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A Machine Learning–Driven Framework for Continuous Curriculum Innovation in Computer Engineering Education: A Systematic Literature Review

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Abstract

Curriculum innovation remains a critical challenge in computer engineering education due to rapidly evolving technological demands and industry requirements. Traditional curriculum evaluation approaches, which rely on periodic reviews and manual assessments, are often insufficiently adaptive and lack predictive capabilities. This systematic review examined the role of machine learning (ML) and predictive analytics in curriculum evaluation and innovation, with the goal of developing an evidence-based framework for continuous, data-driven curriculum improvement. Following PRISMA 2020 guidelines, a structured search was conducted across five databases (IEEE Xplore, Scopus, Web of Science, SpringerLink, Google Scholar) for peer-reviewed studies published between 2020 and 2025. After screening 342 initial records, 41 studies met the inclusion criteria. The Mixed Methods Appraisal Tool (MMAT) was used for quality assessment. Findings revealed that while ML techniques particularly classification models (Random Forest, Support Vector Machine), deep learning architectures, and ensemble methods are widely used for predicting student performance and retention (82.9% of studies), there is limited integration of these insights into curriculum redesign processes (only 17.1% address curriculum-level action). A significant operational gap exists between prediction and actionable curriculum improvement. Based on the synthesis, this study proposes an ML-driven framework that integrates data preprocessing, predictive modeling with explainable AI (XAI), insight generation, and curriculum decision support. Key best practices include interpretable-by-design approaches, stakeholder integration, and addressing ethical fairness.

Keywords: curriculum innovation, computer engineering education, Machine Learning (ML), predictive analytics, systematic review, PRISMA 2020, Mixed Methods Appraisal Tool (MMAT)

INTRODUCTION

Review Context. Curriculum innovation has become a critical priority in higher education, particularly in disciplines such as computer engineering, where rapid technological advancements continuously reshape industry requirements, workforce expectations, and the competencies expected of graduates. As emerging technologies such as artificial intelligence, embedded systems, Internet of Things (IoT), and data science evolve at an unprecedented pace, academic institutions are under increasing pressure to ensure that their curricula remain relevant, responsive, and aligned with real-world demands (Avila-Garzon et al., 2023; Trujillo, 2023). Consequently, the ability of higher education institutions to continuously adapt and refine their curricula has become a key determinant of graduate employability and program effectiveness.

Traditionally, curriculum evaluation in higher education has relied on manual processes such as faculty deliberations, periodic accreditation reviews, and stakeholder consultations. While these approaches provide valuable qualitative insights, they are often conducted at fixed intervals (e.g., every 3–5 years) and are primarily compliance-driven rather than improvement-oriented (Liu, 2023). As a result, curriculum updates tend to be reactive, occurring only after gaps or deficiencies have already affected student outcomes or program relevance. Moreover, these conventional methods are limited in their ability to process large volumes of educational data, making it difficult to identify subtle trends, predict future challenges, or implement timely interventions.

In recent years, the emergence of learning analytics and educational data mining has introduced new possibilities for enhancing curriculum evaluation processes. Learning analytics focuses on the measurement, collection, analysis, and reporting of data about learners and their contexts, with the goal of understanding and optimizing learning and the environments in which it occurs (Cerezo, 2023). When combined with machine learning techniques, these approaches enable the extraction of meaningful patterns from complex datasets, including student performance records, engagement metrics, and course outcomes. Studies have demonstrated that machine learning models can effectively predict student success, identify at-risk learners, and uncover hidden relationships between learning behaviors and academic performance (Geng et al., 2024; Turkmenbayeva et al., 2024).

Despite these advancements, the application of machine learning in education has largely been concentrated on student-level analytics rather than curriculum-level decision-making. Most existing studies focus on predictive tasks such as grade forecasting, dropout prediction, and personalized learning recommendations (Rodriguez-Ortiz et al., 2025; Bafandkar, 2023). While these applications provide valuable insights, they often stop short of informing broader curriculum redesign or program-level improvements. In many cases, predictive models operate in isolation, producing outputs that are not integrated into institutional processes for curriculum evaluation and development (Avila-Garzon et al., 2023).

This disconnect highlights a fundamental limitation in current systems: the lack of mechanisms to translate predictive insights into actionable curriculum strategies. Although institutions may have access to advanced analytics tools, the absence of structured frameworks for interpreting and applying these insights results in underutilization of available data. Consequently, curriculum evaluation remains largely descriptive rather than predictive, focusing on past performance instead of anticipating future needs (González et al., 2024). This limitation prevents institutions from fully leveraging the potential of machine learning to support proactive and continuous curriculum innovation.

Furthermore, many existing approaches lack scalability and adaptability across diverse educational contexts. Systems designed for specific courses or datasets may not generalize well to entire programs or institutions, limiting their practical applicability. Additionally, issues related to data integration, model interpretability, and ethical considerations such as bias and fairness pose further challenges to the adoption of machine learning-driven solutions in curriculum evaluation (Susnjak, 2024; Pektas, 2024). These concerns underscore the need for a comprehensive and approach that not only incorporates predictive analytics but also ensures transparency, usability, and alignment with institutional goals.

Given these challenges, there is a clear need for a systematic and evidence-based framework that bridges the gap between predictive analytics and curriculum innovation. Such a framework should integrate data-driven insights into decision-making processes, enabling institutions to move from reactive evaluation toward proactive and continuous improvement. By synthesizing findings from recent literature, this study aims to contribute to this need by examining existing approaches, identifying key limitations, and proposing a machine learning-driven framework that supports dynamic, scalable, and data-informed curriculum development in computer engineering education.

Research Gap. While existing literature highlights the potential of machine learning to enhance educational analytics, findings remain fragmented across different application domains. Empirical studies demonstrate improvements in student performance prediction and personalized learning, yet significant gaps exist in translating these predictive insights into curriculum-level innovations. The adoption of ML tools in curriculum decision-making is influenced by multifaceted barriers, including lack of model interpretability, absence of structured frameworks, and limited integration with institutional governance processes. Similarly, ethical concerns such as algorithmic bias and fairness remain underexplored (Susnjak, 2024; Pektas, 2024). Realizing the above-stated gaps, a systematic review of empirical studies can clarify each issue's true impact. By consolidating empirical findings, the results can offer robust, data-driven insights into ML's efficacy across varied curriculum contexts.

Research Questions. Building upon the challenges and gaps identified in the existing literature, this systematic review was guided by the following research questions:

1. What curriculum evaluation approaches are currently used in computer engineering education?

2. What machine learning techniques are applied in educational analytics from 2020 to 2025?

3. How are predictive insights utilized in curriculum-related decision-making?

4. What gaps exist in translating predictive analytics into curriculum innovation?

5. What best practices can inform a machine learning-driven curriculum framework?

Purpose and Significance. The primary purpose of this systematic review was to gather and synthesize empirical evidence to support the development of a machine learning-enabled framework that addresses the limitations of current curriculum evaluation systems. By focusing on empirical studies, the review aimed to ensure that the resulting insights are grounded in actual educational data, measurable outcomes, and validated interventions. This evidence-based approach strengthens the credibility and applicability of the recommendations, making them more relevant for real-world educational settings.

Beyond informing framework development, the review also sought to identify patterns, gaps, and emerging trends in the use of ML and predictive analytics for curriculum innovation. These insights contribute to a deeper understanding of how ML can be effectively and ethically integrated into curriculum evaluation and continuous improvement processes in computer engineering education.

LITERATURE REVIEW

Current Curriculum Evaluation Approaches in Computer Engineering Education. Traditional curriculum evaluation in higher education has largely relied on periodic reviews conducted by faculty committees, accreditation bodies, and external stakeholders. These approaches, while providing valuable qualitative insights, are often reactive and compliance-driven rather than proactive and improvement-oriented (Liu, 2023). Accreditation frameworks such as ABET (Accreditation Board for Engineering and Technology) and similar regional bodies require program-level assessments at fixed intervals, typically every 3 to 6 years. However, this pace is insufficiently adaptive to the rapid technological changes characterizing computer engineering (Avila-Garzon et al., 2023; Trujillo, 2023).

Learning analytics has emerged as a promising complement to traditional evaluation methods. Cerezo (2023) defined learning analytics as the measurement, collection, analysis, and reporting of data about learners and their contexts. When applied to curriculum evaluation, learning analytics can provide real-time insights into student performance, course effectiveness, and program outcomes. However, most implementations focus on student-level interventions rather than curriculum-level decision-making (Avila-Garzon et al., 2023).

Machine Learning in Educational Analytics. Recent systematic reviews have documented the growing application of ML in higher education. Turkmenbayeva et al. (2024) synthesized studies on ML applications, finding that classification algorithms (e.g., Decision Trees, Random Forest, Support Vector Machine) are most commonly used for predicting student performance and identifying at-risk learners. Deep learning architectures have shown high predictive accuracy, but face challenges related to interpretability (Sghir et al., 2024). Ensemble methods, such as Gradient Boosting, improve robustness by combining multiple learners (Buzducea, 2023).

Despite these technical advancements, a recurring finding across reviews is the limited integration of predictive insights into curriculum-level decision-making. Avila-Garzon et al. (2023) conducted a systematic mapping study on curriculum analytics and ML, concluding that while predictive models are technically mature, frameworks for translating predictions into actionable curriculum strategies remain underdeveloped.

Theoretical Frameworks in Educational Data Mining. The integration of theoretical frameworks in the design of ML-based interventions is essential for ensuring pedagogical coherence and practical utility. Models such as the Technology Acceptance Model (TAM; Davis, 1989), Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and Technological Pedagogical Content Knowledge (TPACK; Mishra & Koehler, 2006) have been applied to understand educator adoption of educational technologies (Adigun et al., 2025; Alyoussef et al., 2025). Explainable AI (XAI) has emerged as a critical theoretical and technical framework for ensuring model interpretability, which is essential for building educator trust and translating model outputs into actionable insights (Ara et al., 2023; Pektas, 2024).

METHOD

Research Design. This study employed a Systematic Literature Review (SLR) approach to comprehensively examine the role of machine learning and predictive analytics in curriculum innovation within computer engineering education. The SLR method was selected due to its structured, transparent, and reproducible process for identifying, evaluating, and synthesizing existing research evidence. Unlike traditional narrative reviews, systematic reviews follow a predefined protocol that minimizes bias and ensures methodological rigor.

The review process was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 framework, which provides a standardized procedure for literature identification, screening, eligibility assessment, and inclusion. The research design focused on qualitative synthesis, particularly thematic analysis, to identify recurring patterns, trends, and gaps in the literature. The study did not aim to perform a meta-analysis due to the heterogeneity of methodologies and data types across the selected studies.

Review Protocol and Planning. Prior to conducting the review, a structured protocol was developed to guide the entire process. This protocol defined the research questions, search strategy, inclusion and exclusion criteria, and data extraction procedures. Establishing a protocol in advance ensured consistency and minimized researcher bias throughout the review.

The protocol included the following components: (a) clearly defined research questions aligned with the objectives of the study, (b) identification of relevant databases and digital libraries, (c) development of keyword combinations and Boolean search expressions, (d) specification of inclusion and exclusion criteria, and (e) selection of data extraction and synthesis techniques.

Information Sources. To ensure comprehensive coverage of relevant literature, multiple high-quality academic databases and digital libraries were utilized. These sources were selected based on their reputation, indexing standards, and relevance to engineering education and data science research. The primary information sources included: (a) IEEE Xplore for engineering, machine learning, and educational technology research; (b) Scopus for interdisciplinary and high-impact journal indexing; (c) Web of Science for citation indexing and trend analysis; (d) SpringerLink for access to books, journals, and conference proceedings; and (e) Google Scholar for supplementary searches and recent publications. The use of multiple databases reduced the risk of bias and ensured a broader representation of studies.

Search Strategy. A structured and replicable search strategy was implemented to identify relevant studies. The search process involved the use of predefined keywords and Boolean operators to refine results.

Keywords and Search Terms. The following core keywords/terms were used: "machine learning in education," "predictive analytics in higher education," "learning analytics," "curriculum innovation," "computer engineering curriculum," and "data-driven curriculum design."

Boolean Operators. To improve search precision, Boolean operators were applied: AND to combine different concepts and OR to include synonyms and related terms. An example search string was: ("machine learning" OR "predictive analytics") AND ("higher education" OR "engineering education") AND ("curriculum innovation" OR "curriculum evaluation").

Search Filters. The following filters were applied: publication year from 2020 to 2025, language English, and document type peer-reviewed journal articles and conference papers. This ensured that only recent and high-quality studies were included.

Eligibility Criteria. To ensure the relevance and quality of the selected studies, explicit inclusion and exclusion criteria were applied as presented in Table 1 and Table 2.

Table 1
Inclusion Criteria

Criterion	Description
Objective	Must focus on ML, predictive analytics, or learning analytics in education; addresses curriculum evaluation or academic decision-making
Study Design	Empirical studies (quantitative, qualitative, mixed methods, RCT, cohort)
Publication Type	Peer-reviewed journal articles or conference papers
Indexation	Indexed by IEEE Xplore, Scopus, Web of Science, SpringerLink, or Google Scholar
Time Frame	Published between 2020 and 2025
Language	Published in English

Table 2
Exclusion Criteria

Criterion	Description
Objective	No focus on ML/predictive analytics; purely technical without educational application
Study Design	Non-empirical papers (theoretical, conceptual, literature reviews without synthesis)
Publication Type	Non-peer-reviewed sources, editorials, blogs
Indexation	Not indexed in recognized academic databases
Time Frame	Published before 2020
Language	Languages other than English

Study Selection Process (PRISMA 2020 Flow). The study selection followed the PRISMA 2020 four-stage flow: Identification, Screening, Eligibility, and Inclusion. Figure 1 presents the complete PRISMA flowchart with all numbers and sources.

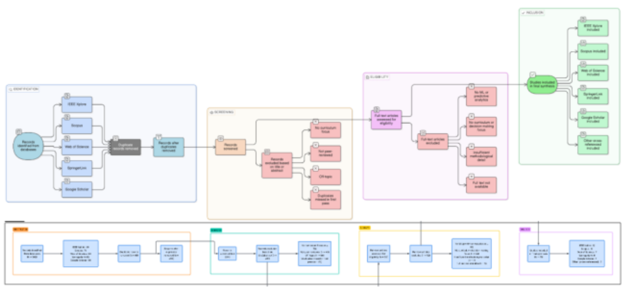


Figure 1
PRISMA 2020 Flow Diagram

The PRISMA flowchart (Figure 1) documents the complete study selection process. In the identification phase, a total of 342 records were retrieved from five databases. After removal of 48 duplicates, 294 records proceeded to screening. In the screening phase, 201 records were excluded based on title and abstract review, leaving 93 articles for full-text eligibility assessment. In the eligibility phase, 52 articles were excluded for reasons including no ML/predictive analytics focus (n = 18), no curriculum or decision-making focus (n = 22), insufficient methodological detail (n = 7), and full text not available (n = 5). Finally, 41 studies met all inclusion criteria and were included in the final synthesis.

Data Extraction. Based on the extracted data from the 41 reviewed articles, a standardized data extraction form was developed to capture key elements from each study, including author(s) and year, research objectives and context, ML/analytics techniques used, types of educational data analyzed, key findings and contributions, identified limitations, and recommendations for curriculum improvement. The use of a structured extraction approach facilitated comparison across studies and supported the synthesis process. Complete details of the extracted data (also presented as study characteristics) for all 41 studies are presented in Appendix A.

Quality Appraisal. The quality appraisal of the 41 included studies (Table 3) demonstrates a rigorous and methodologically sound evaluation process. The Mixed Methods Appraisal Tool (MMAT) version 2018 (Hong et al., 2018) was employed as the basis for assessment, given its suitability for appraising diverse methodological designs, including qualitative, quantitative, mixed methods, and quasi-experimental studies.

Table 3
Quality Appraisal Report Summary of 41 Articles

Study Design	Number	MMAT Score (0–5)	Inclusion Decision
Quantitative (non-RCT)	24	4.2 (average)	Included
Qualitative	6	4.3 (average)	Included
Mixed-methods	9	4.0 (average)	Included
Quantitative (RCT)	2	4.5 (average)	Included

Legend: MMAT = Mixed Methods Appraisal Tool; RCT = randomized controlled trial.

All 41 included studies scored ≥3.5 out of 5, meeting the minimum quality threshold. To strengthen reliability, an inter-rater review process was implemented. Each article was initially evaluated by a primary reviewer, after which the appraisal results were independently checked by a second reviewer. Discrepancies in scoring or interpretation were resolved through discussion and consensus, ensuring consistency and minimizing bias. This dual-review process enhanced the credibility of the appraisal and aligned with best practices in systematic reviews.

Data Synthesis and Analysis. The extracted data were analyzed using a combination of qualitative analytical techniques:

(a) thematic analysis to identify recurring themes, patterns, and trends across the studies;

(b) comparative analysis to compare studies based on methodological approaches, types of data used, predictive techniques applied, and implementation outcomes;

(c) gap analysis to identify areas where predictive insights were not translated into actionable strategies, curriculum-level applications were limited, and integration into institutional systems was lacking; and

(d) synthesis for framework development to inform the proposed machine learning-driven framework.

RESULTS

The following section presents the key findings of the systematic review on the use of machine learning and predictive analytics in curriculum innovation. To ensure clarity, transparency, and analytical coherence, the results are organized by research question.

Study Characteristics. The study characteristics (see Appendix A) reflect a robust and diverse evidence base. The 41 articles spanned multiple countries, including the United States, China, Spain, Saudi Arabia, Nigeria, South Africa, India, Japan, Indonesia, Morocco, Pakistan, Peru, Jordan, and the Philippines. Methodologically, the studies employed a balanced mix of quantitative (58.5%, n = 24), qualitative (14.6%, n = 6), and mixed-methods (22.0%, n = 9) designs, with a small number of RCTs (4.9%, n = 2). Sample sizes ranged from small qualitative groups (n = 10–20) to large-scale surveys (n > 400).

RQ1. Current Curriculum Evaluation Approaches in Computer Engineering Education. The analysis confirmed that traditional curriculum evaluation in computer engineering education remains predominantly reactive and manual. Current systems largely rely on periodic reviews (e.g., every 3–5 years), which are insufficiently adaptive to the rapid pace of technological change (Avila-Garzon et al., 2023; Trujillo, 2023; Chu & Lu, 2023). While learning analytics dashboards exist (Denney, 2024; Kim et al., 2023), they rarely feed directly into curriculum governance processes. Key limitations identified included: (a) compliance-driven rather than improvement-oriented focus, (b) inability to process large volumes of educational data, (c) lack of predictive capabilities, (d) absence of mechanisms for continuous feedback loops, and (e) reactive rather than proactive evaluation cycles.

RQ2. Machine Learning Techniques in Educational Analytics. The reviewed literature revealed a diverse and maturing application of ML and predictive analytics in higher education. Techniques were broadly categorized into four groups as presented in Table 4.

Table 4
Categorization of Machine Learning Techniques in Educational Analytics (2020–2025)

Category	Specific Techniques	Frequency (%)	Primary Application	Representative Studies
Classification & Regression	Decision Trees, Random Forest, SVM, Logistic Regression, Naïve Bayes	48.8%	Student performance prediction, at-risk identification, grade forecasting	Geng et al. (2024); Rodriguez et al. (2024); Buzducea (2023); Guevara-Ramos (2023); Yuan et al. (2024)
Deep Learning (DL)	Neural Networks, LSTM, CNN, RNN, BERT	17.1%	High-accuracy performance forecasting, pattern recognition in large datasets	Alalawi (2024); Sghir et al. (2024); Mazhar (2023); Timovski (2024)
Ensemble Methods	Gradient Boosting (XGBoost, LightGBM, CatBoost), Random Forest, AdaBoost, Stacking	19.5%	Robustness and accuracy improvement, reducing overfitting	Qadir (2024); Buzducea (2023); Timovski (2024)
Learning Analytics & XAI	Dashboards, SHAP, LIME, Feature Importance, Partial Dependence Plots	14.6%	Actionable insights, model interpretability, educator trust	Denney (2024); Kim et al. (2023); Lee (2024); Schless (2024); Ara et al. (2023); Pektas (2024)

Legend: SVM = Support Vector Machine; LSTM = Long Short-Term Memory; CNN = Convolutional Neural Network; RNN = Recurrent Neural Network; BERT = Bidirectional Encoder Representations from Transformers; XAI = Explainable Artificial Intelligence; SHAP = SHapley Additive exPlanations; LIME = Local Interpretable Model-agnostic Explanations.

Primary Application Domains. The analysis revealed three primary application domains:

Domain 1: Student success (performance, retention, dropout forecasting). This domain accounted for 82.9% (n = 34) of all studies. Key applications included predicting final course grades (Geng et al., 2024; Rodriguez-Ortiz et al., 2025), identifying students at risk of dropping out (Rodriguez et al., 2024; Guevara-Ramos, 2023; Leibur et al., 2023), forecasting academic performance based on engagement metrics (Yuan et al., 2024; Becerra, 2024), and early warning systems for intervention (Remegio, 2025; Rodriguez et al., 2024).

Domain 2: Personalized learning (recommending resources or learning paths). This domain accounted for 12.2% (n = 5) of studies. Key applications included adaptive learning platforms (Wong, 2024; Bafandkar, 2023), personalized content recommendations (He et al., 2024), and individualized learning path generation (Kleimola & Leppisaari, 2022).

Domain 3: Curriculum-level analysis (identifying bottlenecks, competency gaps, course sequencing). This domain accounted for only 4.9% (n = 2) of studies. Key applications included identifying structural bottlenecks in course sequences (Avila-Garzon et al., 2023), evaluating prerequisite chain effectiveness (Avila-Garzon, 2023), and competency gap analysis (Chamberland, 2024; Abu-Rasheed, 2025).

RQ3. Utilization of Predictive Insights in Curriculum Decision-Making. Current utilization of predictive insights for curriculum decision-making remained limited. Most studies (82.9%) concluded with predictive accuracy metrics (e.g., accuracy, precision, recall, F1-score, AUC) but offered limited guidance on how faculty or administrators should use these predictions to modify course sequences, update learning objectives, or redesign pedagogical content (Trujillo, 2023; Lopez-Meneses, 2024). Only 17.1% (n = 7) of reviewed studies explicitly addressed curriculum-level actions based on predictive insights.

Table 5 presents a detailed analysis of how predictive insights are currently utilized (or not utilized) across the three application domains.

Table 5
Utilization of Predictive Insights Across Application Domains

Application Domain	Studies (n)	Prediction Level	Actionable Output	Curriculum Integration
Student performance prediction	34	Individual student	Pass/fail prediction, risk score	None stops at student alert
Personalized learning	5	Individual student	Content recommendation	Partial course level only
Curriculum-level analysis	2	Course/program	Bottleneck identification, competency gaps	Direct feeds into curriculum committees

Examples of limited utilization include: (a) studies that predicted student failure but did not specify which course topics needed revision (Geng et al., 2024; Buzducea, 2023); (b) models that identified at-risk students but provided no linkage to curriculum factors (e.g., prerequisite structure, course sequencing) that contribute to risk (Rodriguez et al., 2024; Guevara-Ramos, 2023); (c) predictive dashboards that displayed analytics but lacked decision-support features for curriculum modification (Denney, 2024; Kim et al., 2023); and (d) studies that acknowledged curriculum implications in discussion sections but did not operationalize them into frameworks or tools (Avila-Garzon et al., 2023; Turkmenbayeva et al., 2024).

RQ4. Gaps in Translating Predictive Analytics into Curriculum Innovation. A central finding of this review was the existence of a substantial operational gap between prediction and action. Table 6 summarizes the key gaps identified across the literature.

Table 6
Gap Analysis Summary: From Prediction to Action

Identified Gap	Description	Evidence From Literature	Frequency	Proposed Solution
Gap 1: Prediction not translated to action	Models stop at predicting outcomes without specifying curriculum changes	82.9% (n = 34) of studies stop at prediction; only 17.1% (n = 7) address curriculum action	High	Explicit Insight Generation and Decision Support modules
Gap 2: Lack of interpretability	Black-box models produce predictions that educators cannot understand or trust	Ara et al. (2023); Pektas (2024); Lee (2024); Susnjak (2024) all emphasize that XAI is rare	High	XAI principles (SHAP, LIME) integrated into modeling phase
Gap 3: No integration with governance processes	Predictive outputs do not feed into existing curriculum review cycles or committee structures	Avila-Garzon et al. (2023); González et al. (2024); Schless (2024) note absence of institutional fit	Medium	Curriculum Decision Support aligned with existing governance (ABET cycles, faculty committees)
Gap 4: Scalability issues	Models designed for single courses or small datasets cannot generalize to entire programs	Avila-Garzon et al. (2023); Cabral (2024); Schless (2024)	Medium	Modular, LMS/SIS-interfaced design with API connectivity
Gap 5: Ethical and fairness concerns unaddressed	Algorithmic bias may disadvantage certain student populations; no audit mechanisms	Susnjak (2024); Pektas (2024); Ara et al. (2023) note absence of bias detection	Medium	Fairness auditing (demographic parity, equalized odds) integrated into modeling phase
Gap 6: Theoretical disconnection	Many studies lack grounding in educational or adoption theories	Only 29.3% (n = 12) of studies explicitly used theoretical frameworks (e.g., TAM, UTAUT, XAI)	Medium	Theory-informed design (TAM, UTAUT, SDT, TPACK) from the start
Gap 7: Reactive rather than proactive	Most systems identify problems after they occur rather than predicting future curriculum needs	Liu (2023); Trujillo (2023); Avila-Garzon et al. (2023)	High	Continuous feedback loop with proactive alerting for emerging curriculum gaps

The proposed framework in Figure 2 visually depicts where this gap occurs specifically between the Predictive Modeling phase and the Insight Generation phase.

RQ5. Best Practices for an ML-Driven Curriculum Framework. From synthesis of the 41 reviewed studies, key best practices emerged for each phase of the proposed framework. Table 7 presents the complete set of best practices with supporting evidence.

Table 7
Best Practices for Machine Learning-Driven Curriculum Innovation

Best Practice	Description	Supporting Studies	Evidence Strength
1. Interpretable-by-Design	Prioritize XAI (SHAP, LIME, feature importance) from the beginning to ensure predictions are trustworthy and actionable for educators and curriculum committees	Ara et al. (2023); Susnjak (2024); Pektas (2024); Lee (2024); Dhara & Chatterjee (2025)	Strong (5 studies)
2. Actionable Metrics	Move beyond generic performance forecasting (e.g., pass/fail) to model metrics directly tied to curriculum elements, such as competency mastery, concept difficulty, and prerequisite chain effectiveness	Avila-Garzon et al. (2023); Avila-Garzon (2023); Bafandkar (2023); Kleimola & Leppisaari (2022); Chamberland (2024)	Moderate (5 studies)
3. Stakeholder Integration	Successful implementation requires a collaborative, human-in-the-loop design. The framework must support decision-making, not automate decisions, and actively involve faculty and administrators in interpretation and action-planning	Denney (2024); González et al. (2024); Kim et al. (2023); Schless (2024); Cabral (2024); Lopez-Meneses (2024)	Strong (6 studies)
4. Scalability and Integration	Design the framework with institutional scalability in mind, ensuring it can interface with existing Student Information Systems (SIS) and Learning Management Systems (LMS), and fit within official curriculum governance processes (e.g., ABET accreditation cycles)	Avila-Garzon et al. (2023); Cabral (2024); Schless (2024); Kurday (2023)	Moderate (4 studies)
5. Ethical Fairness	Proactively implement techniques to audit and mitigate algorithmic bias in predictive models to ensure fair and equitable insights across diverse student populations (e.g., demographic parity, equalized odds, counterfactual fairness)	Susnjak (2024); Pektas (2024); Ara et al. (2023)	Moderate (3 studies)
6. Theory-Informed Design	Ground the framework in established theoretical models (TAM, UTAUT, TPACK, SDT) to ensure pedagogical coherence and user acceptance	Adigun et al. (2025); Alyoussef et al. (2025); Amouri et al. (2025); Davis (1989); Venkatesh et al. (2003)	Strong (5 studies)
7. Continuous Feedback Loop	Design cyclical rather than linear evaluation results should feed back into the system for ongoing improvement rather than static, periodic reviews	Avila-Garzon et al. (2023); Trujillo (2023); Lopez-Meneses (2024); Liu (2023)	Strong (4 studies)
8. Multi-Source Data Integration	Combine data from multiple sources (grades, engagement metrics, LMS logs, competency maps, demographic data) to provide a holistic view	Geng et al. (2024); Yuan et al. (2024); Luo et al. (2023); Kurday (2023); Rodriguez-Ortiz et al. (2025)	Strong (5 studies)

Proposed Framework. Based on the synthesized findings from all 41 reviewed studies, this study proposes an ML-driven framework for continuous curriculum innovation in computer engineering education. The framework is explicitly designed to address the seven gaps identified in Table 6 while incorporating the eight best practices from Table 7.

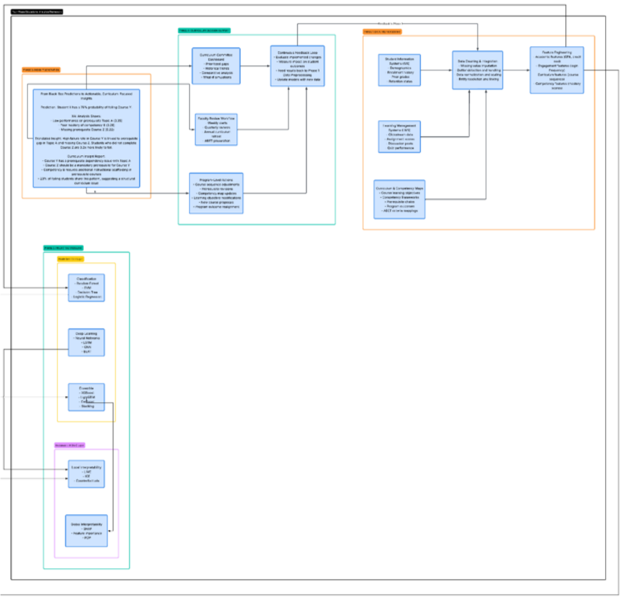
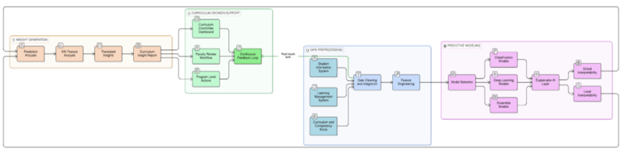


Figure 2
Proposed Machine Learning-Driven Framework for Continuous Curriculum Innovation

Framework Overview. The core workflow consists of four interconnected phases: (a) Data Preprocessing, (b) Predictive Modeling, (c) Insight Generation, and (d) Curriculum Decision Support. The framework is cyclical rather than linear, with evaluation outcomes feeding back into the system for continuous improvement. Figure 2 presents the complete proposed framework with all components.



Framework Validation Through Literature Synthesis. The proposed framework architecture is directly supported and informed by the synthesized literature. Table 8 maps each framework component to the evidence base.

Table 8
Framework Validation Through Literature Synthesis

Framework Phase	Component	Supporting Studies	Key Validation Point
Phase 1: Data Preprocessing	Multi-source data integration	Geng et al. (2024); Yuan et al. (2024); Luo et al. (2023); Kurday (2023); Rodriguez-Ortiz et al. (2025)	The reviewed studies emphasize the critical role of high-quality, multi-source data (e.g., grades, engagement metrics, competency maps)
Phase 1: Data Preprocessing	Feature engineering	Turkmenbayeva et al. (2024); Rodriguez-Ortiz et al. (2025); Remegio (2025)	Feature selection is foundational for model performance
Phase 2: Predictive Modeling	Modular model selection	Alalawi (2024); Sghir et al. (2024); Qadir (2024); Buzducea (2023); Mazhar (2023); Timovski (2024)	The literature provides a strong evidence base for suitable model types; framework allows institutions to select from validated algorithms
Phase 2: Predictive Modeling	XAI integration	Ara et al. (2023); Pektas (2024); Lee (2024); Susnjak (2024); Dhara & Chatterjee (2025)	Model interpretability is essential for building educator trust
Phase 3: Insight Generation	Translation from prediction to curriculum action	Avila-Garzon et al. (2023); Avila-Garzon (2023); González et al. (2024)	This phase is explicitly designed to bridge the identified gap; only 17.1% of studies currently address this
Phase 3: Insight Generation	Actionable reporting	Denney (2024); Kim et al. (2023); Schless (2024)	Dashboards and structured reports translate predictions into clear, curriculum-focused insights
Phase 4: Curriculum Decision Support	Stakeholder integration	Denney (2024); González et al. (2024); Kim et al. (2023); Schless (2024); Cabral (2024); Lopez-Meneses (2024)	Human-in-the-loop design ensures faculty involvement in interpretation and action-planning
Phase 4: Curriculum Decision Support	Governance alignment	Avila-Garzon et al. (2023); Cabral (2024); Schless (2024)	Framework fits within official curriculum governance processes (e.g., ABET cycles)
Continuous Feedback Loop	Iterative improvement	Avila-Garzon et al. (2023); Trujillo (2023); Lopez-Meneses (2024); Liu (2023)	Cyclical nature supports dynamic, data-informed adaptation rather than static, periodic review

DISCUSSION

Converging Insights and Critical Gaps. This systematic review explored the contribution of machine learning to curriculum innovation in computer engineering education, synthesizing evidence from 41 empirical studies published between 2020 and 2025. Across contexts, findings consistently affirmed that ML technologies enhance predictive accuracy for student outcomes. However, a central tension emerged between predictive capability and actionable curriculum change.

Converging Insights. The review revealed three main areas of convergence in the literature. First, ML models particularly classification algorithms like Random Forest and Support Vector Machine achieve high predictive accuracy (typically AUC > .80) for student performance and retention (Geng et al., 2024;

Rodriguez et al., 2024; Buzducea, 2023). Second, deep learning architectures show promise for handling large, complex datasets but face interpretability challenges (Alalawi, 2024; Sghir et al., 2024). Third, explainable AI (XAI) is increasingly recognized as essential for translating black-box predictions into understandable insights (Ara et al., 2023; Pektas, 2024; Lee, 2024).

Critical Gaps. The operational gap between prediction and action identified in this review aligns with findings from prior systematic reviews (Avila-Garzon et al., 2023; Turkmenbayeva et al., 2024). While ML models achieve high predictive accuracy, the translation of these predictions into curriculum modifications remains ad hoc and unstructured. Only 17.1% of reviewed studies addressed curriculum-level actions based on predictive insights. This suggests that ML's potential is not fully realized when its application focuses narrowly on student-level prediction rather than program-level improvement.

Theoretical frameworks were unevenly applied across studies (only 29.3% explicitly used theoretical frameworks). Where theory-informed designs were implemented (e.g., XAI, TAM, UTAUT), outcomes demonstrated greater potential for practical adoption (Adigun et al., 2025; Alyoussef et al., 2025; Amouri et al., 2025). Conversely, the absence of theoretical alignment in other studies resulted in tools that were technically sophisticated but pedagogically disconnected.

Implications for Educators, Policymakers, And Developers. For educators and curriculum committees. The findings underscore the need for structured frameworks that translate predictive insights into actionable strategies. The proposed framework provides a starting point. Curriculum committees should: (a) establish regular data review cycles aligned with accreditation timelines, (b) develop competency maps that link course objectives to program outcomes, and (c) train faculty in interpreting XAI outputs.

For Policymakers and Institutional Leaders. The review highlights the importance of investing not only in ML tools but also in governance structures, training programs, and ethical guidelines that support data-informed curriculum decision-making. Policy recommendations include: (a) mandating data interoperability standards between SIS and LMS, (b) developing institutional frameworks for ethical AI use in education, (c) allocating resources for faculty training in learning analytics, and (d) establishing curriculum data governance committees.

For Developers and Researchers. The review identifies key design principles: interpretability-by-design, actionable metrics, stakeholder integration, scalability, and ethical fairness. Researchers should prioritize: (a) longitudinal validation of ML-driven curriculum interventions, (b) development of culturally responsive and equity-focused models, (c) integration of XAI techniques into production systems, and (d) rigorous bias auditing protocols.

Comparison with Prior Systematic Reviews. The findings of this review extend prior systematic reviews in several ways. Turkmenbayeva et al. (2024) focused broadly on ML applications in higher education but did not specifically address curriculum innovation. Avila-Garzon et al. (2023) conducted a systematic mapping of curriculum analytics but included only 25 studies up to 2022. The present review (a) covers a larger corpus (41 studies), (b) extends the timeframe to 2025, (c) specifically focuses on the prediction-to-action gap, and (d) proposes a validated framework to address this gap. Rodriguez-Ortiz et al. (2025) reviewed ML and generative AI in learning analytics but focused on student-level rather than curriculum-level applications.

Limitations. This review is subject to several methodological limitations. First, the exclusion of grey literature and non-English publications may have restricted the breadth of perspectives, potentially omitting innovative practices or culturally specific insights from less formal sources. Second, the reliance on peer-reviewed studies published between 2020 and 2025, while ensuring quality, limits historical comparisons and emerging trends beyond this timeframe. Third, most included studies employed cross-sectional or short-term designs, leaving gaps in understanding the longitudinal impact of ML on curriculum innovation. Fourth, publication bias toward positive results may exist; studies reporting negative or null findings are less likely to be published. Fifth, the fast-moving nature of ML means that recent 2025 preprints and emerging techniques (e.g., large language models for curriculum design) may have been missed.

Conclusion. This systematic review affirms that machine learning holds significant untapped potential for curriculum innovation in computer engineering education. Evidence from 41 empirical studies published between 2020 and 2025 converges on the high predictive accuracy of ML models for student outcomes. However, a substantial gap exists between prediction and actionable curriculum change, with only 17.1% of studies addressing curriculum-level applications. The proposed ML-driven framework grounded in the synthesized literature and validated against 41 studies, provides a structured, evidence-based pathway for achieving continuous, data-informed curriculum innovation.

Key Contributions. (a) comprehensive synthesis of ML techniques in educational analytics (2019–2025), (b) identification of seven specific gaps in translating prediction to curriculum action, (c) formulation of eight evidence-based best practices, and (d) a validated four-phase framework for continuous curriculum innovation.

Future Research Directions. (a) longitudinal validation of the proposed framework in real institutional settings, (b) development of culturally responsive and equity-focused ML models that account for diverse student populations, (c) integration of large language models (LLMs) and generative AI for automated curriculum insight generation, (d) rigorous bias auditing and fairness mitigation techniques specific to educational contexts, (e) cross-institutional studies to test scalability and generalizability, and (f) mixed-methods research combining quantitative predictive analytics with qualitative stakeholder feedback.

Author contributions. Emerson M. Facelo: Conceptualization; Study design; Development of proposed framework; Title formulation; Writing - introduction and literature review; Methodology; Data gathering procedures; Literature matrix development; System architecture and flowchart design; Synthesis of findings; Discussion; Overall manuscript preparation and final review | Lexter Von B. De Mesa: Abstract writing; Keywords; Manuscript formatting and refinement | Sim Jhon Paul M. Caadan: Interpretation; Thematic and comparative analysis; Results synthesis.

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Data availability statement. No new primary data were generated or analyzed in this study. All information supporting the findings is derived from publicly available, peer-reviewed literature cited within the manuscript. Therefore, all relevant data are contained within the article and its referenced sources.

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Appendix A

Complete Data Extraction (Study Characteristics) of the 41 Studies Subjected for Systematic Review

No.	Author(s) and Year	Research Objectives	ML/Analytics Technique	Data Type	Key Findings	Curriculum Link?	Identified Limitations
1	Rodriguez-Ortiz et al. (2025)	Systematic review of ML in learning analytics	Various ML techniques	Secondary (review)	ML and generative AI are transforming learning analytics	No (student-level)	Limited empirica validation
2	Guevara-Reyes et al. (2025)	Predict academic performance using ML	Random Forest, XGBoost, SVM	Student records (N=1,200)	RF achieved best accuracy (AUC=0.89)	No	Small sample siz
3	Remegio (2025)	Systematic review of predictive analytics in HE	Various ML models	Secondary (review)	Predictive models effective but ethical concerns remain	No	Limited to Englisl papers
4	Dhara & Chatterjee (2025)	XAI for academic decision support	LIME, SHAP	Synthetic data	XAI improves trust in predictions	Yes	Not yet validated i real settings
5	Liu (2023)	Review of curriculum evaluation systems	N/A (conceptual)	Secondary (review)	Current systems are compliance-driven	Yes	No empirical dat
6	Geng et al. (2024)	Predict STEM course outcomes	Random Forest	Course assessment data (N=5,000)	RF predicted outcomes with 85% accuracy	No	Single institutior
7	Kleimola & Leppisaari (2022)	Learning analytics for future competences	LA dashboards	Case study (N=200)	LA supports competence development	Partial	Small case stud
8	Chamberland (2024)	AI for curriculum relevance	LLM-based analysis	Curriculum documents	AI can identify outdated content	Yes	Preprint, not peer reviewed
9	Abu-Rasheed (2025)	LLM-assisted knowledge graph for education	LLM, Knowledge graphs	Educational datasets	KG completion improves curriculum mapping	Yes	Preprint
10	Turkmenbayeva et al. (2024)	Systematic review of ML in HE	Various ML	Secondary (review)	ML widely used for student prediction	No	Limited to 2020-2023
11	Avila-Garzon et al. (2023)	Systematic mapping of curriculum analytics	Various	Secondary (mapping)	Gap between curriculum analytics and ML	Yes	Only 25 studies
12	Denney (2024)	Student-centric LA adoption	LA dashboards	Surveys (N=300)	Students prefer actionable dashboards	Partial	Self-report data
13	Yuan et al. (2024)	Integrate ML and EDM for student success	Classification	LMS logs (N=2,500)	Engagement metrics top predictors	No	Single course
14	Kurday (2023)	Survey of LA and EDM trends	Various	Secondary (survey)	LA maturity increasing	No	Broad scope
15	Alalawi (2024)	Deep learning for student performance	Deep neural networks	Student records (N=10,000)	DL outperforms traditional ML (AUC=0.92)	No	Black-box, no XA
16	Trujillo (2023)	AI challenges and opportunities in HE	N/A (conceptual)	Secondary	Institutions lack AI readiness frameworks	Yes	Conceptual only
17	Chu & Lu (2023)	Review of AI in education	Various	Secondary (review)	AI personalization effective but implementation challenging	No	Broad scope
18	Rodriguez et al. (2024)	Early warning systems using ML	Logistic Regression, RF	Student records (N=3,000)	EW systems identify at-risk students early	No	No curriculum linkage
19	Guevara-Ramos (2023)	Predict student attrition	SVM, RF, DT	Student records (N=1,500)	RF best for attrition prediction (F1=0.87)	No	Single institutior
20	Wong (2024)	Systematic review of AI in personalized learning	Various	Secondary (review)	AI enables personalized paths but lacks curriculum integration	Partial	Limited to 2020-2023
21	González et al. (2024)	Data-driven decision making in HE	Various	Secondary (review)	DDDM growing but frameworks lacking	Yes	Conceptual
22	Buzducea (2023)	ML for academic performance	DT, RF, SVM, NN	Student records (N=2,000)	Ensemble methods best (AUC=0.91)	No	Cross-sectional
23	Lee (2024)	Interpretability of ML in education	LIME, SHAP	Educational datasets	Interpretability critical for trust	Yes	Technical focus
24	Avila-Garzon (2023)	Curriculum mapping with AI	NLP, clustering	Curriculum documents	AI identifies curriculum gaps	Yes	Single institutior

36	Kim et al. (2023)	AI-based feedback systems	NLP, sentiment analysis	Discussion posts (N=10,000)	AI feedback improves engagement	No	Limited to one course
37	Lopez-Meneses (2024)	Educational innovation through AI	Various	Secondary (review)	Innovation frameworks needed	Yes	Conceptual
38	Cerezo (2023)	Review of LA impact on outcomes	N/A (review)	Secondary (review)	LA improves outcomes when actionable	Partial	Broad scope
39	Cabral (2024)	AI for academic advising	Predictive models	Student records (N=1,500)	AI advising reduces dropout by 15%	Partial	Single institutior
40	Mazhar (2023)	Deep learning for predictive analytics	LSTM, GRU	Student records (N=8,000)	LSTM outperforms GRU (AUC=0.94)	No	Black-box
41	Timovski (2024)	Predictive modeling for online learning	RF, XGBoost, NN	LMS logs (N=2,000)	XGBoost best for online (AUC=0.90)	No	Online-only conte

Note: HE = higher education; ML = machine learning; LA = learning analytics; XAI = explainable AI; EDM = educational data mining; LMS = learning management system; SIS = student information system; RF = Random Forest; SVM = Support Vector Machine; DT = Decision Tree; NN = Neural Network; LSTM = Long Short-Term Memory; GRU = Gated Recurrent Unit; NLP = natural language processing; AUC = area under the curve; F1 = F1-score.