OBE Based Attainment Software for Educational Institutions

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Abstract: **The proposed OBE-Based Attainment System for Educational Institutions leverages Natural Language Processing (NLP) to automate the mapping of questions to predefined course outcomes. The system processes data from educational resources and analyzes input questions using keyword matching and proportional scoring. NLP algorithms are used to identify patterns and evaluate the relevance of questions to course objectives. A scoring mechanism allocates points based on match strength, providing insights into student performance and curriculum alignment. This system enhances accuracy in attainment measurement, reduces manual effort, and enables continuous improvement through automated feedback and performance analysis.**

Keywords: **OBE, Attainment System, NLP, Course Outcome Mapping, Automated Scoring, Performance Analysis**

I. INTRODUCTION

Outcome-Based Education (OBE) is a teaching approach that focuses on the attainment of pre-stated learning outcomes via systematic and specific teaching methodologies. In contemporary educational institutions, monitoring student performance in relation to such outcomes is important for measuring the efficacy of the learning process. Nevertheless, conventional outcome-tracking processes are frequently labour- intensive, time-consuming, and susceptible to error. The demand for an automated and efficient means has thus emerged to enhance the accuracy and credibility of outcome measurement.

The Attainment System envisioned here utilizes Natural Language Processing (NLP) to map questions on assessments to particular course learning outcomes automatically. Through question language and structure analysis, the system determines the associated learning outcomes and assesses students' performance in relation to these. Automation in this manner reduces the necessity for manual input, minimizes error, and delivers real-time feedback to both students and teachers.

In addition, the system is integrated with current Learning Management Systems (LMS) to provide smooth data flow and maximize performance monitoring. Teachers are able to track students' progress via customizable dashboards, determine where they need to improve, and modify teaching practices accordingly. The Attainment System supports data-driven decision- making, helping educational institutions learning outcomes and foster a more effective educational environment.

II. LITERATURE REVIEW

Existing research has attempted the application of NLP and AI on educational testing and OBE frameworks. Biggs (2001) proposed constructive alignment to enhance learning among students by harmonizing instruction and assessment practices. Gupta and Sharma (2018) utilized NLP for question classification with high accuracy but encountered scalability problems. Johnson and Brown (2020) employed NLP for automated grading with enhanced consistency but had difficulties with complex sentences.

Lee and Kim (2019) applied machine learning to predict outcomes for students with enhanced accuracy but limited generalizability. Patel and Wong (2021) integrated adaptive learning with OBE, maximizing engagement but encountering challenges in integration. Smith and Taylor (2022) designed an AI system for automated question mapping with enhanced accuracy but experiencing ambiguity problems. The system being proposed integrates NLP for question mapping and automatic performance analysis for the purpose of improving learning outcomes.

III. EXISTING SYSTEM

Instructors manually align questions to course outcomes, which is not only time-consuming but also subject to human error. This manual process makes it challenging to ensure consistency and accuracy in measuring student attainment.

Automated grading tools have been implemented to minimize human effort, but they tend to concentrate on marking alone and not necessarily on correct mapping of questions to individual learning outcomes. Outcome-based dashboards currently employed by educational institutions offer information about student performance but are not capable of incorporating NLP for automated question mapping.

Learning Management Systems like Blackboard and Moodle provide performance tracking and data management tools but lack the capability of automating question-to-outcome mapping through NLP. AI-based learning tools have been found to perform well in student performance analysis and outcome predictions, but they struggle to generalize across varying educational formats and with imprecise language.

The new system bridges such gaps by implementing NLP-based automated question mapping and live performance analysis. It increases the efficiency and precision of outcome-based measurement, enabling instructors to use evidence-based data in improving instructional strategy and student performance.

IV. METHODOLOGY

The development of the OBE-Based Attainment System involves several key phases to ensure accurate mapping of questions to Course Outcomes (COs) using NLP and real-time performance tracking.

1. Requirement Gathering:
Surveys and interviews with educators and stakeholders are conducted to identify specific needs and define key performance indicators (KPIs). This helps establish the learning objectives and the expected outcome mapping process.

2. System Design:
The system architecture is designed to include an automated data collection module, an NLP-based analysis engine, and a user interface for real-time feedback. Wireframes and prototypes are created to visualize the customizable dashboard for monitoring student performance.

3. Development:
The development phase follows an agile approach, allowing iterative progress and continuous feedback. The NLP engine is implemented to analyze and classify questions, and the data processing module is set up to automate score calculation and mapping to COs.

4. Testing:
Unit testing, integration testing, and user acceptance testing (UAT) are conducted to ensure the system functions correctly and meets user expectations. Feedback from educators and students is collected to refine the system.

5. Deployment:
The system is deployed in a pilot phase within selected educational institutions to evaluate real-world performance and usability. Training is provided to educators and students for effective use of the system.

6. Monitoring & Improvement:
The system is continuously monitored for performance and user engagement. Feedback and performance data are used to implement regular updates and improve the accuracy of question mapping and outcome tracking.

This structured methodology ensures that the system is accurate, scalable, and capable of providing real-time insights to improve student performance and teaching strategies.

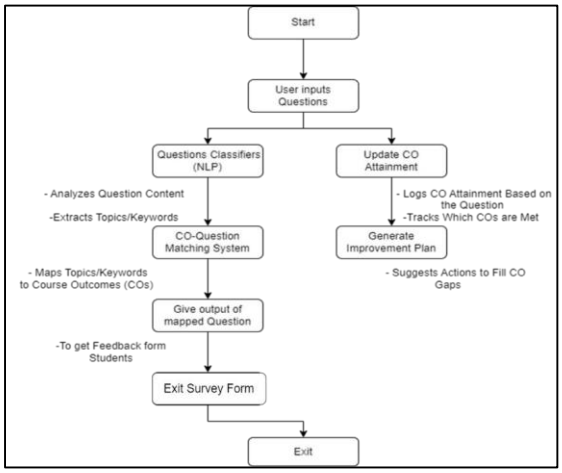


Fig. 1 Flow Chart

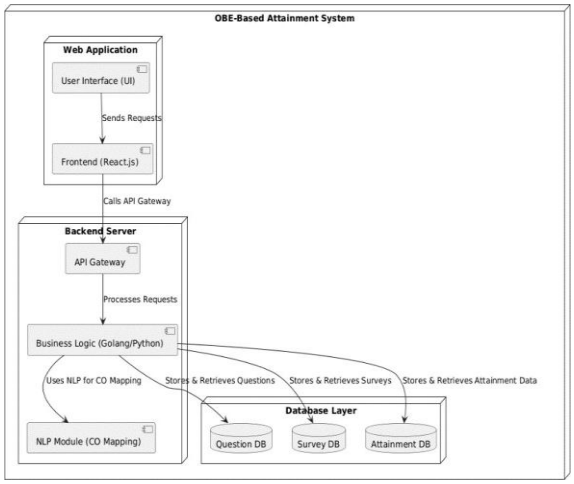


Fig. 2 System Architecture

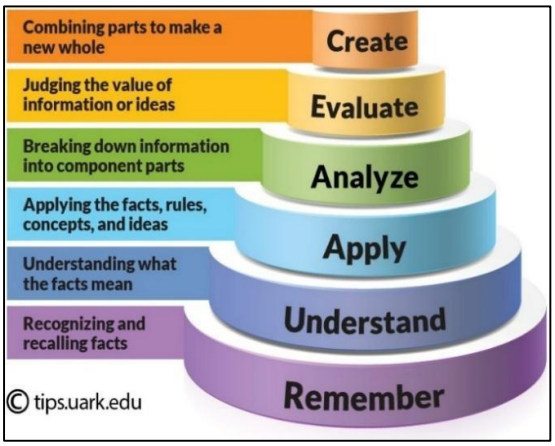


Fig. 3 Functionality of Bloom Taxonomy

V. RESULTS

Fig. 4 Landing Page

Fig. 5 Attainment Page

Fig. 6 Selection for Course, Paper set, Subject

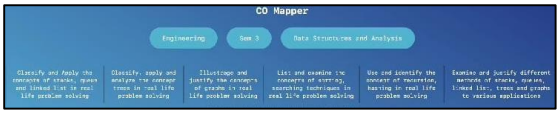


Fig 7 Shows COAs of a Subject

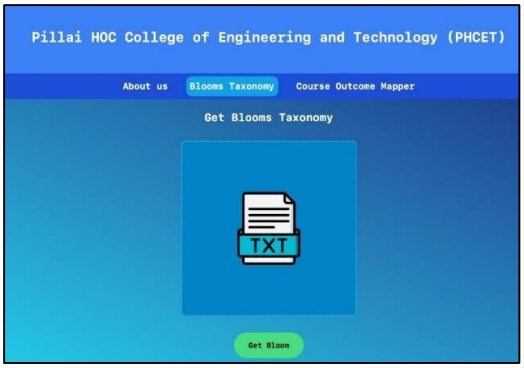


Fig 8 Blooms Taxonomy page

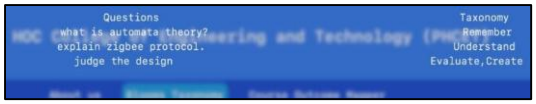


Fig 9 Question Mapping (Blooms):

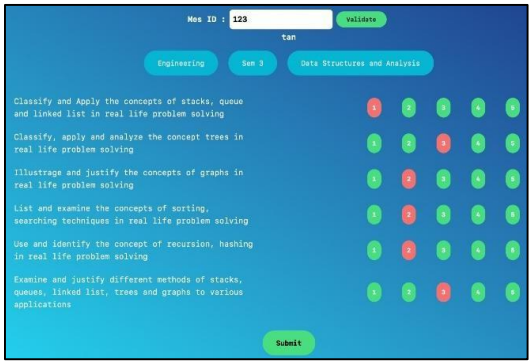


Fig 10 Student feedback Form

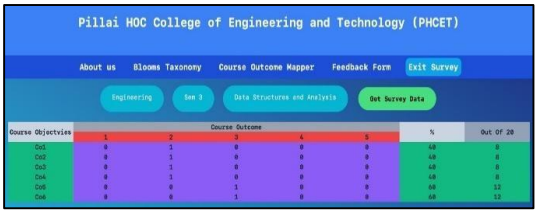
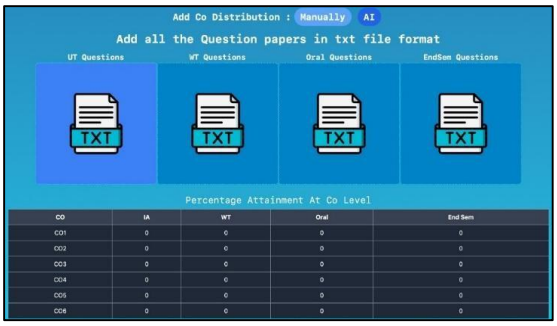


Fig 11 Student feedback

Name	IA Average (20)	TW (25)	Oral (25)	EndSem (80)
Yash Ghadve	17	24	20	60
Sujal Chourasya	20	20	20	40
Aryan Gharat	13	20	20	50
Omkar Gharat	15	22	19	39
Yash Yadav	18	24	20	40
Total number of Students present	5	5	5	5
Average marks	16.6	22	19.8	45.8
Average marks %	83	88	79.2	57.25

Fig 12 Student Marks



CO	IA	WT	Oral	End Sem
CO1	0	0	0	0
CO2	0	0	0	0
CO3	0	0	0	0
CO4	0	0	0	0
CO5	0	0	0	0
CO6	0	0	0	0

Fig 13 CO Tracking

Percentage Attainment At Co Level

CO	IA	WT	Oral	End Sem
CO1	8.300	10.560	15.840	10.734
CO2	12.450	10.560	15.840	10.734
CO3	12.450	17.600	9.504	10.019
CO4	12.450	17.600	9.504	8.588
CO5	16.600	14.080	12.672	8.588
CO6	20.750	17.600	15.840	8.888

Course Outcome	Indirect Measure	Direct Measure 80%					
		IA	TW	ORAL	ENDS	Direct Measurement	Total Attainment
% Weigtage	20	10.4	13.6	13.6	42.4	80	100
CO1	16	0.863	1.197	1.877	7.427	5.564	31.564
CO2	20	1.295	1.795	1.616	3.641	8.347	28.347
CO3	16	1.295	1.795	1.616	3.641	8.347	24.347
CO4	12	1.295	1.795	1.616	3.641	8.347	20.347
CO5	16	1.726	2.394	2.154	4.855	11.129	27.129
CO6	20	2.158	2.992	2.693	6.869	13.912	33.912

Fig 14 CO Tracking

VI. CONCLUSION

The proposed OBE-Based Attainment System leverages NLP to automate the mapping of questions to Course Outcomes (COs), improving the accuracy and efficiency of student performance evaluation. By reducing manual effort and providing real-time feedback, the system enhances the alignment of assessments with learning objectives. The integration with existing Learning Management Systems (LMS) ensures seamless data flow and effective tracking of educational outcomes. Continuous monitoring and updates based on user feedback enable the system to adapt to evolving educational needs, supporting data-driven decision-making and improving overall learning effectiveness.

VII. FUTURE SCOPE

The proposed OBE-Based Attainment System leverages NLP to automate the mapping of questions to Course Outcomes (COs), improving the accuracy and efficiency of student performance evaluation. By reducing manual effort and providing real-time feedback, the system enhances the alignment of assessments with learning objectives. The integration with existing Learning Management Systems (LMS) ensures seamless data flow and effective tracking of educational outcomes. Continuous monitoring and updates based on user feedback enable the system to adapt to evolving educational needs, supporting data-driven decision-making and improving overall learning effectiveness.

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