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Survey on An AI based NLP framework for automatic CO-PO mapping in outcome-based education

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Abstract—*This research presents a comprehensive framework for improving engineering education quality by integrating Outcome-Based Education (OBE) principles, systematic assessment strategies, and advanced Machine Learning (ML) techniques. The framework emphasizes the precise mapping of Course Learning Outcomes (CLOs) to Program Outcomes (POs) using Bloom's Revised Taxonomy, employing a blend of direct and indirect assessment methods, and leveraging ML models for automated evaluation of CLO quality. By analyzing student performance data, identifying attainment gaps, and utilizing data-driven insights, this approach facilitates continuous curriculum improvement, enhances student engagement, and ensures graduates possess the competencies required by industry and accreditation bodies.*

Keywords— *Outcome-Based Education (OBE), Course Learning Outcomes (CLOs), Program Outcomes (POs), Assessment, Machine Learning (ML), Engineering Education, Curriculum Improvement, Bloom's Revised Taxonomy, Continuous Quality Improvement (CQI)*

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I. INTRODUCTION

The landscape of engineering education is continuously evolving, driven by the need to produce graduates who are not only technically proficient but also possess critical thinking, problem-solving, and collaborative skills. Outcome-BasedEducation(OBE)hasemergedasaglobally recognized paradigm to address these demands, shifting the focus from what is taught to what students can actually do upon completion of a course or program. This approach necessitates a robust system for defining, assessing, and continuously improving learning outcomes.

The [8] document highlights the core principles of software engineering, emphasizing the development of reliable,efficient,andmaintainablesoftwareproducts, alongsidetheimportanceoftimelydelivery, costeffectiveness, collaboration, and customer satisfaction. Crucially, it underscores the significance of mapping learning outcomes to course objectives to ensure effectiveteaching, assessment,andongoingcourseenhancement.Thisalignment,oftenguidedbyframeworkslikeBloom'sRevised Taxonomy, isfundamentaltoenhancingstudentunderstanding, engagement,and the achievement of desired skills and knowledge.

While OBE provides the structural foundation, effective implementation requires sophisticated assessment methodologies and continuous quality improvement (CQI) mechanisms. Traditional assessment methods, though vital, can be labor-intensive and sometimes lack the granularity needed for precise feedback. This paper argues for the integration of advanced analytical tools, specifically Machine Learning (ML), to automate and enhance the evaluation of learning outcomes, thereby streamlining the CQI process in engineering education.

II. LITERATURE SURVEY

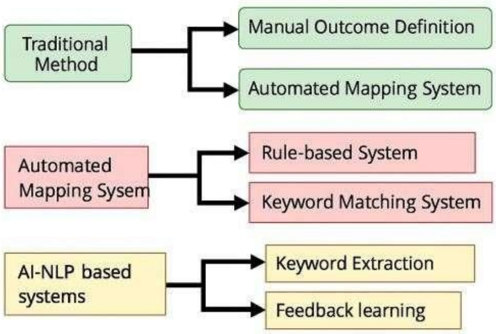

Fig1:ClassificationofOutcomeBasedEducation

Thissectionprovidesasystematicreviewoftheliterature onOutcome-BasedEducation(OBE)andCO–POmappingsystems, tracing their evolution from traditional manual approaches to advanced AI- and NLP-driven automated frameworks.Tostructurethisanalysis,existingtechnologies have been organized into three distinct categories: Traditional Methods, Automated Mapping Systems, and AI–NLP–Based Systems, as illustrated in the classification diagram above.

A). Defining and Mapping Learning Outcomes in OBE

ThecornerstoneofOBEistheclerararticulationoflearningoutcomes.CourseOutcomes(COs),oftenreferredto as Course Learning Outcomes (CLOs), specify what students should know and be able to do after completing a particular course. Program Outcomes (POs) are broader statements describing the knowledge, skills, and attributes that graduates should possess upon completion of an entire engineering program. The [5] document outlines a comprehensiveframeworkfordefiningandmeasuringCOs, POs, and Program Specific Outcomes (PSOs), emphasizing that outcomes must be clear, measurable criteria guiding teaching, learning, and assessment.

TheprocessoflinkingCostoPosiscriticalforensuring curriculum coherence and demonstrating how individual courses contribute to broader program goals. The [9] paper proposes an effective"top-down" method for this linkage, advocating a many-to-one relationship where multiple COs contribute to a single PO. This approach simplifies assessment by eliminating the need for complex weight matrices and ensures a comprehensive measurement of programachievement.ItinvolvesanalyzingeachPOintoits constituent components and then embedding these componentsintorelevantcoursesorCosatvaryinglevelsof detail, ensuringthatallaspectsofaPOare addressedacross the curriculum. This structured linkage is vital for accreditationbodieslikeABET, which requireclearevidence of outcome attainment.

i) TraditionalandML-BasedApproaches(2021–2023):

Traditional and early machine learning (ML)-based approachestoCO–POmappingprimarilyfocusedontextual similarity and statisticalfeature extraction.Methodssuchas TF-IDF combined with Support Vector Machines (SVM) (IEEE, 2023) demonstrated reliable classification performance with low computational requirements, achieving accuracies above 90%. However, these models relied on bag-of-words representations, which ignore word order and contextual meaning.

Hybridmodels,suchasrule-basedframeworksintegrated with Word2Vec embeddings (IJRPR, 2022), improved mappingaccuracybyincludingsemanticsimilaritymeasures, yet they required manual rule definition by domain experts, reducing scalability. Similarly, TF-IDF and Universal SentenceEncoder(USE)combinations(Studocu,2021) enhanced semantic understanding but involved high preprocessing and were sensitive to noisy textual data.

Later studies introduced ensemble methods combining Random Forest and XGBoost classifiers (ResearchGate, 2023), which improved robustness and generalization on limiteddatasets.Despitetheirstrongaccuracy,thesemodels werelessinterpretableandcomputationallymorecomplexto fine-tune. ii). Deep Contextual Embeddings&

Transfer Learning:
The introduction of deep contextual embedding models revolutionized CO–PO mapping by enabling semantic understanding of text. Models like BERT (Bidirectional EncoderRepresentationsfromTransformers)werefinetuned onlabeledCO–POdatasetstocapturecomplexrelationships between learning outcomes. Studies (ResearchGate, 2022) reportedstate-of-the-artF1-scores(~94%),provingBERT's ability to represent meaning contextually. However, fine- tuning BERT requires large labeled datasets and high computationalresources(GPUbasedtraining),makingitless feasible for smaller institutions.

To overcome scalability challenges, Sentence-BERT (SBERT) was introduced. It produced fixed-size sentence embeddings and, when combined with the Hungarian algorithm, effectively performed many-to-many matching between COs and POs (MDPI, 2023). This approach achieved around 91% precision, offering a structured mapping technique. Nonetheless, it introduced computational complexity ($O(n^3)$), making it demanding for large-scale applications.

Further optimization was achieved with DistilBERT, a lightweight, distilled version of BERT. When trained using transfer learning techniques (CURAJ, 2022), DistilBERT achieved87%accuracyevenonsmalldatasets(<200pairs), showing strong generalization with limited labeled data. However, domain shifts between source and target data affected consistency.

Overall, deep contextual and transfer learning approaches havesignificantlyadvancedCO–POmappingautomationby capturingsemanticdepthandreducingdependencyonexpert intervention. They outperform traditional ML models in accuracyandadaptability,buttheircomputationalcost,data requirements, and interpretability remain key challenges. The emergenceofLargeLanguageModels(LLMs)likeGPTand T5 has opened possibilities for zero-shot and few-shot mapping,marking anew directionfor fully automatedOBE analytics.

B). ComprehensiveAssessmentStrategies

Effective assessment is paramount for evaluating the achievement of learning outcomes. The [6] document providesadetaileddiscussiononacomprehensiveapproach utilizing both direct and indirect assessment methods.

i). DirectAssessments:Thesemethodsdirectlymeasure student learning and performance. Examples include:

a. Exams:Quizzes,midterms,andfinalexaminations designed with questions mapped to specific COs.
b. Laboratory Work: Practical experiments and associatedreportsthatdemonstratehands-onskills and data analysis.
c. Projects:Designprojects,researchprojects,andcase studies that require application of knowledge and problem-solving.
d. Assignments:Homework,problemsets,andessays that assess understanding and critical thinking.
e. Presentations: Oral presentations that evaluate communicationskillsanddepthofunderstanding.
f. Rubrics:Usedtoevaluatecomplextaskslikeprojects and presentations, ensuring consistent and objective grading against defined criteria for engineering knowledge, problem-solving, etc.

II)INDIRECTASSESSMENTS:THESEMETHODSGATHERPERCEPTIONSANDFEEDBACKABOUTSTUDENTLEARNINGANDPROGRAMEFFECTIVENESS.EXAMPLESINCLUDE:

a. StudentSurveys:Coursefeedbackquestionnaires,exit surveys, and self-assessment tools.
b. Alumni Feedback: Surveys and interviews with graduatestogaugethelong-termimpactoftheprogram.
c. EmployerSurveys:Feedbackfromemployersonthe competencies of graduates.
d. FocusGroups:Discussionswithstudents,faculty, and alumni to gather qualitative insights.

The [5] further elaborates on how CO attainment is evaluatedthroughassessmentsmappedtospecificCOs,using student marks from various activities. Attainment levels are typically graded basedon percentagescores(e.g., <50%,50- 60%,>60%), and targets are set (e.g.,>60% of students achieving>60% in a CO). PO/PSO attainment is then measured by combining direct and indirect measures, often with weighted contributions(e.g., 80%direct, 20%indirect).

C). CONTINUOUSQUALITYIMPROVEMENT(CQI)
Thecorepurposeofassessmentistodrivecontinuous improvement.The[6]emphasizestheimportanceofCQI, whereassessmentdataisusedtoidentifygapsandinform correctiveactions. AnExcel-basedsystemisdescribedfor mappingCostoPosandanalyzingattainmentlevels.Analysis often reveals that some POs, such as PO1 (EngineeringKnowledge),PO4 (Investigation),PO7 (EnvironmentandSustainability),andPO12(Lifelong Learning),maynotbefullyachieved.Thisindicatespotential gaps in content alignment, teaching methods, or assessment strategies.

Toaddressthesegaps,recommendationsincludeupdating course content, incorporating active learning techniques, diversifying assessments, and providing instructor training. Student feedback, while highlighting strengths like course organization andresourceaccessibility, also pointstoareasfor improvement such as clearer quiz questions and more practical examples.This iterative process of assessment, analysis, and action forms a crucial feedback loop for enhancing overall quality and stakeholder satisfaction, as detailed in [2].

D). THEROLEOFLEARNINGMOTIVATION
While robust curriculum design and assessment are critical, student motivation also plays a role in learning outcomes.The[7]researchinvestigatesthecorrelation between learning motivation and learning outcomes among students in an Arabic language education program, specifically focusing on Nahwu (Arabic grammar) courses. Thestudy,usingaquantitative,correlationalapproachwith 23 randomly selected sixth-semester students, found that students generallyexhibitedhighmotivation(averagescore~82.87) and good learning outcomes (average score ~84.2). However, statistical analysis indicated a weak and not statisticallysignificantcorrelation(correlationcoefficientr≈0.133), with motivation contributing only 2% to learning outcomes.Thisfindingsuggeststhatwhilehighmotivationis desirable, it alone does not guarantee high learning outcomes, implyingthatotherfactorssuchaseffectivepedagogy,clear learning objectives, and well-structured assessments are more influential.

E). MACHINE LEARNING FOR AUTOMATED OUTCOMEEVALUATION
The increasing volume of educational data presents an opportunity for advanced analytical techniques. The "JITEIIPv21p061-075Kacem8323.pdf" and Kacem (2023) documents highlight the application of Machine Learning (ML) in Education Data Mining (EDM) to improve course delivery quality and student achievement assessment. They propose a methodology called CLOCML (Course Learning OutcomeClassificationusingMachineLearning)toclassify CLOs into categories like Knowledge, Skills, and Value, or to identify poorly written CLOs (e.g., Not Clear, Not Concise, Not Measurable).
The research involved collecting 3,200 CLOs from multiple universities, which were thenexpertly annotated.To address data imbalance, data augmentation techniques such asparaphrasing,noising,andsamplingwereemployed.Text processing involved NLP methods like stop-word removal, stemming, and sparse matrix creation. Various MLclassifiers, including SupportVector Machine (SVM), Random Forest, NaiveBayes,andXGBoost,weretrainedandevaluated.The SVMclassifierachievedthehighestaccuracyof83%andan F1-score of 0.80, demonstrating its effectiveness in reliably automatingCLOcategorization.Thiscapabilitysignificantly aidseducatorsandaccreditationbodiesinensuringCLOsare well-written, measurable, and aligned with Program Learning Outcomes(PLOs),therebyenhancingeducationalstandards.

III. CHALLENGESOFEXISITINGSOLUTIONS
AutomatingtheCO–POorCLO–PLOmappingprocessin Outcome-Based Education (OBE) systems addresses several longstanding challenges in traditional manual methods. The following explanation outlines how modern AI and NLP techniques mitigate these issues effectively.
A). Subjectivity and Inconsistency of Manual Mapping: Traditional manual mapping often varies from one educator to another, introducing subjective interpretations and inconsistent results across

departments. AI-based Natural Language Processing (NLP) frameworks mitigate this by applying standardized similarity algorithms and predefined linguisticrules,ensuringobjectivityandreproducibility. Byreplacinghumanbiaswithdata-drivencomputation,thesesystemsestablishaconsistentmappingframework across multiple courses and programs.

B). Time-Consuming Nature of Manual Mapping: Manual mapping is labor-intensive and slows down curriculum designandaccreditationprocesses.Automatedmapping toolsdramaticallyreduceprocessingtimebyperforming large-scale text comparisons instantly. This allows educators and administrators to focus on higher-level academicdesignandimprovementratherthanrepetitive mappingwork.Theautomationalso facilitatesfrequent updates to CO– PO matrices whenever curricula are revised.

C). Challenges in Semantic Understanding: Despite improvements, NLP models can still struggle with contextual nuances, especially when learning outcomesusebroadorambiguousverbssuchas“apply,” “develop,” or “evaluate.”Thissemantic gap may lead to inaccurate mappings. The use of advanced transformerbased architectures (e.g., BERT, GPT, or USE)enhancescontextualcomprehension,whileexpert- inthe-loop validation ensures that the system’s interpretations remain aligned with academic intent.

D). Threshold Optimization: Determining the optimal similaritythresholdformappingiscriticaltoohigh,and relevantconnectionsaremissed;toolow,andirrelevant mappings are included. Adaptive thresholding techniquesandmachinelearning-basedcalibrationnow allow systems to automatically learn ideal thresholds based on expert-validated datasets. This dynamic approach ensures precision across diverse program contexts.

E). LackofTransparencyinAutomatedDecisions:SomeAI systems function as “black boxes,” providing little insight into why a particular mapping was chosen.This canreducetrustamongeducators.ExplainableAI(XAI) methodsaddressthisbypresentingtherationale behind each decision—such as similarity scores, key matched phrases, or highlighted terms. These transparency features make the system more interpretable and foster user confidence.

F). LimitedScopeofCurrentResearch:Mostexistingstudies onautomatedmappinghavebeenconductedwithsmall datasets or within specific engineering disciplines, limiting generalizability. Expanding research through broader, mixed-method approaches combining quantitativeaccuracyanalysiswithqualitativeeducator feedback can improve the validity and applicability of results across different academic domains.

G). DifficultyinIdentifyingPoorlyWrittenOutcomes:Many CO–POmappingsystemsassumethatlearningoutcomes are clearly defined, which is notalwaysthe case. Poorly written CLOs, such as those that are vague or non- measurable, reduce mapping accuracy. Developing specialized ML classifiers trained on datasets of “well- written” versus “poorly written” outcomes, supplemented with iterative expert feedback, can enable automated systemstoflagandhelpreviselow-qualityCLOsbefore mapping.

IV. CONCLUSION

Thisresearchpresentsarobustandinnovativeframework forenhancingengineeringeducationthroughthesynergistic integration of Outcome-Based Education principles, comprehensive assessment methodologies, and advanced Machine Learning techniques. By systematically defining andmappingCourseLearningOutcomes(CLOs)toProgram Outcomes (POs) using a top-down approach, employing a balanced mix of direct and indirect assessments, and leveraging ML models for automated CLO quality evaluation, the framework provides a powerful mechanism for continuous curriculum improvement.

The findings demonstrate that this integrated approach effectively identifies attainment gaps in key program outcomes,facilitatestargetedcorrectiveactions,andensures the quality and measurability of learning objectives. The application of ML, specifically the SVM classifier, proves highly effective in automating the assessment of CLO quality, thereby standardizing outcome formulation and reducing manual effort.While studentmotivation is apositive factor, the study reinforces that a well-structured, outcome-based educational environment with rigorous assessment and continuous feedback loops is paramount for achieving desired learning outcomes.

Ultimately,thisframeworkempowersengineeringprograms tonotonlymeetaccreditationstandardsbutalsotocultivate a culture of excellence, producing graduates who are wellequipped with the knowledge, skills, and professional attributes demanded by the global engineering landscape.

V. FUTURE WORK

Futureresearchdirectionsinclude:
i). Expansion of ML Models:Applying the ML-based CLO quality assessment to a broader range of engineering disciplinesandeducationalcontexts,andexploringtheuseof deeplearningmodelsform morenuancedsemanticanalysisof CLOs.
ii). Predictive Analytics: Developing predictive models that can forecast student performance in specific CLOs or POs based on early assessment data, allowing for proactive interventions.
iii).PersonalizedLearningIntegration:Investigatinghowthe insights from CLO and PO attainment data can be used to inform personalized learning pathways and adaptive assessmentstrategies.
iv).LongitudinalStudies:Conducting longitudinal studies to track the long-term impact of curriculumchangesandpedagogicalinterventionsonalumni career success and professional development.

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