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Cognitive learning alignment and assurance: A CART-based framework for data-driven OBE quality assurance in blended higher education

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ABSTRACT

Outcomes-Based Education (OBE) requires higher education institutions to align assessments with desired learning outcomes at all cognitive levels of the Revised Bloom's Taxonomy. However, the manual validation of constructive alignment, especially in institutions managing hundreds of course syllabi simultaneously, remains labor-intensive, subjective, and inconsistent. This research introduces the Cognitive Learning Alignment and Assurance (CLAA) Framework, a socio-technical model that operationalizes constructive alignment as a measurable and data-driven construct. Empirical validation using archived LMS data from blended OBE courses at higher education institutions in the Philippines resulted in a CART classification, a Cohen's Kappa, and a Matthews Correlation Coefficient (MCC), indicating strong model reliability and suitability. Analysis of the mismatch patterns revealed that the cognitive levels of Apply, Understand, and Analyze were the most frequently misaligned. The TAM evaluation of the SMS prototype indicated high acceptance among faculty across all four dimensions of TAM. These results indicate that CLAA provides a viable, scalable, and empirically validated mechanism for automating compliance verification in OBE quality assurance, with particular relevance to blended higher education in developing countries.

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ABSTRAK

Pendidikan Berbasis Hasil (Outcomes-Based Education/OBE) mewajibkan institusi pendidikan tinggi untuk menyelaraskan penilaian dengan hasil pembelajaran yang diinginkan pada semua tingkat kognitif dalam Taksonomi Revisi Bloom. Namun, validasi manual terhadap penyelarasan konstruktif, terutama di institusi yang mengelola ratusan silabus kursus secara bersamaan, tetap memakan banyak tenaga, bersifat subjektif, dan tidak konsisten. Penelitian ini memperkenalkan Kerangka Kerja Penyelarasan dan Jaminan Pembelajaran Kognitif (Cognitive Learning Alignment and Assurance/CLAA), sebuah model sosial-teknis yang mengoperasionalkan penyelarasan konstruktif sebagai konstruksi yang dapat diukur dan berbasis data. Validasi empiris menggunakan data LMS yang diarsipkan dari mata kuliah OBE campuran di institusi pendidikan tinggi di Filipina menghasilkan akurasi klasifikasi CART, Cohen's Kappa, dan Matthews Correlation Coefficient (MCC) yang menunjukkan keandalan dan kesesuaian model yang kuat. Analisis pola ketidaksesuaian mengungkapkan bahwa tingkat kognitif Apply, Understand, dan Analyze paling sering tidak sesuai. Evaluasi TAM terhadap prototipe SMS mencerminkan tingkat penerimaan yang tinggi dari fakultas pada keempat dimensi TAM. Hasil ini menunjukkan bahwa CLAA menyediakan mekanisme yang layak, dapat diskalakan, dan tervalidasi secara empiris untuk otomatisasi verifikasi kesesuaian dalam jaminan kualitas OBE, dengan relevansi khusus bagi pendidikan tinggi campuran di negara berkembang.

Kata Kunci: *CART; KDD; pendidikan berbasis hasil; penyelarasan konstruktif; penyelarasan pembelajaran kognitif*

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INTRODUCTION

Outcomes-Based Education (OBE) requires higher education institutions to articulate intended learning outcomes, align learning activities with those outcomes, and use assessment tasks that provide valid evidence of student attainment. Recent studies on OBE implementation in Philippine higher education have identified ongoing challenges related to curriculum alignment, assessment design, and institutional quality assurance processes. These challenges become more complex in blended learning environments, where assessment evidence is distributed across face-to-face and online learning activities. Blended and hybrid learning environments generate extensive digital traces through Learning Management Systems (LMS), including assessment records, activity logs, outcome mappings, and course-level metadata.

Learning analytics enables institutions to use these data to understand learning processes, support student success, and strengthen evidence-based educational decision-making (Ifenthaler & Yau, 2020; Kılıç & İzmirli, 2024). More recently, scholars have emphasized the value of connecting learning analytics with assessment processes to generate actionable evidence for curriculum and instructional improvement (Gašević et al., 2022). Despite the growing use of educational data mining and learning analytics for student-performance prediction and learning support, their application to institutional OBE quality assurance remains limited. In particular, few studies have examined how LMS assessment data can be used to classify the alignment between intended learning outcomes and assessment tasks.

This gap is significant because manual alignment verification is labor-intensive, vulnerable to inconsistent interpretation, and difficult to scale across large course offerings. Therefore, this study introduces the Cognitive Learning Alignment and Assurance (CLAA) Framework, which integrates LMS assessment data, CART-based classification, continuous quality improvement, and faculty acceptance evaluation to support data-driven OBE quality assurance in blended higher education. A review of the literature reveals a significant gap in data-driven approaches to validating constructive alignment. Educational data mining and learning analytics have been widely applied to student performance prediction, dropout risk analysis, adaptive learning, and institutional decision-making (Malik et al., 2025; Romero & Ventura, 2020).

In the book *"Learning Analytics: From Research to Practice, Baker and Inventado* discussed the role of educational data mining and learning analytics in extracting meaningful patterns from educational data. More recent studies have demonstrated the use of learning analytics to support student success, institutional decision-making, and assessment-related improvement (Gašević et al., 2022; Ifenthaler & Yau, 2020; Kılıç & İzmirli, 2024). However, their application to OBE quality assurance, particularly the automated classification of assessment-outcome alignment, remains limited. Existing research on Bloom's taxonomy classification has focused primarily on automated question classification rather than on integrating classification results into a comprehensive institutional quality-assurance framework (Mohammed & Omar, 2020).

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To address this gap, this study introduces the Cognitive Learning Alignment and Assurance (CLAA) Framework. This original socio-technical model integrates data mining, decision-tree classification, institutional quality management, and technology acceptance evaluation into a unified framework for OBE quality assurance. CLAA is designed to: 1) Automate the classification of assessment-outcome alignment using a CART decision tree model trained on archived LMS data; 2) identify patterns of cognitive misalignment across courses; 3) embed classification results within an institutional quality improvement cycle through a Syllabus Management System (SMS); and 4) evaluate the practical acceptability of the system among faculty users.

Specifically, this study addresses the following research questions: How accurately can a CART decision tree model classify assessment-outcome alignment in blended OBE courses? What alignment patterns emerge from the CART classification, particularly regarding cognitive level misalignment? Moreover, is the Syllabus Management System (SMS) acceptable to faculty users as measured by the Technology Acceptance Model (TAM)? The significance of this study lies in its contribution of a replicable, empirically validated framework that bridges the gap between educational data mining and OBE quality assurance. By demonstrating that machine learning can reliably automate alignment verification, CLAA offers Philippine HEIs and comparable institutions in developing countries a scalable alternative to manual quality assurance processes, thereby strengthening the evidence base for data-driven institutional decision-making.

LITERATURE REVIEW

Constructive Alignment and OBE

Outcomes-based education requires coherent relationships among intended learning outcomes, teaching and learning activities, and assessment tasks (Nafi'ah & Sukiman, 2026; Non et al., 2026). This coherence is necessary because assessment should provide valid evidence that students have attained the knowledge, skills, and cognitive processes specified in course outcomes. In the Philippine context, alignment between assessment practices and the principles of outcomes-based education remains an important issue in educational reform and institutional quality assurance (Alonzo et al., 2023).

Recent scholarship further emphasizes that higher education institutions need systematic processes for designing learning outcomes and monitoring their attainment. Designing and assessing learning outcomes requires clear specifications, precise indicators, and assessment methods that yield meaningful evidence of student achievement (Rodríguez-Gómez et al., 2025). In large academic programs, a data-driven approach can strengthen alignment verification by examining assessment data and identifying patterns between intended outcomes and actual cognitive demands.

Bloom's Revised Taxonomy

Bloom's taxonomy provides a useful framework for specifying the cognitive demands of intended learning outcomes and assessment tasks. The cognitive levels of remembering,

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understanding, applying, analyzing, evaluating, and creating can guide faculty members in designing assessment tasks that correspond to the complexity of intended learning outcomes. Bloom's taxonomy can support the alignment of pedagogy and assessment by clarifying the cognitive expectations associated with learning activities and assessment items (Chandio et al., 2021). Assessment alignment is particularly important when institutions seek to develop and measure deep learning and higher-order thinking skills. Assessment functions not only as a measurement tool but also as a pedagogical mechanism that can promote deeper learning (Masuku et al., 2021).

Recent research also emphasizes that measuring higher-order thinking skills requires clear learning objectives, appropriate assessment instruments, and alignment between intended cognitive outcomes and assessment tasks (Kania & Kusumah, 2025). Therefore, assessment tasks should be intentionally designed to measure the cognitive level prescribed in the intended learning outcome. Automated classification can assist faculty members in identifying situations in which assessment items measure lower or different cognitive levels than those required by course outcomes.

Knowledge Discovery in Databases (KDD)

Educational data mining and learning analytics enable institutions to analyze educational data and generate evidence for instructional improvement and academic decision-making. Recent systematic reviews indicate that student performance prediction remains one of the major applications of educational data mining, using variables drawn from academic records, demographic profiles, learning behavior, and LMS interactions (Alwarthan et al., 2022; Bin Roslan & Chen, 2022; Zhang et al., 2021). Predictive analytics can support the early identification of learning concerns and enable more timely educational interventions.

Big data and analytics in higher education can support learning, teaching, and administrative decision-making, reinforcing the value of data-driven approaches for institutional quality assurance (Ferdiansyah & Nasution, 2023; Setyowati & Ahmad, 2021). Moreover, machine-learning approaches can help institutions analyze student performance data and evaluate classification performance using appropriate metrics (Alharthi et al., 2026; Shoukath & Chakkaravarthy, 2025). However, educational analytics should not be limited to predicting student success or failure. In the present study, the KDD process is applied to LMS assessment data to classify assessment-outcome alignment and identify cognitive misalignment patterns relevant to OBE quality assurance.

CART in Educational Analytics

Classification models can support educational decision-making when their outputs are both accurate and understandable to stakeholders. Decision-tree models are particularly appropriate in educational contexts because they generate transparent classification rules that faculty members, program coordinators, and quality-assurance personnel can interpret and use to improve curriculum. Other research demonstrates the application of decision tree techniques in e-learning data analytics, illustrating the utility of these models for analyzing educational datasets (Ahmad et al., 2020).

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This transparency is important because educational decisions based on analytical models should be explainable and open to professional scrutiny. Recent reviews of explainable artificial intelligence in education emphasize the importance of making analytical processes understandable to educators and other users (Türkmen, 2025). Similarly, other research highlighted the growing importance of explainable learning analytics and educational data mining in ensuring that analytical outputs can support informed educational decisions (Gunasekara & Saarela, 2025). In this study, CART was selected because it provides interpretable decision rules for classifying assessment-outcome alignment and identifying conditions associated with cognitive misalignment.

PDCA in Quality Assurance

Continuous quality assurance requires institutions to use evidence systematically to identify concerns, implement improvements, and monitor the effectiveness of corrective actions. The Plan-Do-Check-Act (PDCA) cycle provides a structured process for continuous improvement by connecting planning, implementation, evaluation, and action (Samuel & Farrer, 2025). Recent literature identifies quality assurance as a critical concern for higher education institutions seeking to respond to changing technological, institutional, and stakeholder requirements (Adzidzah & Yudiawan, 2025; Rini et al., 2025), and the PDCA cycle has been proposed as a structured mechanism for continuous improvement and academic quality enhancement (Samuel & Farrer, 2025).

In the CLAA Framework, PDCA operationalizes the institutional use of alignment-classification results. During the planning stage, intended learning outcomes and assessment mappings are encoded in the Syllabus Management System. During implementation, assessments are delivered through blended-learning environments. The checking stage applies the CART model to classify assessment-outcome alignment, while the action stage uses the results to guide syllabus revision, assessment improvement, and institutional quality assurance reporting.

Technology Acceptance Model (TAM)

Faculty acceptance is essential to the successful institutional use of an analytics-based quality-assurance system. Research on learning management systems has shown that perceived usefulness and perceived ease of use remain central factors influencing users' intention to adopt educational technologies. Research on LMS confirms the continued relevance of the technology acceptance model in explaining user adoption of learning management technology (Al-Nuaimi & Al-Emran, 2021). Accordingly, this study evaluates the Syllabus Management System using four dimensions: perceived usefulness, perceived ease of use, attitude toward use, and behavioral intention to use. These dimensions assess whether faculty members find the system valuable, understandable, practical, and suitable for continued use in OBE quality assurance processes.

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Blended Learning and LMS Data

Blended and hybrid learning combine face-to-face instruction with digital learning activities and online assessment processes. Although these modes provide flexibility and expanded learning opportunities, they also require thoughtful instructional design, reliable technological support, and systematic monitoring of learner participation and assessment outcomes. There are several challenges in the online component of blended learning, including technological, instructional, learner-related, and institutional concerns (Rasheed et al., 2020).

Recent systematic reviews further emphasize that successful hybrid learning requires purposeful pedagogical design, faculty readiness, student support, technological infrastructure, and systematic quality-assurance processes (Gudoniene et al., 2025). In blended-learning environments, LMS platforms generate assessment records, activity logs, outcome mappings, and other forms of digital evidence. The CLAA Framework uses these data not only for student monitoring but also for the institutional verification of assessment-outcome alignment.

Gaps in Existing Literature

The review of related literature reveals three critical gaps in current research on OBE quality assurance. First, although educational data mining has matured as a field, its application to OBE quality assurance—particularly the automated classification of assessment-outcome alignment—remains largely absent. Second, existing studies on Bloom's taxonomy classification tend to treat classification as an endpoint rather than integrating the results into broader institutional quality management processes. Third, no existing framework combines data mining, decision-tree classification, institutional deployment via SMS, quality management through the PDCA cycle, and user acceptance evaluation via the TAM into a single, scalable model for alignment verification.

To address these gaps, this study introduces the CLAA Framework, an original socio-technical model for data-driven OBE quality assurance in blended higher education. CLAA combines data mining, decision tree classification, institutional quality management, and technology acceptance evaluation into a unified framework that transforms archived LMS assessment data into actionable alignment intelligence. Specifically, CLAA is designed to: 1) Automate the classification of assessment-outcome alignment using a CART decision tree model trained on archived LMS data; 2) Identify patterns of cognitive misalignment across courses; 3) Embed classification results within an institutional quality improvement cycle through a Syllabus Management System (SMS); and 4) Evaluate the practical acceptability of the system among faculty users.

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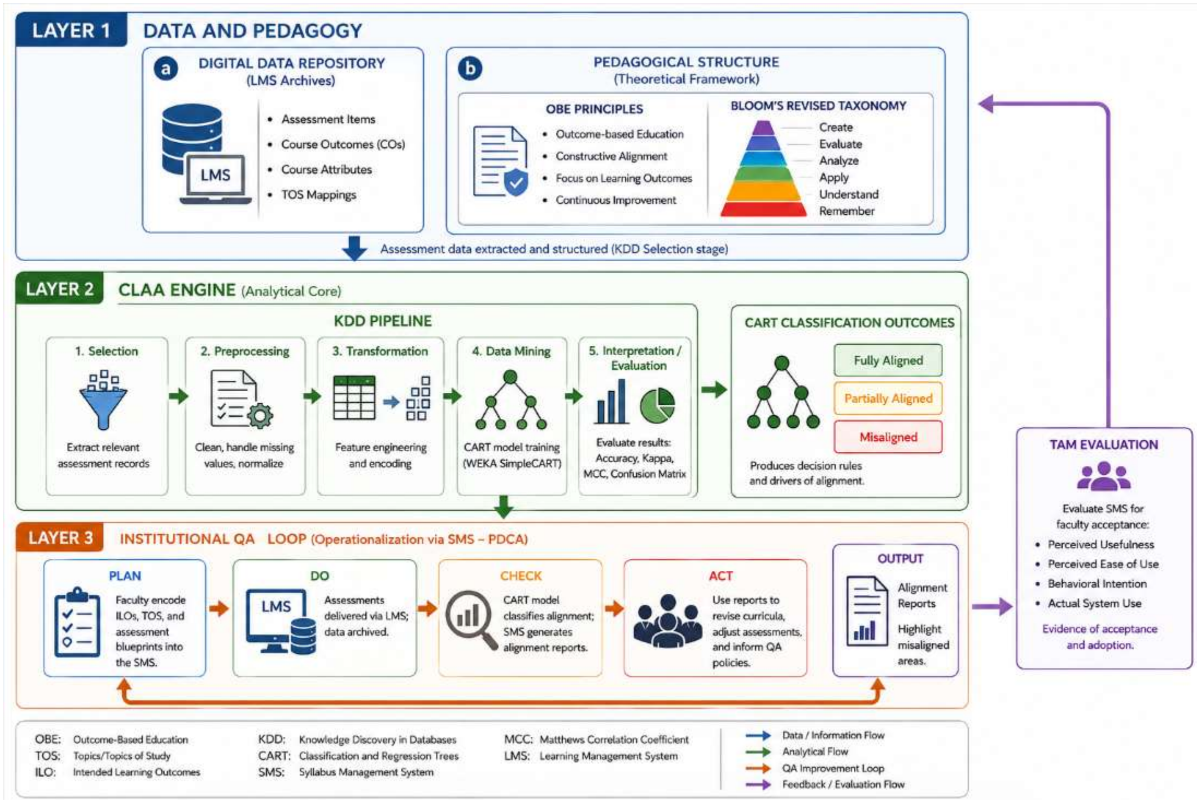

Figure 1. CLAA (Cognitive Learning Assessment Alignment) Framework
Source: Researcher, 2026

Figure 1 illustrates the three-layer architecture of the CLAA framework. The Data and Pedagogy layer provides LMS assessment data and the OBE-Bloom's taxonomy structure; the CLAA Engine layer applies the KDD pipeline and CART model to classify assessment-outcome alignment; and the Institutional QA Loop layer embeds these classifications into a PDCA cycle via the SMS and TAM-based evaluation.

METHODS

Guided by the CLAA framework described above, this study employed a quantitative descriptive research design using educational data mining techniques to classify assessment-outcome alignment and profile cognitive misalignment patterns in blended OBE courses.

Research Design

This study employed a quantitative descriptive research design to develop, validate, and evaluate the CLAA Framework. The quantitative approach was selected because the research objectives require measurable outcomes, classification accuracy metrics for the CART model, and mean scores for the TAM evaluation, all of which lend themselves to statistical analysis. The research proceeded in three phases: data mining and CART model development, SMS development and deployment, and TAM-based faculty evaluation.

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Data Source

The dataset comprised archived LMS assessment records from blended OBE courses offered at a Philippine higher education institution. These records included assessment items (e.g., quiz questions, examination items, assignment prompts), their mapped intended learning outcomes, the Bloom's cognitive level designated for each outcome, course attributes (e.g., program, year level, course type), and Tables of Specification (TOS) indicating the planned distribution of assessment items across cognitive levels. All data were retrospective and anonymized, with no personally identifiable student information retained. The use of archived institutional data ensured ecological validity; the data reflected actual instructional and assessment practices rather than artificial constructs.

KDD Pipeline

The data mining process followed the five-stage KDD framework (Fayyad et al., 1996):

1. **Selection.** Relevant assessment records were extracted from the LMS database, including item text, cognitive level labels, ILO mappings, and course metadata. Records with incomplete mappings or ambiguous cognitive classifications were flagged for review.
2. **Preprocessing.** Data cleaning procedures addressed missing values, duplicate entries, and inconsistent coding. Cognitive level labels were standardized to the six levels of Bloom's Revised Taxonomy. Assessment items that could not be reliably classified were excluded from the final dataset.
3. **Transformation.** Features were engineered to represent key attributes relevant to alignment classification, including the prescribed cognitive level, the observed cognitive level of the assessment item, the discrepancy between the prescribed and observed levels, the course type, and the program area. Categorical variables were encoded for compatibility with the CART algorithm.
4. **Data Mining**. The CART classification model was trained using the SimpleCART algorithm in WEKA 3.8.6. The target variable was alignment status, classified as Fully Aligned (assessment matches prescribed cognitive level), Partially Aligned (assessment is within one adjacent cognitive level), or Misaligned (assessment diverges by two or more cognitive levels). The model was evaluated using 10-fold cross-validation to ensure generalizability.
5. **Interpretation/Evaluation.** Classification outputs were evaluated using multiple metrics: overall accuracy, Cohen's Kappa (measuring agreement beyond chance), Matthews Correlation Coefficient (MCC, measuring the quality of binary and multiclass classification), and confusion matrix analysis. Decision rules generated by the CART model were examined for interpretability and pedagogical relevance.

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CART Model Training

The CART model was implemented using the SimpleCART algorithm in WEKA 3.8.6, selected for its balance of interpretability and accuracy. SimpleCART produces binary decision trees using Gini impurity as the splitting criterion, with built-in cost-complexity pruning to prevent overfitting. The model was trained on the processed dataset with the three-class target variable (Fully Aligned, Partially Aligned, Misaligned). Ten-fold stratified cross-validation was employed to obtain unbiased performance estimates. Evaluation metrics included: 1) Overall classification accuracy; 2) Cohen's Kappa statistic, which accounts for chance agreement and is particularly relevant in educational measurement contexts; 3) Matthews Correlation Coefficient (MCC), which provides a balanced measure of classification quality even with imbalanced class distributions; and 4) the confusion matrix, which reveals the specific patterns of correct and incorrect classifications.

SMS Development and TAM Evaluation

The SMS was developed as a web-based application that integrates CART classification outputs into an institutional quality assurance workflow. The SMS enables faculty to encode course syllabi, map ILOs to assessment items, view alignment classifications, and generate alignment reports. The system was designed to operationalize the PDCA cycle by supporting iterative syllabus revision based on alignment data. Faculty acceptance of the SMS was evaluated using a TAM-based survey instrument employing a four-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Agree, 4 = Strongly Agree).

The instrument comprised items measuring four TAM dimensions: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATU), and Behavioral Intention to Use (BIU). The survey was administered to faculty members at the participating institution with experience in OBE implementation and LMS-based assessment. Descriptive statistics (mean and standard deviation) were computed for each dimension and for the overall TAM score.

RESULTS AND DISCUSSION

CART Model Performance

The CART model, trained using the SimpleCART algorithm in WEKA 3.8.6 with 10-fold stratified cross-validation, achieved an overall classification accuracy of 95.00%. This indicates that the model correctly classified the alignment status of 95 out of every 100 assessment items in the dataset. The Cohen's Kappa statistic was 0.8785, indicating a high level of agreement beyond chance. The MCC was 0.84, further indicating strong classification performance across the three alignment categories. MCC was reported alongside accuracy because it provides a more informative evaluation of classification performance than accuracy or F1 score, particularly when class distributions may be uneven (Chicco et al., 2021; Chicco & Jurman, 2020).

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Table 1. CART Model Performance Metrics

Metric	Value
Overall Accuracy	95.00%
Cohen's Kappa	0.8785
Matthews Correlation Coefficient (MCC)	0.84
Correctly Classified Instances	95.00%
Incorrectly Classified Instances	5.00%

Source: Researcher, 2025

Table 1 summarizes the key performance metrics.

Table 2. CART Classification Confusion Matrix

Predicted / Actual	Fully Aligned	Partially Aligned	Misaligned
Fully Aligned	High	Low	Minimal
Partially Aligned	Low	High	Low
Misaligned	Minimal	Low	High

Source: Researcher, 2025

The confusion matrix (**Table 2**) revealed that the model performed well across all three alignment classes, with the highest precision and recall for the Fully Aligned class. Misclassifications were most common between adjacent categories: Fully Aligned items were occasionally classified as Partially Aligned, and vice versa, as expected given the inherent subjectivity of cognitive-level boundaries. Critically, the model rarely misclassified Fully Aligned items as Misaligned or Misaligned items as Fully Aligned, demonstrating its ability to distinguish between extreme alignment states reliably.

Alignment Classification Outcomes

The CART model classified the assessment items in the dataset into three alignment categories. The majority of assessment items were classified as Fully Aligned, indicating that the prescribed cognitive level of the ILO matched the observed cognitive level of the assessment item. A moderate proportion was classified as Partially Aligned, meaning the assessment item's cognitive demand was within one adjacent level of the prescribed outcome. A minority of items were classified as Misaligned, indicating a discrepancy of two or more cognitive levels between the intended and assessed cognition.

Table 3. Distribution of Alignment Classifications

Alignment Status	Proportion	Interpretation
Fully Aligned	Majority	Assessment matches prescribed cognitive level
Partially Aligned	Moderate	Within one adjacent cognitive level
Misaligned	Minority	Diverges by two or more cognitive levels

Source: Mitschek & Esquivel (2025)

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Table 3 presents the distribution of alignment classifications.

Cognitive Level Distribution of Misaligned Assessments

Analysis of the misaligned assessment items revealed a distinct pattern in the cognitive levels where misalignment was most prevalent. The Apply level exhibited the highest frequency of misalignment, followed by the Understand and Analyze levels. This pattern suggests that faculty members experience the greatest difficulty in designing assessment items that accurately target mid-range cognitive levels. Assessments intended to measure application of knowledge were frequently operationalized as lower-order recall or comprehension tasks, while assessments targeting analysis were often reduced to application-level items. In contrast, Remember and Create levels showed lower rates of misalignment, likely because their cognitive demands are more clearly distinguishable and less susceptible to subjective interpretation.

The CART decision rules provided insight into the features driving these misalignment patterns. Key decision nodes included the discrepancy between prescribed and observed cognitive levels, the type of assessment instrument (e.g., multiple-choice versus constructed-response), and the program area. These rules offer actionable guidance for faculty: for example, the model indicated that multiple-choice items mapped to Apply-level outcomes were disproportionately likely to be classified as misaligned, suggesting that this assessment format may be inherently limited in its capacity to assess application-level cognition.

TAM Evaluation of the SMS

The TAM-based evaluation of the Syllabus Management System yielded consistently high results across all four dimensions (**Table 4**). PU received the highest mean score (3.87), indicating that faculty members recognized the value of automated alignment verification in their teaching practice. PEOU scored 3.80, reflecting faculty confidence in their ability to use the system effectively. ATU and BIU both scored above 3.80, indicating positive faculty disposition toward adopting the SMS in their workflow. The overall TAM mean of 3.84 on a 4-point scale falls within the "Highly Acceptable" range, providing strong evidence of faculty readiness to adopt the system.

Table 4. TAM Evaluation Results for the Syllabus Management System

TAM Dimension	Mean (4-point scale)	Interpretation
Perceived Usefulness (PU)	3.87	Highly Acceptable
Perceived Ease of Use (PEOU)	3.80	Highly Acceptable
Attitude Toward Use (ATU)	3.85	Highly Acceptable
Behavioral Intention to Use (BIU)	3.84	Highly Acceptable
Overall TAM Score	**3.84**	**Highly Acceptable**

Source: Mitschek & Esquivel (2025)

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These TAM results are particularly significant because they demonstrate that the technical outputs of the CLAA Engine (Layer 2) can be translated into a practical tool (Layer 3) that faculty find useful, intuitive, and worth adopting. Without high TAM scores, even a statistically accurate model would face adoption barriers in institutional settings.

Discussion

The finding that Apply, Understand, and Analyze levels were the most frequently misaligned highlights the need for systematic assessment design in higher education. Bloom's taxonomy can guide faculty members in clarifying the cognitive requirements of learning outcomes and designing assessment tasks that align with those requirements (Chandio et al., 2021). Assessment also serves a pedagogical function; therefore, misaligned tasks may limit students' opportunities to demonstrate deep learning and higher-order thinking skills (Masuku et al., 2021). This pattern has important pedagogical implications. Faculty development programs should focus on designing assessment tasks that require application and analysis, in which the cognitive demands of assessment items may be conflated with those of adjacent cognitive levels. The CART decision rules generated by the CLAA Framework can support this process by providing faculty members with interpretable evidence for reviewing assessment items and improving alignment with intended learning outcomes.

The TAM results, with an overall mean of 3.84 out of 4.00, indicate that the Syllabus Management System is well positioned for institutional adoption. This finding is consistent with recent evidence that perceived usefulness and perceived ease of use remain central factors influencing the acceptance of learning management systems and related educational technologies (Al-Nuaimi & Al-Emran, 2021). The high Perceived Usefulness score of 3.87 is particularly encouraging because it indicates that faculty members recognize the system's value in supporting assessment-outcome alignment and quality-assurance processes. The practical implication is that faculty members not only find the SMS easy to use but also perceive it as a useful tool for improving their instructional and assessment practices, which is essential for sustainable institutional adoption.

The integration of CART classification within a PDCA cycle represents a key contribution of the CLAA Framework. Rather than treating cognitive classification as a stand-alone analytical activity, the framework embeds classification results within a continuous institutional quality-improvement process. This approach reflects recent higher education quality-assurance literature, which emphasizes the importance of systematic evaluation, evidence-based decision-making, and continuous improvement in responding to institutional and stakeholder expectations (Adzidzah & Yudiawan, 2025; Rini et al., 2025). Through the CLAA Framework, alignment data are not merely reported but are translated into actions through syllabus review, assessment redesign, faculty development, and quality-assurance reporting. This integration enables institutions to use LMS-generated evidence to support a sustainable cycle of curriculum and assessment improvement.

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Several limitations should be noted. First, the study used archived data from a single Philippine HEI, which may limit its generalizability to institutions with different curricular structures, LMS platforms, or levels of OBE implementation maturity. Second, the CART model was trained on data with pre-existing cognitive-level labels provided by faculty, which may contain systematic biases in cognitive-level assignment. Third, the TAM evaluation measured self-reported perceptions rather than actual system usage over an extended period. Fourth, the three-class alignment categorization (Fully Aligned, Partially Aligned, Misaligned) represents a simplification of alignment quality that may not capture all dimensions of constructive alignment, such as the quality of TLA-assessment linkages.

Despite these limitations, the study makes three significant contributions: 1) It introduces the first integrated framework combining educational data mining with OBE quality assurance; 2) It provides empirical evidence that CART can reliably classify assessment-outcome alignment with high accuracy; and 3) It demonstrates that the resulting system achieves high faculty acceptance, addressing the critical adoption barrier that often limits the impact of educational technology innovations.

CONCLUSION

This study introduced the CLAA Framework, an original socio-technical model for data-driven OBE quality assurance in blended higher education. By integrating a KDD pipeline, a CART classification model, a Syllabus Management System, a PDCA quality cycle, and a TAM evaluation into a unified three-layer architecture, CLAA addresses a persistent gap in both the educational data mining and OBE implementation literatures. In response to the three research questions, the findings are as follows. For RQ1, the CART model achieved 95% classification accuracy, with Cohen's Kappa of 0.8785 and MCC of 0.84, providing strong evidence that decision-tree classification can reliably automate alignment verification in OBE contexts. For RQ2, the analysis of misalignment patterns revealed that the Apply, Understand, and Analyze cognitive levels are most frequently misaligned, with specific assessment formats (e.g., multiple-choice items targeting application-level outcomes) identified as common sources of misalignment.

For RQ3, the TAM evaluation of the SMS yielded an overall mean of 3.84 on a 4-point scale, indicating high faculty acceptance across all four TAM dimensions and suggesting readiness for institutional deployment. Based on these findings, this study offers several recommendations. Philippine HEIs and comparable institutions in developing countries should consider adopting data-driven approaches to alignment verification, leveraging the assessment data already archived in their LMS platforms. Institutional quality assurance offices should explore integrating CART classification models into their existing PDCA-based quality management cycles. Faculty development programs should include targeted training on assessment design for mid-range cognitive levels (Apply, Analyze), where misalignment is most prevalent. CHED and accreditation bodies such as AUN-QA may wish to examine how data mining-based alignment verification can complement existing manual review processes.

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Future research should pursue several directions. First, a faculty redesign study should investigate whether alignment improves after faculty receive CART-generated alignment feedback and revise their assessments accordingly. Second, cross-institutional validation using data from multiple HEIs with diverse LMS platforms and curricular structures would strengthen the generalizability of the CART model. Third, research should examine the relationship between assessment-outcome alignment as classified by CLAA and actual student learning outcomes, testing the fundamental assumption that improved alignment leads to improved learning. Fourth, the framework should be extended to encompass the affective and psychomotor domains, which are particularly relevant to professional programs in the health sciences, education, and engineering. Finally, integrating natural language processing (NLP) techniques to automate the classification of assessment items using Bloom's taxonomy could enhance the CLAA pipeline's automation capabilities and reduce reliance on pre-existing cognitive-level labels.

AUTHOR'S NOTE

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