SUPPORTING ACCOUNTABILITY IN OUTCOME-BASED EDUCATION THROUGH AI-DRIVEN LEARNING ANALYTICS: A CASE STUDY AT THANG LONG UNIVERSITY

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Abstract: *Outcome-Based Education (OBE) positions accountability at the center of higher education by requiring institutions to demonstrate alignment between intended learning outcomes and verified student achievement. However, in practice, accountability mechanisms often remain procedural and fragmented, limiting their capacity to inform continuous improvement. Recent advances in artificial intelligence (AI) and learning analytics offer new possibilities for transforming accountability into a more systematic, data-driven process. This study examines how AI-assisted learning data analysis can strengthen accountability within an OBE-oriented program through a qualitative-dominant case study at Thang Long University, Vietnam. Drawing on institutional documents and aggregated assessment data, the analysis explores how AI-supported aggregation and outcome-level reporting enhance evidence-based decision-making. Findings indicate that AI-enabled analytics consolidate fragmented assessment data, identify outcome-level performance gaps, and support structured feedback loops linking evidence to curricular refinement. Rather than replacing academic judgment, AI functions as an infrastructural mechanism that strengthens the evidentiary foundations of accountability in OBE implementation.*

Keywords: *accountability, artificial intelligence, learning analytics, outcome-based education, quality assurance*

I. Introduction

Outcome-Based Education (OBE) has become a major paradigm in contemporary higher education, emphasizing clearly defined learning outcomes as the foundation for curriculum design, teaching, and assessment (Spady, 1994). Within this framework, an educational program's effectiveness is evaluated by the extent to which students demonstrate the intended competencies upon completion. As a result, institutions are increasingly required to align curriculum structures, teaching strategies, and assessment practices with measurable learning outcomes to ensure educational quality and transparency.

As OBE has been widely adopted, accountability has emerged as a central requirement in higher education systems. Institutions are expected not only to define learning outcomes but also to demonstrate, through systematic assessment, that these outcomes have been achieved (Biggs & Tang, 2011). However, translating this principle into

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practice remains challenging. Although course and program learning outcomes are often formally articulated, many institutions lack coherent mechanisms for consolidating assessment evidence across courses and programs, limiting the effectiveness of accountability processes.

The rapid digitization of higher education has significantly expanded the availability of learning data generated through learning management systems, online assessments, and digital feedback platforms. These data provide valuable evidence of student learning and performance across courses and programs. At the same time, advances in artificial intelligence (AI) have increased the capacity to process large, complex educational datasets through automated aggregation and pattern recognition. As a result, AI-supported learning analytics offers new possibilities for consolidating assessment evidence and strengthening data-informed accountability in outcome-based education.

Despite the parallel development of OBE frameworks, accountability mechanisms, learning analytics, and artificial intelligence applications, their integration within a coherent analytical framework remains limited. In many institutions, assessment data are collected across multiple courses but remain fragmented within separate systems and administrative units. This situation creates what may be described as an "aggregation gap," where outcome-related data exist but cannot easily be consolidated into meaningful program-level indicators of learning achievement. Consequently, the connection between outcome articulation and verifiable evidence of attainment often remains weak, limiting the effectiveness of accountability processes in OBE implementation.

Addressing this gap, the present study examines how artificial intelligence-supported learning data analysis can strengthen accountability within an Outcome-Based Education framework. Through a qualitative-dominant case study conducted at Thang Long University in Vietnam, the research explores how assessment data aligned with course learning outcomes (CLOs) and program learning outcomes (PLOs) can be systematically aggregated and interpreted to support program-level accountability. By analyzing institutional documents and aggregated learning data, the study seeks to illustrate how AI-assisted learning analytics can function as a decision-support mechanism that enhances evidence-based curriculum evaluation and continuous improvement in higher education.

II. Literature review

2.1. Outcome-based education and accountability in higher education

Outcome-Based Education (OBE) emerged as an alternative to traditional content-oriented educational models by emphasizing clearly defined learning outcomes that students are expected to achieve (Spady, 1994). Within this framework, educational quality is evaluated based on learners' demonstrated competencies rather than instructional inputs. Learning outcomes therefore become the central organizing principle guiding curriculum design, teaching strategies, and assessment practices.

A defining feature of OBE is its explicit linkage between learning outcomes, assessment, and accountability. Institutions adopting OBE are expected not only to define intended outcomes but also to provide credible evidence that these outcomes have been achieved (Biggs & Tang, 2011). As Dill and Beerkens (2010) argue, contemporary accountability frameworks in higher education increasingly require evidence-based demonstrations of educational effectiveness. However, OBE effectiveness

depends heavily on the reliability of the assessment systems used to measure outcome attainment. Without credible assessment evidence, outcome statements risk becoming symbolic declarations rather than meaningful indicators of educational quality (Harden, 2007).

2.2. The role of learning data in supporting accountability

Assessment data constitute the primary empirical basis for accountability in OBE-oriented systems. Outcome attainment evidence is typically generated through a variety of assessments, including examinations, projects, coursework, and formative evaluation activities. When aggregated systematically across courses and cohorts, these data provide valuable insights into the extent to which program learning outcomes are achieved.

The increasing digitization of higher education has significantly expanded access to learning data through learning management systems, online assessments, and digital feedback platforms. Learning analytics has emerged as a field concerned with systematically collecting and analyzing these data to support educational decision-making (Siemens, 2012). While early applications of learning analytics focused primarily on student engagement and retention, more recent studies highlight its relevance for assessment and quality assurance processes (Ferguson, 2012). In Vietnam, Nguyen and Nguyen (2026) examined LMS records and lecturers' perceptions at Hanoi Open University, reporting that learning activity data could inform student engagement monitoring and teaching adjustments. Their focus was on learner participation and teaching support; the present study examines how assessment evidence can be aggregated across courses to support program-level accountability in OBE.

Despite this potential, the use of learning data for accountability remains challenging. Assessment results are often distributed across courses, stored in heterogeneous formats, and interpreted inconsistently. As a result, institutions may have large volumes of learning data but lack coherent mechanisms to consolidate it into meaningful indicators of program-level outcome attainment.

2.3. Artificial intelligence in learning analytics

Advances in artificial intelligence (AI) have significantly enhanced the analytical capabilities of learning analytics systems. AI techniques enable the automated processing of large-scale educational datasets, facilitating pattern recognition, classification, and predictive analysis beyond the capacity of traditional descriptive approaches. Holmes et al. (2019) note that AI can support educational decision-making by identifying relationships within learning data that may not be readily observable through conventional analysis.

In assessment contexts, AI-supported analytics can help consolidate assessment results, identify patterns of outcome attainment, and generate program-level insights from distributed course-level data. Viberg et al. (2018) emphasize that such analytical capabilities can improve the consistency and timeliness of educational evaluation. Nevertheless, scholars caution that AI should function as a decision-support mechanism rather than a substitute for academic judgment, ensuring that data-driven insights remain aligned with pedagogical goals and institutional values (Selwyn, 2019).

2.4. Research gap and conceptual positioning

Although educational research has widely discussed OBE, accountability frameworks, learning analytics, and artificial intelligence, studies that integrate these domains remain limited.

Existing literature often examines learning analytics as a tool for monitoring student engagement or predicting academic performance, while accountability is typically addressed within policy and governance discussions. As a result, the role of AI-supported learning analytics in operationalizing accountability within OBE-based programs remains insufficiently explored.

This gap is particularly evident in higher education systems where OBE is being implemented as part of broader quality assurance reforms. Institutions are increasingly required to demonstrate outcome attainment but often lack systematic mechanisms to aggregate and interpret assessment evidence at the program level.

2.5. Conceptual integration: AI-enabled accountability in OBE

When examined together, OBE, accountability mechanisms, learning analytics, and artificial intelligence reveal a structural convergence. OBE establishes clearly defined learning outcomes as institutional commitments, while accountability requires verifiable evidence of achieving these outcomes. Learning analytics provides the methodological infrastructure for collecting and analyzing educational data, and AI enhances the scalability and interpretive capacity of such analytics.

Within this integrated framework, AI-supported learning analytics can be conceptualized as an enabling mechanism that transforms dispersed assessment data into structured accountability evidence. Accountability therefore becomes a cyclical process: learning outcomes inform assessment design; assessments generate learning data; AI-supported analytics synthesize evidence; and the resulting insights inform curriculum improvement. In this way, AI functions not as a pedagogical substitute but as an infrastructural component supporting evidence-based governance in outcome-based education.

III. Methodology

3.1. Research design

This study adopts a qualitative-dominant case study design, complemented by document and learning data analysis, to examine how AI-assisted learning data analysis can support accountability within Outcome-Based Education (OBE). A case study approach is particularly appropriate for investigating complex educational phenomena that are deeply embedded in specific institutional and policy contexts (Yin, 2018). Rather than seeking statistical generalization, the study aims to generate in-depth analytical insights into how accountability is operationalized within an OBE framework.

The choice of a single-case study is guided by the exploratory nature of the research and the need to examine interactions among learning outcomes, assessment data, and AI-supported analytics in a real-world setting. This design allows for a holistic examination of institutional practices, data flows, and decision-making processes related to accountability in OBE-based training programs.

3.2. Research context

The case study was conducted at Thang Long University, a private higher education institution in Vietnam that has been undergoing curriculum reform aligned with Outcome-Based Education. Like many higher education institutions in transitional systems, the university has shifted from content-oriented program structures toward outcome-based curriculum design, emphasizing clearly articulated course learning outcomes (CLOs) and program learning outcomes (PLOs).

In parallel with OBE implementation, the institution has expanded its use of digital learning platforms, including learning management systems and electronic assessment tools. These developments have resulted in the accumulation of diverse learning data, creating favorable conditions for examining how such data can be analyzed and utilized to support accountability and quality assurance processes.

3.3. Data sources

To address the research objectives, multiple data sources were collected to enable triangulation and enhance analytical rigor. The data sources include:

1. Curriculum and policy documents, such as program descriptions, CLO-PLO mappings, assessment plans, and internal quality assurance reports related to OBE implementation.

2. Learning and assessment data, including aggregated course-level assessment results aligned with CLOs, records of student performance across cohorts, and summary data extracted from the institutional learning management system.

3. Quality assurance documentation, including self-evaluation reports and internal review materials that reflect institutional accountability practices.

These data sources were selected to capture both the formal articulation of accountability requirements and their operationalization through assessment and data analysis practices.

This study's dataset was derived from an undergraduate program at Thang Long University during the 2022-2024 academic years. The dataset included aggregated assessment records from twelve courses involving approximately 430 students across three cohorts. Course-level assessment results were aligned with five program learning outcomes through the institutional CLO-PLO mapping matrix. AI-supported aggregation procedures were analytically modeled to consolidate CLO-level assessment data into program-level indicators of outcome attainment.

3.4. Data analysis procedures

Data analysis followed a systematic, iterative process across several stages. First, curriculum and policy documents were analyzed using qualitative content analysis to identify how the OBE framework conceptualizes and operationalizes accountability. Particular attention focused on the alignment between stated learning outcomes, assessment methods, and quality assurance requirements.

Second, learning and assessment data were examined to explore how evidence of outcome attainment is generated and aggregated at the program level. Descriptive and pattern-based analyses identified trends in CLO and PLO achievement across courses and cohorts. At this stage, AI-supported analytical procedures were modeled to simulate automated aggregation and pattern-recognition processes relevant to program-level outcome reporting, thereby improving the efficiency and consistency of accountability-related analyses.

Third, findings from document analysis and learning data analysis were integrated to construct an analytical model illustrating the role of AI-assisted learning analytics in supporting accountability within OBE. This integrative analysis focused on identifying points at which AI can add value, such as data consolidation, outcome-level reporting, and feedback loops for curriculum improvement.

3.5. Trustworthiness and research rigor

To ensure the study's trustworthiness, the researchers employed several strategies. The study achieved data

triangulation by using multiple data sources, including documents, assessment records, and quality assurance reports. The study maintained analytical transparency by clearly documenting data selection and analysis procedures. In addition, the study emphasizes analytical generalization by linking findings to existing theoretical constructs related to OBE, accountability, and learning, rather than generalizing them statistically to other institutions (Stake, 1995).

3.6. Ethical considerations

The study adheres to ethical principles governing educational research. The study analyzed all learning and assessment data in aggregated, anonymized forms to protect student privacy. The study used institutional documents and data in accordance with internal regulations and ethical guidelines. Importantly, AI-supported analysis was treated as a decision-support mechanism rather than an automated evaluative authority, ensuring that academic judgment and institutional responsibility remain central to accountability processes.

3.7. Methodological limitations

As a single-case study, this research's findings are context-specific and not intended to be universally applicable. The study focuses on illustrating mechanisms and analytical possibilities rather than providing definitive prescriptions for all institutions. Nevertheless, the insights generated offer transferable conceptual guidance for higher education institutions seeking to strengthen accountability within OBE through data-informed approaches.

IV. Results and discussion

To illustrate how AI-supported learning analytics strengthens accountability in OBE implementation, the following analysis presents examples of outcome alignment, aggregated learning data, and pattern detection derived from institutional assessment records.

The findings are organized around three interrelated mechanisms through which AI-supported learning analytics enhance accountability within OBE: data consolidation, outcome-level pattern detection, and feedback-loop integration. These mechanisms collectively illustrate how AI functions not as an autonomous evaluator, but as an infrastructural mediator within institutional governance processes.

The case study findings indicate that accountability has become central to implementing Outcome-Based Education (OBE). Institutional documents and internal quality assurance reports consistently emphasize the requirement to demonstrate learning outcome attainment through evidence-based assessment. This shift reflects a broader transition from procedural accountability, which focuses on compliance with prescribed inputs and processes, to performance-oriented accountability grounded in demonstrable educational outcomes.

Analysis of assessment practices shows that learning data are the primary evidence for accountability in OBE-based programs. At the course level, course learning outcomes (CLOs) are typically assessed through a combination of summative and formative assessments, supported by rubrics and performance criteria. To examine how course-level assessments contribute to program-level accountability, we analyzed the alignment between course learning outcomes (CLOs) and program learning outcomes (PLOs). Table 1 presents an example of this alignment within the selected program.

Table 1. Example of CLO-PLO alignment in the selected program

Course	CLO	Linked PLO	Assessment Method
ENG1101	CLO1	PLO1	Final exam
ENG1102	CLO2	PLO2	Presentation
ENG1103	CLO3	PLO3	Research project

Table 1 illustrates how course learning outcomes are aligned with program learning outcomes within the selected program. This alignment provides the structural basis for aggregating assessment evidence at the program level.

Learning data are often fragmented across courses and stored in heterogeneous formats, limiting their direct usability for evaluating program learning outcomes (PLOs). To address this challenge, we aggregated course-level assessment results according to their alignment with program learning outcomes. Table 2 presents an example of aggregated outcome achievement derived from CLO-aligned assessment data across multiple courses.

Table 2. Aggregated achievement of Program Learning Outcomes

Program Learning Outcome	Students Achieving (%)
PLO1	78%
PLO2	72%
PLO3	85%

As illustrated in Table 2, aggregated learning data provide a clearer picture of outcome attainment at the program level. The results indicate that PLO2 demonstrates comparatively lower achievement than the other outcomes, suggesting a potential area for curricular improvement. These aggregated indicators allow institutions to move beyond isolated course-level evaluations and assess program performance more systematically.

Integrating AI-supported learning data analysis offers a practical response to these challenges. By enabling automated aggregation and pattern-based analysis, AI-assisted approaches facilitate the systematic consolidation of CLO-aligned assessment data into program-level indicators of outcome attainment. In the case examined, AI-supported analytical modeling demonstrated how assessment results were systematically mapped across courses and cohorts to provide a more coherent picture of PLO achievement. This process enhances the efficiency of accountability reporting while reducing the risk of inconsistency associated with manual data handling.

From an analytical perspective, AI-supported learning analytics strengthens OBE accountability through three key mechanisms.

First, automated data processing improves the reliability of outcome-level reporting by ensuring consistent aggregation across courses and academic units. Second, pattern recognition identifies trends in learning outcome attainment, including persistent underachievement that may not appear in isolated course-level evaluations. Third, AI-assisted synthesis supports evidence-based decision-making by generating summaries that are readily usable for internal quality assurance and external review processes.

By applying AI-assisted aggregation and pattern recognition to the consolidated assessment dataset, we can identify recurring trends in outcome attainment across student cohorts. Table 3 illustrates outcome-level patterns detected through AI-supported analysis.

Table 3. Outcome performance trends identified through AI-supported aggregation

Cohort	Lowest-performing PLO	Achievement Rate
2022	PLO2	70%
2023	PLO2	71%
2024	PLO3	74%

As shown in Table 3, AI-assisted aggregation reveals recurring patterns in outcome attainment across cohorts. The analysis indicates that PLO2 consistently shows lower achievement levels than other outcomes, suggesting a persistent area requiring curricular attention. By identifying such patterns, AI-supported learning analytics enables institutions to detect structural weaknesses in program performance that may not be visible through isolated course-level evaluations.

Importantly, the findings do not suggest that AI replaces academic judgment in accountability mechanisms. Rather, AI functions as a decision-support tool that enhances the interpretability and usability of learning data. Academic staff remain responsible for interpreting analytical outputs, contextualizing findings, and determining appropriate curricular or pedagogical responses. This distinction is critical, as OBE accountability depends not only on data availability but also on informed professional judgment and institutional responsibility.

These findings align with existing literature emphasizing the central role of assessment and data in outcome-based accountability. Previous studies have noted that OBE risks becoming symbolic when outcome statements are not supported by systematic evidence of attainment (Harden, 2007). This case study extends the literature by showing how AI-supported learning analytics can operationalize accountability in practice, particularly in institutional contexts where large volumes of assessment data must be analyzed across programs.

Based on the integrated analysis, accountability in OBE can be conceptualized as a cyclical process linking learning outcomes, assessment, data analysis, and continuous improvement. Within this cycle, AI-supported analytics transform raw assessment data into actionable accountability evidence. When these elements align coherently, accountability becomes an embedded feature of OBE implementation rather than an external administrative burden.

Overall, the results suggest that AI contributes to OBE not by altering its foundational principles, but by enhancing the feasibility and robustness of data-driven accountability practices. In contexts where institutions are required to demonstrate outcome attainment to multiple stakeholders, AI-supported learning data analysis offers a viable pathway for strengthening evidence-based accountability while preserving the central role of academic judgment.

V. Conclusion and recommendations

This study examined how AI-assisted analysis of learning data can support accountability within Outcome-Based Education (OBE), using a case study at Thang Long University. The findings demonstrate that accountability is not an ancillary requirement in OBE, but a core managerial function that depends on the institution's capacity to generate, interpret, and utilize evidence of learning outcome attainment.

The study shows that learning data aligned with course and program learning outcomes constitute the primary empirical foundation for accountability in OBE-based training programs. However, when such data are fragmented across courses and assessment practices, accountability risks becoming procedural rather than evidence-based. In this context, AI-supported learning analytics offer a practical mechanism to consolidate outcome-related data, improve reporting consistency, and enable systematic interpretation at the program level.

Importantly, the findings suggest that AI's contribution lies not in redefining educational goals or replacing academic judgment, but in strengthening the evidentiary infrastructure of accountability. By transforming dispersed assessment data into coherent indicators of outcome attainment, AI enables institutions to demonstrate compliance with OBE requirements while simultaneously supporting continuous quality improvement. Accountability thus emerges as an integrated and operational component of OBE rather than an external administrative burden.

While the study is limited to a single institutional context, it offers analytical insights into how OBE accountability can be operationalized through data-informed approaches. Future research may extend this line of inquiry through comparative studies across institutions or by examining the long-term impact of AI-supported accountability mechanisms on curriculum development and learning quality.

Ultimately, this study suggests that the future of accountability in OBE does not lie in additional documentation, but in the intelligent orchestration of learning data infrastructures. When AI-supported analytics are embedded within principled governance frameworks, accountability evolves from retrospective reporting into continuous institutional learning.

From a policy perspective, higher education institutions implementing OBE should prioritize developing integrated learning data infrastructures that consolidate assessment evidence across courses and programs. Institutional leaders should ensure that AI-supported learning analytics functions as a decision-support mechanism that complements academic judgment while strengthening evidence-based quality assurance in Outcome-Based Education.

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TĂNG CƯỜNG TRÁCH NHIỆM GIẢI TRÌNH TRONG GIÁO DỤC DỰA TRÊN CHUẨN ĐẦU RA THÔNG QUA PHÂN TÍCH DỮ LIỆU HỌC TẬP DỰA TRÊN TRÍ TUỆ NHÂN TẠO: ĐIỂN CỨU TẠI TRƯỜNG ĐẠI HỌC THĂNG LONG

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Tóm tắt: *Giáo dục dựa trên chuẩn đầu ra (Outcome-Based Education - OBE) đặt trách nhiệm giải trình ở vị trí trung tâm của giáo dục đại học bằng cách yêu cầu các cơ sở đào tạo chứng minh sự phù hợp giữa các chuẩn đầu ra dự kiến và kết quả học tập đã được xác thực của người học. Tuy nhiên, trong thực tiễn triển khai, các cơ chế trách nhiệm giải trình thường mang tính thủ tục và rời rạc, làm hạn chế khả năng hỗ trợ cải tiến liên tục. Những tiến bộ gần đây trong lĩnh vực trí tuệ nhân tạo (AI) và phân tích dữ liệu học tập mở ra các khả năng mới nhằm chuyển đổi trách nhiệm giải trình thành một quá trình mang tính hệ thống và dựa trên dữ liệu. Nghiên cứu này phân tích cách thức phân tích dữ liệu học tập có hỗ trợ AI có thể tăng cường trách nhiệm giải trình trong một chương trình đào tạo theo định hướng OBE thông qua nghiên cứu trường hợp thiên về định tính tại Trường Đại học Thăng Long, Việt Nam. Dựa trên các tài liệu nội bộ và dữ liệu đánh giá tổng hợp, nghiên cứu xem xét cách thức việc tổng hợp dữ liệu và báo cáo ở cấp độ chuẩn đầu ra với sự hỗ trợ của AI có thể nâng cao chất lượng ra quyết định dựa trên bằng chứng. Kết quả cho thấy các phân tích dữ liệu được hỗ trợ bởi AI giúp hợp nhất các dữ liệu đánh giá rời rạc, xác định các khoảng trống trong mức độ đạt chuẩn đầu ra và hỗ trợ xây dựng các vòng phản hồi có cấu trúc nhằm liên kết bằng chứng với việc điều chỉnh chương trình đào tạo. Thay vì thay thế phán đoán học thuật, AI đóng vai trò như một cơ chế hạ tầng giúp củng cố nền tảng bằng chứng cho trách nhiệm giải trình trong quá trình triển khai OBE.*

Từ khóa: *trách nhiệm giải trình, trí tuệ nhân tạo, phân tích học tập, giáo dục dựa trên chuẩn đầu ra, đảm bảo chất lượng*

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