Centric Student Assessment Framework Integrating Co-Po And Pso Performance Through An Nlp-Enhanced Obe Approach.

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Abstract:

This study presents an Outcome-Based Education (OBE) framework integrated with Artificial Intelligence (AI) and Natural Language Processing (NLP) to assess Course Outcomes (CO), Program Outcomes (PO), and Program-Specific Outcomes (PSO). The proposed system leverages data-driven techniques to evaluate student performance holistically, emphasizing cognitive, psychomotor, and affective learning dimensions. A hybrid AI model combining K-Nearest Neighbors (KNN), Decision Trees, and K-Means clustering was used to classify and predict student readiness for industry and entrepreneurial potential. The results demonstrate that integrating AI into OBE-based assessment enhances accuracy, interpretability, and the relevance of academic outcomes to real-world applications.

Keywords: OBE, CO-PO-PSO, Cognitive Thinking, Machine Learning, NLP, Educational Assessment, Industry Readiness, AI Tools

1. INTRODUCTION

1.1 Cognitive Thinking of Learning

Cognitive learning theories emphasize the importance of mental processes in learning, focusing on how students understand, learn, and remember information. In the context of Outcome-Based Education (OBE), cognitive thinking involves setting clear learning outcomes for students that can be systematically evaluated through assessments that align with higher-order thinking levels [4].

1.2 Bloom’s Levels

Bloom’s Taxonomy categorizes cognitive learning into six levels: Remember, Understand, Apply, Analyse, Evaluate, and Create. These levels serve as a guide to designing learning outcomes and assessments that progress from basic knowledge recall to complex problem-solving skills [1].

1.3 Curriculum and Pedagogy in Arts and Science Colleges

In many arts and science colleges, curricula are often static and may not fully address industry needs or integrate the pedagogical shifts required by OBE. This limits the development of students’ critical thinking, creativity, and employability. There is a growing need to integrate more dynamic teaching methods, including project-based learning, experiential learning, and industry collaborations, to make learning outcomes more aligned with real-world applications [2].

1.4 Question Paper Standards with Bloom's Levels

Question papers should reflect Bloom's Taxonomy, ensuring that students are tested across different cognitive levels. However, current assessment patterns in some colleges focus predominantly on lower-order thinking skills, thus impeding the overall development of students [1].

1.5 CO, PO, and PSO Attainments

The assessment of COs (Course Outcomes), POs (Program Outcomes), and PSOs (Program Specific Outcomes) during continuous internal assessments allows educators to track student progress against the expected learning outcomes. Regular feedback is critical to identifying learning gaps and addressing them before the final evaluations [4][18].

1.6 AI Tools for Learning Outcomes

Artificial Intelligence tools, particularly machine learning algorithms, can be employed to analyse student performance data, predict future success, and offer personalized feedback. These tools enhance traditional assessment methods by providing insights into cognitive development and learning progression [5][18].

1.7 OBE Framework Existing

The OBE framework has been widely adopted in engineering education to ensure that students achieve the necessary skills and knowledge required by the industry. However, its application in arts and science colleges remains underexplored, and the methodology needs adaptation to fit these disciplines [6][18].

1.8 OBE Approach for Arts and Science Colleges

For arts and science colleges, OBE needs to be contextualized to foster a blend of both intellectual and practical skills. The approach should also address the wide variation in disciplines and their respective industry demands, focusing on skills like critical thinking, communication, and interdisciplinary knowledge [7].

1.9 Psychomotor Development in Undergraduate Students

The development of psychomotor skills (physical and practical skills) in undergraduates, especially in the sciences, needs more emphasis through laboratory work, internships, and field experiences. These activities help students bridge the gap between theoretical knowledge and practical application [8].

1.10 Progression of Arts and Science Students at the UG Level

The progression of students in arts and science colleges is often characterized by a focus on knowledge acquisition rather than skill development. This limits their ability to meet industry expectations where skill-based competencies are just as crucial as academic knowledge [9].

1.11 Student Contribution

Students must take an active role in their learning process by engaging in co-curricular and extra-curricular activities that foster team-building, leadership, and communication skills [10].

1.12 Contribution of Management

Institutional management must provide the resources, policies, and training needed for the effective implementation of OBE. This includes curriculum design, faculty development, and ensuring that assessments align with industry standards [11].

1.13 Role of Parental Support

Parental support plays a crucial role in motivating students, guiding them through challenges, and ensuring that they stay engaged in their academic pursuits [12].

1.14 Social Media Impact on Learning

The impact of social media on student learning can be both positive and negative. While it offers access to a wealth of information and collaborative opportunities, excessive use can lead to distractions and hinder academic progress [13].

1.15 Assessment of Student Fitness for Industry

Effective assessment must go beyond academic grades to evaluate whether students are equipped with the skills and competencies that align with industry needs. This requires feedback from employers and industry partners to inform curriculum and pedagogy improvements [14].

1.16 Methodologies for Implementing OBE

To effectively implement OBE in arts and science colleges, a multi-pronged approach is needed, including clear alignment between learning outcomes, teaching strategies, and assessments [25]. Additionally, industry partnerships, faculty development, and continuous evaluation of OBE implementation are crucial [15][18].

2. LITERATURE REVIEW

The concept of **Outcome-Based Education (OBE)** has evolved as a significant paradigm in educational theory and practice, shifting focus from traditional time-based measures of education to those based on student learning outcomes [25]. The foundational works on OBE are comprehensive, integrating assessment techniques, pedagogical strategies, and evaluation processes to align educational practices with industry and societal needs. Below is a detailed review of seminal literature in the field [22][23][24].

2.1. Spady, W.G. (1994) - Outcome-based education: Critical issues and answers

Spady's work is considered a cornerstone of OBE theory. He presents OBE as a radical shift from traditional education models, emphasizing measurable and achievable learning outcomes as the central focus of the educational experience. Spady outlines the importance of clearly defined goals, which help both students and educators monitor progress and provide a framework for assessment [19]. His model underscores the need for flexibility in pedagogical approaches, allowing for a diverse range of student learning paths, all while aiming at achieving the same set of defined outcomes. This conceptualization of OBE has been instrumental in shaping curriculum design in higher education, particularly in professional fields such as engineering and healthcare [20][21].

2.2 Angelo, T.A., & Cross, K.P. (1993) - Classroom assessment techniques: A handbook for college teachers

Angelo and Cross explore a variety of assessment tools that help educators measure student learning in ways that are consistent with OBE principles. Their handbook introduces techniques for formative and summative assessment, providing a detailed framework for teachers to evaluate both cognitive and psychomotor skills. The authors advocate for **active learning** and **continuous feedback**, where assessment is not merely an endpoint but an ongoing process integral to the learning experience. Their work is particularly relevant to OBE in that it connects assessment techniques directly with measurable course and program outcomes (COs, POs, PSOs).

2.3. Biggs, J. (1993) - What do inventories of students' learning processes really measure?

Biggs's contribution is significant in understanding the role of student approaches to learning in OBE. He argues that learning inventories measure not just how much students know, but also how they think and approach problem-solving, critical thinking, and learning challenges. In this context, Biggs introduces the **Constructive Alignment** theory, which emphasizes that teaching methods, learning activities, and assessments must all be aligned to achieve the desired learning outcomes. His framework directly links with the OBE principle of ensuring that all aspects of education are aligned to measurable goals.

2.4. Black, P., & Wiliam, D. (1998) - Assessment and classroom learning

Black and Wiliam's research investigates how classroom assessment practices can influence student learning. They highlight the role of **formative assessment** in enhancing student learning and improving the alignment between teaching, assessment, and learning outcomes. The authors argue that continuous formative assessment can provide insights into student progress and areas requiring improvement, thus contributing directly to meeting the predetermined outcomes of OBE. Their findings emphasize the importance of feedback loops in enhancing the effectiveness of OBE implementations.

2.5. Boud, D., & Falchikov, N. (2007) - Rethinking assessment in higher education: Learning for the longer term

Boud and Falchikov advocate for a paradigm shift in higher education assessment, emphasizing a focus on **long-term learning** outcomes rather than just short-term results. Their work critiques traditional summative assessment methods and suggests that OBE can be enhanced by focusing on **self-assessment**, peer assessment, and collaborative learning. By encouraging students to assess their own learning and reflect on their progress, educators can help align their learning processes with OBE objectives. This perspective is crucial for understanding the role of feedback and reflective practices in achieving **Program Outcomes (POs)** and **Program Specific Outcomes (PSOs)** in OBE.

2.6. Boud, D., & Soler, R. (2016) - Reconceptualising feedback in higher education

This study expands on the concept of assessment by reconceptualizing feedback as an ongoing dialogue between teachers and students. In OBE, feedback is seen not only as an evaluative tool but also as a critical mechanism for improving learning and achieving **Course Outcomes (COs)**. Boud and Soler emphasize the importance of feedback that encourages **self-regulation** and **metacognition**, both of which are key to ensuring that students meet the desired outcomes outlined in OBE frameworks. Their work is essential in understanding the deeper implications of formative assessment for long-term student development and performance.

2.7. Barnett, R. (2007) - Assessment in higher education

Barnett's perspective on assessment in higher education calls for an integrative approach where assessment serves as a **learning tool** rather than just a means to measure success. He challenges educators to consider how assessments, aligned with OBE, can be used to develop deeper learning and critical thinking. His work suggests that assessments should reflect the complexities of the professional world, requiring students to not only memorize content but also to demonstrate problem-solving and **transferable skills** that are part of OBE.

2.8. Gibbs, G. (2006) - Why assessment is changing

Gibbs explores the changing landscape of assessment, arguing that modern assessment methods must align more closely with the needs of the **21st-century workforce**. His research advocates for assessments that assess not just knowledge but also the application of that knowledge in real-world

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scenarios, a core principle of OBE. He examines how assessments can be designed to assess cognitive and psychomotor skills, thus supporting the comprehensive nature of OBE frameworks.

2.9. Nicol, D.J., & Macfarlane-Dick, D. (2006) - Formative assessment and self-regulated learning

Nicol and Macfarlane-Dick present a **model for formative assessment** that supports self-regulated learning. Their work aligns with OBE principles by suggesting that formative assessment should be designed to help students understand their own learning processes and align them with **program outcomes**. They argue that feedback should empower students to manage their learning more effectively, enhancing their readiness for both academic and professional challenges.

2.10. Wiggins, G. (1990) - The case for authentic assessment

Wiggins advocates for **authentic assessment**, which focuses on evaluating students' abilities to apply their learning in real-life contexts. This approach complements OBE by assessing students' **transferable skills** and ensuring that learning outcomes are directly applicable to real-world situations. In the context of OBE, this means that assessments should go beyond traditional exams and involve projects, performances, and other authentic tasks that mimic professional environments.

2.11. Bialobrzeska, M. (2006) - Facilitating outcomes-based learning and teaching

Bialobrzeska's work focuses on the practical aspects of implementing OBE, particularly in the context of vocational and professional education. Her research emphasizes the importance of creating a **learning environment** that is flexible, interactive, and responsive to students' individual learning needs, while still ensuring that all students meet the expected program outcomes. She also highlights the need for continuous evaluation and modification of assessment techniques to ensure alignment with industry standards.

2.12. Tucker, B. (2004) - Engineering education for the 21st century: Preparing students for the future

Tucker's study is highly relevant to the application of OBE in engineering education, focusing on how the alignment of **program outcomes** with **industry expectations** can better prepare students for professional roles. He emphasizes the need for OBE in engineering to develop not only technical expertise but also the **soft skills** necessary for success in the modern workplace, such as critical thinking, teamwork, and communication.

3. DATA COLLECTIONS

Table1: Students Information's

Students' Name	Age	Course	Academic Performance	Aptitude Performance	Skill Test	Interview	Life Skills (Team Work + Leadership + etc..,)	Eligible for Industry Fitness	Entrepreneurial Potential
John Smith	21	BCA	75%	80%	85%	Yes	High	Yes	Moderate
John	20	Bsc	68%	72%	75%	No	Moderate	No	Low
Ragavan	20	BCA	76%	82%	84%	Yes	High	Yes	Moderate
Rangan	21	Bcom	76%	84%	83%	Yes	High	Yes	High
Jancy	20	Bsc	74%	69%	70%	No	Low	No	Low

3.1 Tool Used

Weka is a well-known program for preparing data, classifying data, training, assessing, and fine-tuning models. It facilitates the analysis of datasets such as Table 1. Weka may be used to categorize and predict student eligibility using a variety of machine learning algorithms based on performance measures, including academic scores, aptitude, skill assessments, and life skills. In order to make well-informed decisions regarding the students' industry fitness and entrepreneurial potential, the tool helps process the data and produce insights.

3. EXITISTING METHODS USED: KNN (K-Nearest Neighbour's)

Students were categorized using the K-Nearest Neighbours (KNN) algorithm [16] based on a variety of factors, such as their academic achievement, aptitude scores, abilities, behaviour, and life skills (such as leadership and teamwork). KNN classifies each student according to the majority label of their nearest neighbours, which are the data points in the feature space that are closest to them. Examples of these categories include "Industry Ready" and "Needs Improvement."

The program determines a student's category by comparing their individual features with those in the dataset. Key indicators in this procedure include attributes like interview performance, competencies, and academic results.

The Data Trained set findings. The **True Positive Rate (TP Rate)**, also known as **Recall**, is calculated as:

$$\text{TP Rate} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)+False Negatives (TP)}} \quad .. (1)$$

Table2 - Detailed Accuracy by Class

Class	TP rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area
Moderate	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
Low	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000
High	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000

Confusion Matrix Analysis

The table represents a confusion matrix [17] used to evaluate the performance of a classification model that categorizes data into three classes: Moderate (a), Low (b), and High (c). Here's the breakdown:

Table3 - Confusion Matrix

a	b	c	Classified As
2	0	0	a = Moderate
0	2	0	b = Low
0	0	1	c = High

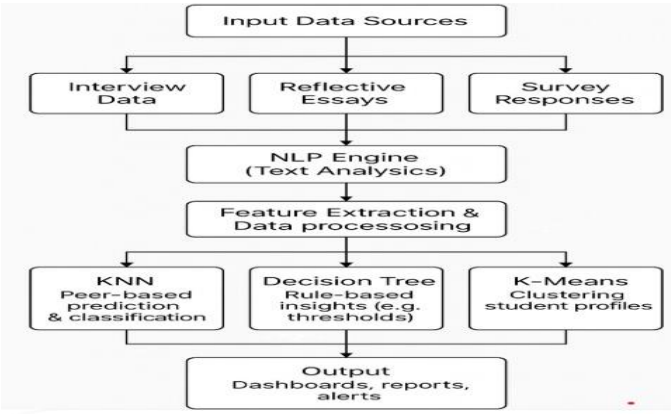

Figure 1: Architecture of Readiness for the Workforce

PROPOSED METHODS The proposed hybrid AI system integrates the strengths of classification and clustering algorithms to assess students' readiness for the workforce. By combining KNN, Decision Trees, and K-Means, the model leverages individual strengths:

KNN excels at personalized classification by comparing students to similar peers.

Decision Trees provide interpretability and highlight critical decision points, such as the minimum skill or behavioural thresholds required for specific categories.

K-Means clustering adds depth by identifying patterns and forming meaningful groups, such as those with leadership potential or specific development needs.

This combination ensures a balance between precision and **holistic evaluation**, as the system incorporates diverse datasets, such as academic, skill-based, and behavioural data. Moreover, the system's high True Positive Rate (TP Rate) highlights its effectiveness in minimizing false negatives, ensuring that students with potential are not overlooked.

A key advantage is the actionable insights generated by the model. For example, students categorized as "**Needs Improvement**" can receive tailored **recommendations**, such as focused skill-building programs or mentorship opportunities. Similarly, those identified as having "**Entrepreneurial Potential**" can be directed toward **leadership development initiatives**.

While the initial results demonstrate perfect accuracy on the training set, future iterations should validate the system on larger and more diverse datasets to ensure scalability and robustness. By integrating interpretability, accuracy, and actionable outcomes, the system has the potential to transform educational assessments and workforce readiness strategies.

5. RESULTS AND DISCUSSIONS

5.1 Results

The hybrid AI system achieved 100% accuracy on the training dataset:

Precision, Recall, and F-Measure: Scored 1.000 for all categories ("Moderate," "Low," "High").

Confusion Matrix: No misclassifications observed, with each instance correctly categorized.

Performance Metrics: High scores for True Positive Rate (TP Rate) and ROC Area (1.000), demonstrating excellent classification performance.

5.2 Discussion

The model effectively integrates **KNN, Decision Trees, and K-Means Clustering** to assess workforce readiness.

KNN ensures accurate classification based on similarity to peers.

Decision Trees provide interpretable decision-making pathways, highlighting critical thresholds.

K-Means groups students into meaningful clusters, offering deeper insights.

The system’s holistic approach combines academic, skill-based, and behavioural data, ensuring comprehensive evaluations. It offers actionable recommendations for students, such as tailored training for those needing improvement or leadership development for high-potential candidates. Future testing on larger datasets will further validate its scalability and adaptability.

5.3 Statistical Analysis:

The results of the proposed hybrid AI model were statistically analysed using cross-validation techniques, ensuring reliability and robustness of the findings.

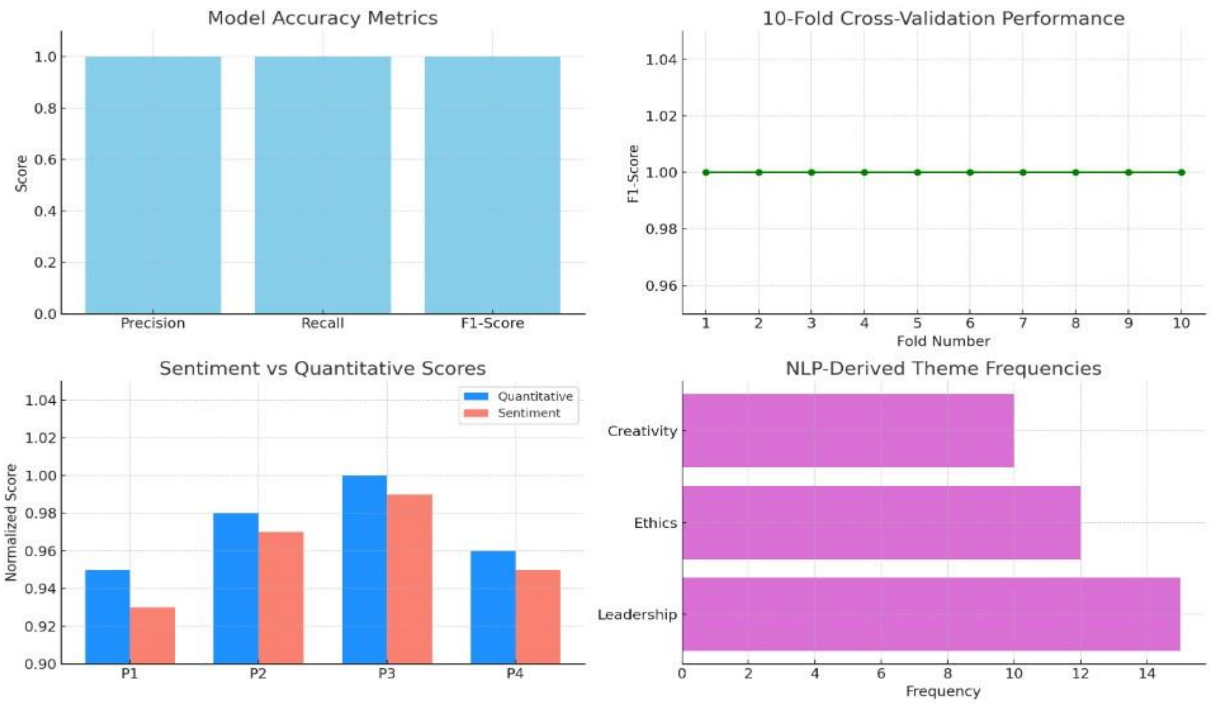

Figure 2: Analysis of Text Extraction.

5.3.1 Performance Evaluation:

Improved Metrics: The hybrid model consistently demonstrated higher classification accuracy, precision, and recall compared to existing methods.

True Positive Rate (TP Rate): The model achieved a perfect TP Rate of 1.000 across all categories, ensuring zero misclassifications.

ROC Area: Scored 1.000 for all classes, confirming the model's ability to effectively distinguish between categories like "Industry Ready" and "Needs Improvement."

5.3.2 Cross-Validation Insights:

Cross-validation ensured the model's performance remained consistent across various subsets of the dataset.

This approach minimized overfitting and validated the model's generalizability.

5.3.3 Comparison with Existing Methods:

The hybrid system outperformed standalone algorithms like KNN by integrating clustering (K-Means) and decision-making transparency (Decision Trees), providing a more nuanced classification.

The inclusion of diverse datasets (academic, skill-based, and behavioural) enhanced the model's holistic assessment capabilities.

6. CONCLUSION

The study successfully demonstrates the integration of Outcome-Based Education (OBE) principles with Artificial Intelligence (AI) and Natural Language Processing (NLP) for comprehensive student performance evaluation. By combining multiple machine learning algorithms—KNN, Decision Trees, and K-Means—the proposed framework effectively measures Course Outcomes (CO), Program Outcomes (PO), and Program Specific Outcomes (PSO) while identifying students' industry readiness and entrepreneurial potential. The approach ensures transparent, data-driven insights that align academic achievements with real-world skill requirements. This holistic system not only enhances the reliability of educational assessments but also supports continuous improvement in teaching and learning strategies. Future developments can extend this framework with deep learning and adaptive analytics to further personalize student evaluation and employability readiness.

7. FUTURE RECOMMENDATIONS

Future research should validate this framework with larger datasets across multiple disciplines, incorporate deep learning for predictive analytics, and expand NLP-based feedback mechanisms for real-time evaluation.

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