the system to identify learning difficulties early and provide adaptive learning pathways that matched individual learning needs. As a result, students were able to focus on concepts requiring additional practice rather than following a uniform learning sequence, thereby improving learning efficiency and conceptual mastery.

Natural Language Processing further contributed to these learning gains by analyzing students' written responses and providing automated formative feedback during the learning process. Rather than waiting for lecturer evaluation, students received immediate feedback that helped them recognize misconceptions, revise their responses, and strengthen their communication skills. Such timely feedback promotes self-regulated learning by encouraging learners to reflect on their performance and continuously improve their understanding. The combination of adaptive content delivery and immediate formative feedback likely explains the substantial increase in post-test performance reflected by the N-Gain value.

The advancement of information technology has accelerated the development of digital modules in education. In Communication courses, AI integration enhances these modules by enabling real-time data analysis, adaptive content delivery, and intelligent feedback. These capabilities not only improve access to interactive learning resources but also create individualized learning experiences that respond dynamically to students' progress. Previous studies have shown that multimedia-based digital modules significantly improve learning outcomes and communication skills, especially when enriched with videos, animations, and interactive content. The present findings extend this evidence by demonstrating that integrating AI-based adaptation and feedback mechanisms can further enhance learning effectiveness beyond conventional digital modules.

Digital modules also provide flexibility, allowing students to learn anytime and anywhere. With AI capabilities, these modules can adapt to individual learning styles, generate personalized recommendations, and provide immediate feedback through NLP-based analysis (Calamlam, 2020) (Mandouit & Hattie, 2023). This is particularly important in online learning environments where direct lecturer interaction is limited (Alawamleh et al., 2020). Furthermore, Learning Analytics enables continuous monitoring of student progress, allowing lecturers to identify students requiring additional support while helping learners become more aware of their own learning progress. This combination of instructor support and learner self-monitoring creates a more responsive learning environment that contributes to higher engagement and improved academic performance.

The integration of AI also promotes collaboration and interaction through discussion forums, collaborative tasks, and communication analysis. Increased interaction has been shown to enhance student engagement and participation, which positively impacts learning outcomes. The developed module aligns with course objectives, student characteristics, and current technological advancements, and is implemented through the SIDIA LMS. It incorporates various media formats, including text, images, videos, and interactive elements, to enhance engagement and understanding while supporting both conceptual and project-based learning.

However, challenges remain in implementing digital modules in online learning. Unequal access to technology, including devices and internet connectivity, can limit student participation. Additionally, varying levels of digital literacy among students and lecturers, as well as resistance to adopting new technologies, may reduce effectiveness (Atabek, 2020) (Backfisch et al., 2021). Student motivation and engagement also remain concerns, as limited social interaction in online environments can lead to feelings of isolation. AI-based systems can help address these challenges by offering personalized recommendations, adaptive feedback, and interactive learning experiences. Nevertheless, because this study employed a one-group pretest-posttest design without a control group, the observed learning gains should be interpreted with appropriate caution. Future studies using experimental or quasi-experimental designs are needed to more rigorously isolate the specific contribution of individual AI features to student learning outcomes.

3.2.1 Implications

The findings of this study have important implications for higher education, particularly in the design and implementation of online learning. The integration of AI in digital modules demonstrates the potential to create more adaptive, personalized, and efficient learning environments. For lecturers, Learning Analytics provides valuable insights into student performance, enabling more precise and timely interventions. For students, AI-driven modules support independent learning by offering flexible access, personalized pathways, and immediate feedback. Institutions can leverage these technologies to standardize learning quality across different universities while maintaining adaptability to individual learner needs.

3.2.2 Research contribution

This study contributes to the field of educational technology by developing and validating an AI-driven adaptive digital module specifically for Communication courses. It extends existing research by integrating Learning Analytics and NLP into digital learning environments, enabling real-time personalization and automated feedback. The study also provides empirical evidence of the effectiveness of AI-enhanced modules in improving student learning outcomes, as indicated by high N-Gain results. Furthermore, it offers a practical framework for implementing AI-based learning systems within Learning Management Systems (LMS), supporting both theoretical and project-based learning.

3.2.3 Limitations

Despite its contributions, this study has several limitations. First, the study employed a one-group pretest-posttest design involving only 30 undergraduate students, which limits the generalizability and statistical robustness of the findings. Second, the absence of a control group makes it difficult to attribute improvements in learning outcomes solely to the AI-driven digital module, as other factors such as prior knowledge, maturation, or external learning experiences may also have influenced the results. Third, the implementation of the digital module is dependent on technological infrastructure, which may not be equally accessible to all students. Limited internet connectivity and device availability can hinder participation and reduce learning effectiveness. Fourth, the study was conducted within a single Communication course in one university, which may limit the applicability of the findings to other disciplines, institutions, or educational contexts. Fifth, the effectiveness of AI-driven modules is influenced by users' digital literacy; insufficient AI and digital competencies among students and lecturers may limit effective use of the system. Finally, this study focused primarily on short-term learning outcomes measured immediately after implementation and did not examine the long-term effects of the AI-driven module on knowledge retention, communication competencies, or sustained learning performance.

3.2.4 Suggestions

Future research should explore the implementation of AI-driven digital modules across different disciplines and educational levels to enhance generalizability. Longitudinal studies are also recommended to examine the long-term impact of AI-based learning on student competencies and performance. To address technological disparities, institutions should invest in improving infrastructure and ensuring equitable access to digital tools. Additionally, training programs for lecturers and students are essential to improve digital literacy and maximize the benefits of AI integration. Finally, further development of interactive and collaborative features such as AI-supported discussion forums and group projects can enhance engagement and reduce the sense of isolation in online learning environments.

4. CONCLUSION

Based on the research results and discussions, the AI-enhanced RPS OBE-based online digital module in the Communication course is declared suitable for implementation. The validation results from material experts and media experts fell into the "very good" category, indicating that the integration of AI-supported features such as Learning Analytics and Natural Language Processing (NLP) aligns well with both content quality and instructional design standards.

The results of user testing involving Educational Technology students, through individual and small group trials, also fall into the "very good" category. This indicates that students positively perceive not only the usability of the digital module but also the added value of AI-driven features, such as personalized feedback, adaptive learning pathways, and interactive content delivery.

The implementation of this module is expected to assist lecturers in delivering more adaptive, data-driven, and efficient learning processes. At the same time, it provides students with flexible, accessible, and personalized learning experiences that are not limited by time and space. The AI integration further ensures that learning materials can dynamically adjust to students' needs, thereby improving engagement and learning effectiveness.

It is recommended that future development includes more advanced AI-driven interactive features, such as intelligent quizzes, automated feedback systems, and real-time communication analysis using NLP. These features can further enhance students' understanding, critical thinking, and communication skills. Additionally, strengthening system integration within the Learning Management System (LMS) will optimize the use of Learning Analytics for more precise and personalized learning support.

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6. AUTHOR CONTRIBUTION STATEMENT

UD and AK: Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Data Curation, and Writing-Original Draft; AP, HM, and RRU: Methodology, Formal Analysis, Resources, Data Curation, and Writing -Review & Editing; ANC, FAS, and MDN: Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Data Curation, and Writing -Review & Editing.

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