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Designing an AI-Assisted Self-Evaluation Framework to Support Multi-Accreditation Study Program in Indonesian Higher Education

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ABSTRACT

The adoption of multi-accreditation schemes in Indonesian higher education has increased the complexity of self-evaluation processes at the study program level. Study programs must align internal quality assurance practices with multiple national accreditation standards, often leading to overlapping indicators, fragmented evidence management, and increased administrative burden. This study aims to design an AI-assisted self-evaluation framework to support structured and coherent self-assessment in multi-accreditation contexts. A design-based qualitative approach was employed through document analysis of the BAN-PT IAPS 5.1 instrument and selected Lembaga Akreditasi Mandiri (LAM) accreditation frameworks, followed by indicator harmonization and framework development. The results reveal a strong convergence of core quality indicators across accreditation instruments, enabling the formulation of unified indicators linked to shared evidence sources. Based on these findings, an AI-assisted analytical layer utilizes natural language processing for document scanning, indicator-evidence mapping, evidence completeness checking, and performance trend identification, while maintaining human-in-the-loop validation to ensure accountability and interpretability. The framework enhances efficiency, consistency, and evidence traceability in self-evaluation under multi-accreditation conditions and provides a practical foundation for future empirical implementation and integration with international accreditation and ISO-based education quality standards.

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1. INTRODUCTION

In the Indonesian higher education quality assurance landscape, study programs accreditation plays a central role in promoting institutional accountability and continuous improvement. According to *Naskah Akademik Instrumen Akreditasi Program Studi (IAPS 5.1)* published by the National Accreditation Board for Higher Education (Badan Akredtiasi Nasional Perguruan Tinggi / BAN-PT) in 2025, accreditation instruments are designed not only to determine the accreditation status of study programs but also to foster not only of quality through systematic, evidence-based evaluation processes [1]. This academic manuscript emphasizes that self-evaluation (*Laporan Evaluasi Diri*) constitutes an integral component of accreditation, reflecting institutional responsibility in implementing internal quality assurance and continuous improvement aligned with national higher education standards.

While the *Naskah Akademik* BAN-PT (2025) emphasizes self-evaluation as a systemic and evidence-based foundation for accreditation, its practical implementation at the study program level has become increasingly complex. In practice, study programs are often required to align internal self-evaluation processes with multiple external accreditation schemes, including national accreditation instruments, discipline-specific standards developed by Lembaga Akreditasi Mandiri (LAM), and, in some cases, international or professional accreditation frameworks. This multi-accreditation context introduces overlapping indicators, heterogeneous evidence requirements, and diverse reporting formats, which significantly increase the cognitive and administrative burden on academic and quality assurance staff. Previous studies have shown that accreditation processes are demanding in terms of time, effort, and human resources, and may shift institutional focus toward documentation compliance rather than continuous quality improvement [2], [3]. In addition, accreditation guidelines consistently emphasize the importance of valid evidence, traceability, and consistency between self-evaluation claims and supporting data, which are difficult to ensure through manual processes alone [4], [5]. As accreditation instruments continue to evolve, conventional approaches face limitations in efficiency and coherence, highlighting the need for supportive mechanism beyond traditional documentation workflows.

Recent studies indicate a growing interest in the use of digital technologies and artificial intelligence (AI) to support quality assurance processes in higher education. Prior research has explored the role of information systems, analytics, and AI-based tools in improving data management, monitoring institutional performance, and supporting evidence-based decision making within academic quality management systems [6], [7]. Systematic reviews on AI in higher education further highlight that most applications focus on teaching and learning analytics, student assessment, or administrative automation, while fewer studies address institutional-level quality assurance and accreditation processes [6], [8]. Emerging literature on AI for quality assurance suggests that AI can assist in organizing large volumes of accreditation data, identifying patterns, and supporting compliance-related activities; however, these studies also emphasize the importance of human oversight and governance to ensure transparency and accountability [7], [9]. Despite these developments, there remains a limited number of studies that operationalize AI within a structured self-evaluation framework that explicitly addresses the challenges of multi-accreditation at the study program level, particularly in the context of Indonesian higher education systems characterized by diverse and evolving accreditation requirements.

To address this gap, this study proposes an AI-assisted self-evaluation framework that strengthens the alignment between internal quality assurance practices and multi-accreditation requirements through structured evidence management and human-centered decision support. The framework is designed as an integrated workflow consisting of (1) a standardized indicator structure to harmonize accreditation criteria across schemes, (2) an evidence repository to enhance traceability between institutional data sources and self-evaluation claims, and (3) an AI assistive layer to support indicator-evidence mapping a preliminary gap analysis. This approach aligns with international recommendations that emphasize the importance or coordinated institutional practices, reliable evidence mechanism, and governance in digitally supported quality assurance systems [10]. Technically, the AI component may employ document intelligent techniques, such as natural language processing (NLP), to assist in extracting, classifying, and mapping accreditation-related evidence, while preserving human validation and interpretative authority [6], [7].

The innovation and new value of this research lie in the design of an AI-assisted self-evaluation framework that explicitly addresses the operational realities of multi-accreditation in Indonesian higher education. While existing studies have discussed AI application for quality assurance and accreditation in general terms [6]-[9], this study contributes a structured, framework that integrates internal quality assurance mandates defined by national regulations [1] with diverse external predictive evaluation, the proposed framework advances a human-centered model focusing in indicator harmonization, evidence traceability, and assistive AI support. Theoretically, this research extends the application of AI in higher education quality assurance by situating it within self-evaluation as a continuous improvement mechanism. Practically, it offers study programs and quality assurance units a scalable and governance-aware model to reduce administrative burden, improve consistency of evaluation narratives, and enhance the usability of self-evaluation outputs across accreditation regimes, in line with global perspectives on digitally enabled quality assurance in higher education [10].

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2. RESEARCH METHOD

This study adopts a design-based qualitative research approach to develop an AI-assisted self-evaluation framework for study programs operating under multi-accreditation requirements. Design-based research (DBR) and framework-oriented qualitative approaches are widely used in higher education studies to address complex, context-dependent quality assurance problems through iterative analysis and conceptual model development rather than experimental validation [11], [12]. The research is organized into sequential stages that guide framework development and analysis, which directly inform the presentation of results and discussion.

To improve clarity, this study presents the research methodology in the form of a flowchart. Figure 1 illustrates the research methodology flowchart. This study begins with a research design, followed by identification and analysis of accreditation requirements, mapping self-evaluation indicator and evidence, and the design of an AI-assisted self-evaluation framework. The final stage involves framework analysis and interpretation.

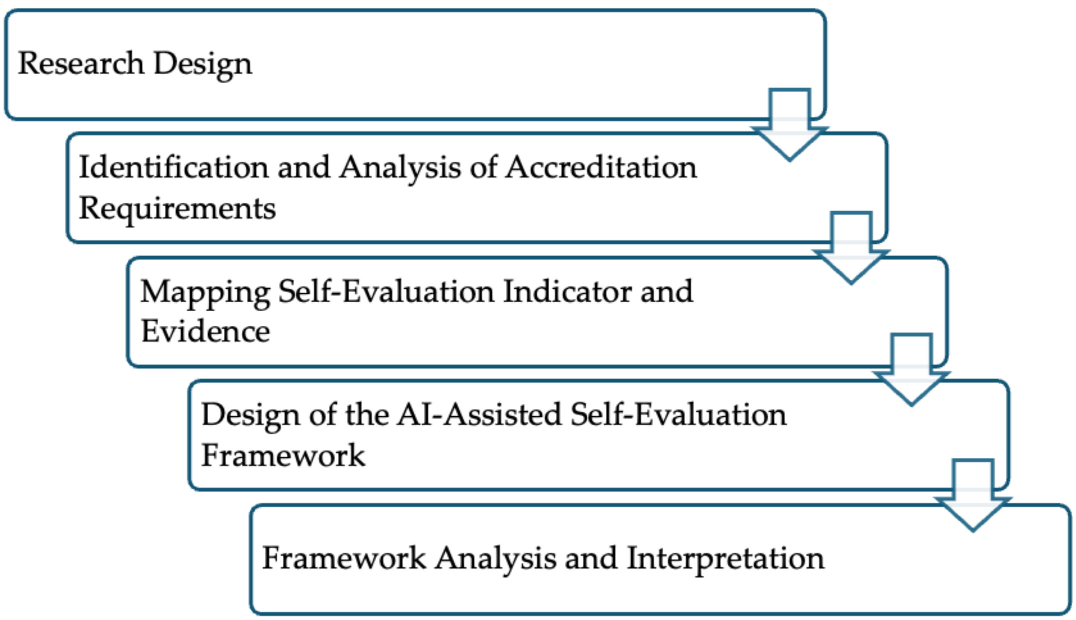

Figure 1. Flowchart of Research Methodology

2.1. Research Design

The research employs a framework development an analytical design, appropriate for studies focusing on quality assurance models and accreditation-related processes. Recent higher education quality assurance studies commonly use qualitative and design-oriented methodologies to analyze accreditation instruments, institutional practices, and evaluation workflows, particularly in policy-driven and multi-standard environment [13],

[15]. This design enables systematic examination of accreditation requirements while remaining adaptable to diverse accreditation schemes.

In this study, the research design focuses on a conceptual analysis of self-evaluation practices in higher education. For example, common challenges such as duplicated evidence submission for different accreditation instruments and inconsistent indicator interpretation were identified as the initial design problem.

2.2. Identification and Analysis of Accreditation Requirements

The first stage involves document analysis of an accreditation instruments and quality assurance guidelines. Document analysis is a recognized qualitative method for examining policy texts, standards, assessment criteria, and accreditation documents in educational research [15]. In this study, national accreditation instruments issued by BAN-PT and selected LAM (LAM-EMBA, LAM-INFOKOM, LAM-DIK, LAM-TEKNIK, LAM-SAMA, LAM-SPAK), along with internal self-evaluation components within SPMI, are analyzed to identify evaluation dimensions/ criteria, indicators, and evidence requirements. Similar document-based approaches have been used to assess alignment between quality assurance systems and external accreditation frameworks [16], [17].

At this stage, accreditation instruments such as BAN-PT IAPS 5.1 and selected LAM were examined. For instance, indicators related to graduate outcome, learning process, and lecturer performances were analyzed to identify similarities and differences in structure, terminology, measurement, and evidence requirements.

2.3. Mapping Self-Evaluation Indicator and Evidence

The second stage focuses on mapping accreditation indicators to self-evaluation components and institutional evidence sources at the study program level. Indicator-evidence mapping is frequently applied in quality assurance research to enhance traceability, coherence, and transparency between evaluation claims and supporting data [18], [19].

This stage links indicators to qualitative and quantitative evidence such as curriculum documents, learning assessments, research outputs, tracer study reports, student satisfaction surveys, and lecturer performance reports, forming the basis of AI-assisted support. As an illustrative example, that evidence was mapped to relevant indicators across multiple accreditation frameworks. A tracer study document may serve as evidence for graduate profile indicators in national accreditation instruments.

2.4. Design of the AI-Assisted Self-Evaluation Framework

In the third stage, the AI-assisted self-evaluation framework is designed based on the results of indicator and evidence mapping. The framework is structured into three

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layers: an accreditation indicator layer, an evidence management layer, and an AI assistive layer. Recent studies indicate that document intelligence techniques, including rule-based classification and natural language processing (NLP), are effective for supporting document organization, classification, and preliminary contemporary governance-oriented perspective, the AI component is designed to assist human evaluators rather than automate judgment, incorporating validation checkpoints to ensure transparency and accountability [8], [22].

In designing the AI-assisted framework, AI is positioned as an analytical support mechanism. For example, natural language processing is conceptually applied to scan accreditation documents, identify key entities such as graduation rates or learning outcomes, and suggest preliminary mapping between evidence and accreditation indicators.

2.5. Framework Analysis and Interpretation

The final stage involves analyzing the proposed framework in relation to multi-accreditation challenges and self-evaluation practices. Analytical evaluation of conceptual frameworks is commonly used to assess relevance, coherence, and applicability within higher education quality assurance contexts [12], [14]. This analysis examines how the framework addresses efficiency, consistency, and usability in self-evaluation processes and provides the analytical basis for the Result and Discussion section.

To enrich the analytical stage, an illustrative model is employed to demonstrate how the framework operates in practice as shown in Table 1. For example, when a study program uploads a tracer study report, the AI-assisted layer analyzed the document, proposes relevant indicator mappings, and highlights potential evidence gaps. These outputs are then interpreted by quality assurance units to support decision-making and accreditation readiness assessment.

Table 1. Illustrative Example of Methodology Application

Methodology Stage	Example of Methodology Application
Accreditation analysis	Comparison of graduate outcome indicators in IAPS 5.1 and LAM
Indicator mapping	Tracer study linked to multiple accreditation indicators
AI-assisted analysis	NLP scans documents and suggest evidence mapping
Human validation	QA unit confirms or revises AI suggestions

3. RESULTS AND DISCUSSION

This section presents the result of the study and discuss their implication for self-evaluation and multi-accreditation practices in Indonesian higher education. The results are derived from the identification and analysis of accreditation requirements, indicator harmonization, and the design of an AI-assisted self-evaluation framework as described in Research Metod section. Specifically, this section highlights (1) the unified accreditation indicators identified across national and LAM accreditation instruments, (2) the structure and role of the AI-assisted framework in supporting self-evaluation workflows, and {3} the implications of the proposed framework for quality assurance practices and management decision-making. The discussion situates these results within the context of existing literature and emphasizes their relevance for addressing administrative complexity, evidence traceability, and continuous improvement in multi-accreditation environments.

3.1 Unified Accreditation Indicators

As an initial result of the accreditation requirement analysis stage, this study identified a set of unified indicators that are consistently assessed across national accreditation instruments and multiple LAM. The identification process involved a comparative analysis of the latest BAN-PT IAPS 5.1 instrument and selected LAM accreditation frameworks, focusing on evaluation dimensions, assessment criteria, and required evidence. Although the structure and terminology of the instruments vary, the analysis reveals substantial convergence in core quality dimensions assessed at the study program level.

Table 2 below summarizes the unified indicators that are consistently assessed across national (BAN-PT and LAM) accreditation instruments. Thes indicators represent the core dimensions of study program quality, aligning internal self-evaluation (SPMI) with external accreditation requirements. The evidence example illustrates typical documentation that study program prepares for each indicator category. The table mark (✓) denotes that the corresponding unified indicator is explicitly stated and assessed in the accreditation instrument of the respective accreditation board, either as standalone criterion or as a clearly defined sub-criterion. Indicators labeled as (embedded) indicate that the aspect is implicitly covered within broader assessment categories, while (general) refers to indicators addressed at a policy or narrative level without separate scoring rubrics. These distinctions clarify that the table does not imply equivalence of scoring or weighing across accreditation boards but rather highlights functional alignment of evaluation dimensions. From a quality assurance perspective, this alignment provides a practical basis for indicator harmonization and integrated self-evaluation, directly supporting the design of the proposed AI-assisted framework, in which unified indicators and shared evidence sources AI-assisted mapping, gap analysis, and decision support under multi-accreditation conditions.

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Table 2. Unified Indicator Across Accreditation Instruments

Unified Indicators	BAN-PT (IAPS 5.1)	LAM-EMBA	LAM-INFOKOM	LAM-DIK	LAM-TEKNIK	LAM-SAMA	LAM-SPAK	SPMI	Evidence Example
Vision, Mission, Goals, and Strategy (VMTS)	✓	✓	✓	✓	✓	✓	✓	✓	VMTS document, strategic plan
Governance and Leadership	✓	✓	✓	✓	✓	✓	✓	✓	Organizational structure, decision records
Curriculum Design and Relevance	✓	✓	✓	✓	✓	✓	✓	✓	Curriculum matrix, OBE documents
Learning Process and Assessment	✓	✓	✓	✓	✓	✓	✓	✓	RPS, assessment rubrics, evaluation reports
Learning Outcomes and Graduate Competence	✓	✓	✓	✓	✓	✓	✓	✓	CPL–OPL mapping, tracer study results
Lecturer Qualifications	✓	✓	✓	✓	✓	✓	✓	✓	Lecturer CVs, certifications, workload reports
Student Profile and Graduate Profile	✓	✓	✓	✓	✓	✓	✓	✓	Enrollment data, graduation statistics
Research Performance	✓	✓	✓	✓	✓	(embedded)	(embedded)	✓	Research output records, publications
Community Service (PkM)	✓	✓	✓	✓	✓	(embedded)	(embedded)	✓	PkM reports, community impact evidence
Facilities and Learning Resources	✓	✓	✓	✓	✓	✓	✓	✓	Infrastructure inventory, lab utilization
Internal Quality Assurance System	✓	✓	✓	✓	✓	✓	✓	✓	SPMI documents, AMI reports
Stakeholder Satisfaction	✓	(general)	(general)	(general)	(general)	(general)	(general)	✓	Satisfaction surveys, feedback analysis
Risk Management and Continuous Improvement	(implicit)	(implicit)	(implicit)	(implicit)	(implicit)	(implicit)	(implicit)	✓	Risk register, PPEPP action plans

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3.2. Role of AI Based Unified Indicators

To further clarify the operational role of AI within the proposed framework, Table 2 compares selected quality assurance tasks under conventional manual practices and AI-assisted support. The table illustrates how AI can enhance efficiency and analytical consistency by supporting routine and data-intensive activities, while maintaining human oversight in evaluative decision making.

Table 3. Role of AI Based on Unified Accreditation Indicators

Quality Assurance Task	Manual Practice	AI-Assisted Role	Basis of AI-Assisted Recommendation
Indicator mapping	Manual cross-check across accreditation instruments	Suggest indicator–evidence matching	Unified indicator definitions, keyword patterns, and historical mapping rules
Evidence completeness checking	Manual checklist review	Flag missing or inconsistent evidence	Required evidence list per unified indicator and document metadata analysis
Performance trend identification	Manual comparison over time	Highlight performance trends	Longitudinal data comparison across unified indicators and time periods

As shown in Table 3, AI-assisted support primarily targets tasks that are repetitive and time-consuming when performed manually, such as indicator mapping, evidence completeness checking, and trend identification. By providing suggestions, flags, and visual cues rather than automated judgment, AI contributes to more coherent and manageable self-evaluation workflows. This operationalization reinforces the role of AI as an assistive mechanism grounded in unified indicators, directly supporting the implementation of the proposed AI-assisted self-evaluation framework.

For example, if a study program uploads a Tracer Study Report as supporting evidence, the AI component scans the document and identifies relevant entities such as graduation rate, employment status, and waiting period. Based on these recognized entities, the system automatically suggests mapping to the "Student Profile and Graduate Data" indicator. The same evidence can be mapped simultaneously to corresponding indicators in both the selected LAM accreditation instrument and the IAPS BAN-PT 5.1 instrument. These mapping suggestions are then reviewed and validated by internal auditor before being finalized.

Processing accreditation and quality assurance documents written in Indonesian presents specific challenges for Natural Language Processing (NLP), particularly due to bureaucratic language, long sentence structures, and domain-specific terminology. This study acknowledges that conventional keyword matching techniques may be insufficient for accurately interpreting such documents. Therefore, the proposed framework envisions the use of domain-adapted NLP approaches, such as fine-tuned Large Language Models (LLMs) trained on Indonesian academic and accreditation texts, combined with rule-based

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indicator dictionaries. This hybrid approach is expected to improve the recognition of relevant entities while maintaining interpretability.

The interaction between human evaluators and AI is designed to be complementary. AI functions as an analytical assistant by processing documents, identifying patterns, and generating preliminary indicator-evidence mapping suggestions. Human evaluators, including internal auditors and quality assurance units, retain full control over evaluative decisions by reviewing, validating, or revising AI-generated outputs.

3.3. AI-Assisted Self-Evaluation Framework

The result of this study is an AI-assisted self-evaluation framework designed to support study programs in managing self-assessment processes under multi-accreditation requirements. The framework integrates the unified accreditation indicators, AI-assisted analytical roles, and quality assurance governance mechanisms into a coherent end-to-end workflow. By structuring self-evaluation around shared indicators and evidence sources, the framework addresses fragmentation and redundancy commonly experienced when study programs prepare self-evaluation reports for multiple accreditation boards.

Figure 2. AI-Assisted Self-Evaluation Framework for Multi-Accreditation Study Programs

As illustrated in Figure 1, the framework begins with study program data inputs, including governance documents, academic and non-academic performance data, stakeholder feedback, and internal quality assurance records. These inputs are processed through an AI-assisted analytics layer that supports data integration, indicator-evidence mapping, pattern and trend analysis, and preliminary recommendation generation based on unified indicators. From a technical perspective, the AI-assisted layer operates through a sequence of analytical processes rather than autonomous decision making. Accreditation and quality assurance documents are first processed using natural language processing techniques to identify relevant entities, such as learning outcomes, graduate profiles, and study program performance indicators. The extracted entities are then matched against a unified indicator repository derived from harmonized accreditation standards to generate preliminary indicator-evidence mapping suggestions and relevant scores. The resulting outputs serve as analytical inputs for human elevators, who validate and contextualize them within institutional quality assurance processes.

Importantly, the framework embeds human-in-the-loop validation throughout the self-evaluation process. The AI-assisted components generate preliminary analytical output, such as suggested mappings between evidence and accreditation indicators, relevance scores, and identification of potential evidence gaps. The outputs are not treated as final decisions; instead, they are reviewed by human evaluators, including internal assessors and quality assurance units, who validate, revise, or reject the AI-generated recommendations based on contextual understanding and institutional policies. The results are then presented through a dashboard layer, enabling visualization of quality performance, gap analysis, performance trends, and access to an organized evidence repository. This layered structure ensures transparency and traceability from raw data to evaluative insights.

Outputs from the AI-assisted layer and dashboard are translated into quality assurance recommendations, such as areas for improvement, action priorities, and assessments of multi-accreditation readiness. These recommendations inform management decision-making, including Management Review Meeting (RTM), the implementation of the PPEPP cycle, and the formulation of quality strategies. By aligning AI-assisted support with existing quality assurance governance structures, the framework reinforces self-evaluation as a continuous improvement mechanism rather than a compliance-driven exercise. This integrated approach demonstrates how AI can be responsibly leveraged to enhance efficiency, consistency, and strategic use of self-evaluation outcomes in multi-accreditation contexts.

To further clarify the practical implications of the proposed framework, this section elaborates how the AI-assisted components can be applied in real self-evaluation activities and how human elevators interact with AI throughout the process. In practical settings, the proposed framework can be applied by study programs and internal quality assurance

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units during routine self-evaluation and accreditation preparation. For example, when an internal quality assurance develops SAE instruments for internal audit, the AI-assisted layer can analyze multi-accreditation instruments and suggest unified indicator definitions, keyword patterns, and historical mapping rules.

Through this mechanism, the framework can improve consistency in indicator interpretation, reduce redundant indicator and evidence handling, and enhance evidence traceability across accreditation schemes. As a result, self-evaluation and internal audit activities can shift from predominantly administrative tasks toward more analytical and improvement-oriented discussion. This human-AI collaboration ensures that accountability, contextual judgment, and institutional knowledge remain under human authority, while AI contributes scalability and analytical efficiency. Such an arrangement is particularly relevant in complex accreditation environments, where qualitative interpretation and professional judgment cannot be fully automated.

4. CONCLUSION

This study set out to address the increasing complexity of self-evaluation processes faced by study programs operating under multi-accreditation requirements in Indonesian higher education. As outlined in the introduction, the research aimed to examine how an AI-assisted approach could support self-evaluation by harmonizing accreditation indicators, improving evidence traceability, and reducing administrative burden, while preserving human judgment and quality assurance governance structures. The Results and Discussion demonstrate that these objectives can be achieved through the development of a structured AI-assisted self-evaluation framework grounded in unified accreditation indicators.

The findings confirm that, despite variations in structure and terminology, core quality indicators are consistently assessed across BAN-PT and multiple Lembaga Akreditasi Mandiri (LAM) accreditation instruments. By identifying and harmonizing these indicators, the proposed framework enables integrated self-evaluation workflows that align internal quality assurance practices (SPMI) with external accreditation demands. Within this framework, AI functions as an assistive analytical layer that supports indicator-evidence mapping, evidence completeness checking, and performance trend identification based on unified indicators. Importantly, decision-making authority remains with the human evaluators, who interpret, validate, and contextualize AI-generated outputs. This human-in-the-loop positioning ensures transparency, accountability, and traceability, reinforcing self-evaluation as a continuous improvement mechanism rather than a compliance-driven exercise. Accordingly, the framework fulfills the objectives stated in the introduction and provides a coherent response to the challenges discussed.

Within the Indonesian higher education context, the framework provides a practical pathway for strengthening quality evaluation by enhancing indicator consistency, evidence traceability, and decision support within existing SPMI structures, while preserving human-centered governance. By enabling more consistent and transparent self-evaluation practices, the framework has the potential to improve the quality of academic planning, monitoring, and continuous improvement in higher education institutions.

Regarding future research and application prospects, several extensions are recommended. First, empirical pilot implementation in selected study programs would enable assessment of usability, effectiveness, and organizational impact. Second, the framework can be expanded to incorporate international accreditation standards, including discipline and institution-level bodies such as ABET, AACSB, and IABEE. Integrating these standards into the unified indicator structure would support cross-border accreditation readiness and enhance comparability with global benchmarks. In addition, future work may incorporate ISO-based management system standards for education, particularly ISO 21001:2018, alongside related ISO quality and risk-management standards. Such integration would strengthen alignment between accreditation, internal quality assurance, and internationally recognized management principles, broadening the framework's applicability toward sustainable, globally aligned quality assurance practices.

From an implementation perspective, the adoption of international standards within the proposed framework can be conducted through a staged integration process. First, international accreditation criteria can be systematically mapped to the existing unified indicator structure derived from national accreditation requirements. Second, shared evidence elements – such as learning outcomes, curriculum alignment, graduate performance, and academic governance – can be identified and aligned across standards. Third, the AI-assisted analytical layer can be utilized to support continuous monitoring of indicator alignment and evidence readiness, while human evaluators validate contextual relevance and compliance. This staged approach allows higher education institutions to progressively adopt international standards without disrupting established internal quality assurance processes.

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