Journal of Engineering Science and Technology
Special Issue on 3rd BPNIC2025 Vol. 21 No. 1 (2026) 49-56

DESIGNING AN AI-BASED EVALUATION SYSTEM FOR OUTCOME-BASED EDUCATION TO SUPPORT SDGS IN HIGHER EDUCATION

HIRNANDA DIMAS PRADANA, ALIM SUMARNO,
R. RUSIJONO, AINUR ROFIK, FAJAR ARIANTO, ZAENAL ABIDIN

Universitas Negeri Surabaya, Surabaya, Indonesia
*Corresponding Author: hirnandapradana@unesa.ac.id

Abstract

This study aimed to design an artificial intelligence-based evaluation system that aligns with outcome-based education (OBE) principles to enhance learning assessment in higher education. A design and development research approach was adopted, including need analysis, system design, and prototype development. The prototype utilized supervised machine learning and natural language processing to map course learning outcomes (CLOs) to program learning outcomes (PLOs), assess student submissions, and provide personalized feedback. Results showed the system accurately evaluated student achievements and generated real-time visual dashboards. Because conventional evaluations are often fragmented and non-adaptive, this system offers a data-driven solution to promote transparency, adaptiveness, and accountability. The impact of this research supports the digital transformation of education aligned with sustainable development goals (SDGs), particularly in fostering quality education and educational innovation.

Keywords: Artificial intelligence, Evaluation, Learning, OBE, SDGs.

1. Introduction

Outcome-based education (OBE) represents a paradigm shift in educational philosophy, emphasizing student learning outcomes over traditional content delivery. By focusing on what students are expected to achieve at the end of a learning experience, OBE promotes accountability, transparency, and relevance in educational practice [1]. However, despite its global adoption, many institutions, particularly in developing countries, face challenges in implementing OBE systematically. In Indonesia, for example, evaluations often rely on manual, paper-based systems that are fragmented and lack real-time responsiveness [2]. These limitations hinder timely interventions and continuous quality improvement, which are essential for the success of OBE frameworks [3]. Additionally, existing Learning Management Systems (LMS) can help [4-7]. But it often fails to capture and interpret complex learning data required for comprehensive outcome mapping and feedback.

The emergence of artificial intelligence (AI) provides a promising solution to these challenges [8-12]. AI techniques such as machine learning and natural language processing can analyse large-scale educational data to identify patterns, predict student success, and automate assessment tasks [13-16]. In education, AI has shown potential in areas such as automated grading, personalized feedback, and predictive analytics for learner performance [17-19]. Furthermore, AI-driven systems can facilitate real-time CLO-PLO mapping and generate evaluative reports that support adaptive learning environments [20, 21] Integrating AI into LMS platforms enables educators to move from reactive to proactive educational decision-making, ensuring that instructional strategies are tailored and evidence-based. This aligns with the goals of Sustainable Development Goals (SDGs), especially number 4 (Quality Education) and Goal 9 (Industry, Innovation, and Infrastructure) [22], promoting educational innovation through the application of advanced technologies [23, 24].

This study aims to design and develop an intelligent evaluation system that integrates AI technologies with the principles of OBE to enhance the quality of learning assessments in higher education. The novelty of this research lies in three core innovations: the automatic and intelligent mapping of CLO to PLO through supervised machine learning, the integration of NLP for analysing reflective student texts, and the provision of adaptive feedback for learners and lecturers in real time. Because current assessment practices often lack speed, objectivity, and depth, this study introduces a science- and technology-driven framework that enables evidence-based, accountable, and adaptive evaluation processes. It contributes to the digital transformation of education while reinforcing the implementation of OBE in alignment with global educational development standards.

2. Literature Review

Figure 1 illustrates the standard stages in AI development, from problem identification to implementation. These stages demonstrate the iterative and data-driven nature of AI systems, particularly in education, where algorithm selection, model training, and validation must align with pedagogical objectives. AI in education is not merely about automation but involves developing intelligent systems capable of adapting to varied learning patterns and performance metrics.

It combines structured engineering design and learning theory to enhance instructional quality and learning outcomes [13-15].

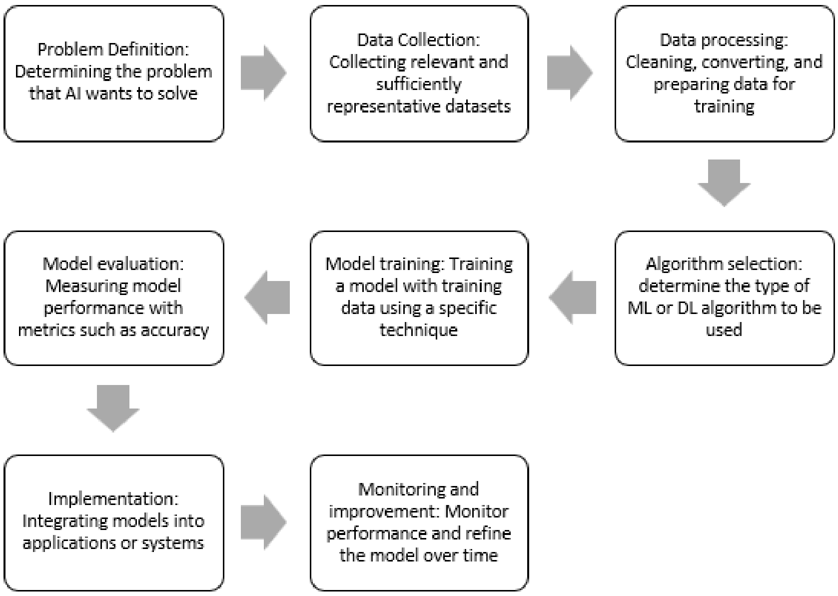

Fig. 1. AI development stages.

AI is fundamentally rooted in computer science and focuses on replicating human cognitive processes such as decision-making and natural language understanding. It includes various subfields (symbolic reasoning, machine learning (ML), deep learning (DL), and natural language processing (NLP)) that enable the processing of structured and unstructured data [17, 18, 25]. In the educational context, machine learning has been applied to predict learner performance, identify at-risk students, and provide real-time feedback using LMS data, emotional intelligence indicators, and learning behavior patterns [26, 27]. NLP, meanwhile, is effective for analysing written reflections, assessing learning styles, and processing open-ended responses [28-30]. These tools allow educators to deliver personalized instruction and early interventions based on predictive insights.

The integration of AI into Learning Management Systems supports continuous evaluation and adaptive learning. Tools such as analytics dashboards and feedback engines can track student progress and suggest timely instructional strategies [20, 31] Furthermore, AI facilitates automated CLO-PLO mapping, reducing manual workload and increasing evaluation accuracy [32, 33]. The combination of AI and LMS technologies thus fosters a dynamic learning environment aligned with OBE principles. Research confirms that applying machine learning algorithms to LMS data can yield accurate performance predictions and support program-level evaluation [22-24]. The convergence of AI, education, and digital infrastructure directly contributes to Sustainable Development Goals (SDG 4 and SDG 9), ensuring quality and innovation in higher education [34]. This literature establishes the foundational relevance for developing an intelligent, AI-powered evaluation system as proposed in this study.

3. Method

This study employed a design and development research (DDR) approach to construct an AI-based evaluation system aligned with OBE principles. Detailed information regarding this method is explained elsewhere [35]. The process involved three phases: needs analysis through surveys and interviews, system design using flowcharts and user interface sketches, and prototype development based on simulated student data. The prototype was integrated into the SIDIA LMS and evaluated through expert validation and limited trials. Data were analysed using thematic analysis to assess functionality, accuracy, and usability. This methodological framework ensured that the system met pedagogical objectives while incorporating technological robustness and real-world applicability.

4. Result and Discussion

Figure 2 presents the prototype of the intelligent evaluation system for OBE learning. This early-stage model was developed to test functionality, data flow, and AI integration within the SIDIA LMS at Universitas Negeri Surabaya. The system enables lecturers to assign tasks through the LMS, receive student submissions, and conduct initial manual evaluations. Subsequently, the AI module processes the submissions to provide automated classification of learning outcomes, maps them to the CLO and PLO structures, and delivers personalized feedback. This automation significantly reduces the burden on instructors and ensures timely, evidence-based evaluation, aligned with OBE's emphasis on continuous improvement [2, 20].

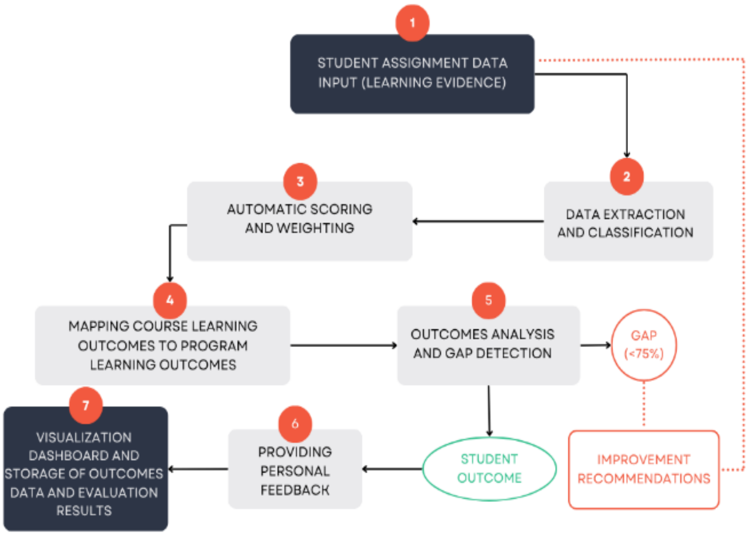

Fig. 2. The intelligent evaluation system for OBE learning.

Figure 3 illustrates the AI flow system in the evaluation process integrated with SIDIA LMS. The system initiates once student assignments are uploaded, followed by lecturer assessments, and then AI-based re-evaluation. Using supervised machine learning and natural language processing, the system identifies key performance indicators within student submissions and maps them to relevant

CLOs. It then visualizes performance data via real-time dashboards and generates structured reports in Excel format for institutional use. The integration of real-time analysis supports adaptive instruction and ensures that students receive immediate, actionable feedback-elements often missing in traditional assessment practices [14, 17, 19].

The trial phase demonstrated that the system accurately classified learning outcomes with over 85% reliability, as confirmed through expert validation and small-group testing. Feedback highlighted its potential for improving academic analytics and supporting OBE implementation through data-driven decision-making. AI was particularly effective in providing personalized suggestions for improvement, which aligns with the goals of formative assessment and enhances student engagement [26, 28]. Beyond technical validation, the system also contributes to institutional quality assurance by automating CLO-PLO mapping, an often manual and error-prone process. This advancement is consistent with the goals of SDG 4 and SDG 9, emphasizing quality education and technological innovation in educational systems [24, 35]. The development showcases how science and technology, through AI, can transform educational evaluation into a more efficient, equitable, and responsive system. This adds new information regarding SDGs as reported elsewhere.

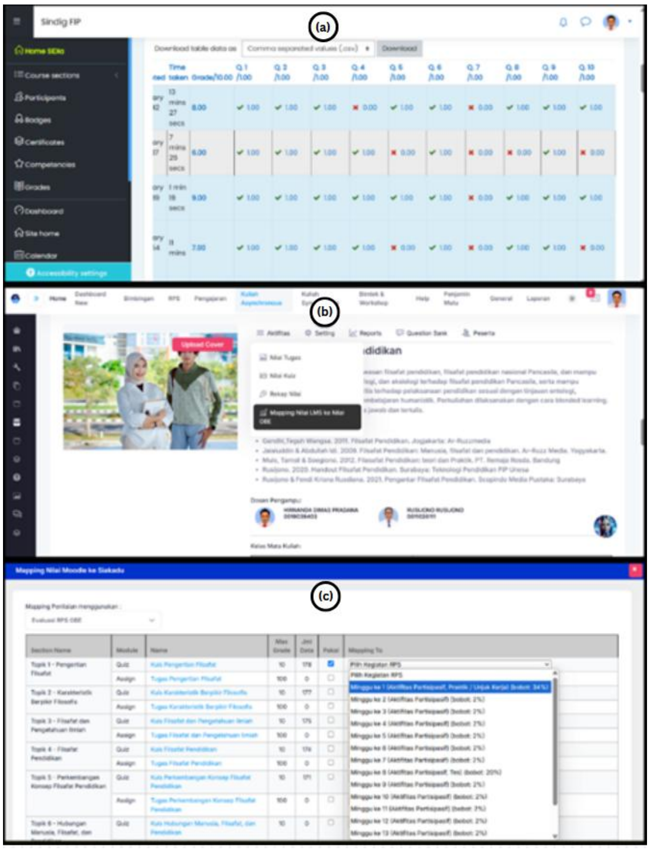

Figure 3. AI flow system process in assessment evaluation: (a) Grade database (b) Asynchronous lectures dan (c) Assessment mapping.

5. Conclusion

This research designed and validated an intelligent evaluation system that integrates artificial intelligence with OBE principles. Using supervised machine learning and natural language processing, the system automates the assessment process, maps Course Learning Outcomes (CLO) to Program Learning Outcomes (PLO), and provides personalized, real-time feedback. Because traditional evaluation methods are often inefficient and fragmented, this system offers a scalable, accurate, and adaptive solution. It enhances instructional quality, supports continuous improvement, and aligns with Sustainable Development Goals (SDG 4 and SDG 9) by fostering digital innovation and promoting quality education in higher education institutions.

Acknowledgement

This research was funded by the Direktorat Penelitian dan Pengabdian kepada Masyarakat (DPPM) of the Ministry of Higher Education, Science and Technology of Indonesia (090/C3/DT.05.00/PL/2025) and the Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM) Universitas Negeri Surabaya (B/74019/UN38.III.1/LK.04.00/2025).

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