DAYANANDA SAGAR COLLEGE OF ENGINEERING

(An Autonomous Institute affiliated to Visvesvaraya Technological University (VTU), Belagavi,
Approved by AICTE and UGC, Accredited by NAAC with 'A' grade & ISO 9001-2015 Certified Institution)

Shavige Malleshwara Hills, Kumaraswamy Layout, Bengaluru - 560 111.

Department of Artificial Intelligence & Machine Learning

Project Synopsis

Title of the Project

Submitted by

Name: NAMRATHA USN: 1DS22AI026

Name: PUNITH G USN: 1DS22AI035

Name: SNEHA P PRATAP USN: 1DS22AI051

Name: T RAHUL PRABHU USN: 1DS22AI056

Under the Guidance of

Name: ANUPAMA V P Designation: Assistant Professor

1. Abstract

In the present higher education ecosystem, particularly under frameworks such as Outcome-Based Education (OBE) mandated by VTU and other accreditation bodies, the systematic monitoring of Course Outcomes (COs) and Program Outcomes (POs) is essential for ensuring quality and accountability in teaching–learning processes. Traditionally, this attainment analysis is performed manually by faculty using spreadsheets, where they record marks, map individual questions to corresponding outcomes, and calculate the percentage of students achieving threshold targets. While this approach satisfies regulatory requirements, it is labor-intensive, error-prone, and lacks the granularity to identify gaps at the level of specific modules, lab components, or individual students. As a result, faculty often receive feedback too late in the semester to take corrective actions, and students miss opportunities for timely interventions and skill development.This project aims to design and implement an intelligent, automated platform that overcomes these limitations by integrating three core components: (i) a CO/PO generation module that ingests diverse course materials such as textbooks, PPTs, Word documents, and PDFs, and synthesizes concise outcome statements aligned with Bloom's Taxonomy; (ii) an assessment ingestion pipeline that processes standardized Excel sheets of internal tests, assignments, and labs, where each question is tagged with relevant COs and POs; and (iii) a competency engine that computes both student-level and cohort-level attainment dynamically, enabling real-time analysis. The system further incorporates an adaptive recommendation engine, which generates balanced and personalized learning resources for all students, helping them strengthen weaker COs while reinforcing overall mastery.The expected outcome is a scalable, transparent, and data-driven framework that supports continuous improvement in pedagogy and student performance. Faculty benefit from actionable insights through dashboards highlighting attainment heatmaps and curriculum gaps, while students gain individualized feedback and resources for growth. By directly enhancing inclusivity, fairness, and effectiveness in higher education assessment, this project contributes to **SDG-4: Quality Education**, ensuring that learners not only meet regulatory benchmarks but also achieve deeper, sustainable competency development.

2. Introduction

The field of higher education is undergoing a paradigm shift from traditional, content-driven teaching to outcome-based education (OBE), where the focus lies on measurable skills, competencies, and performance of students. Under this framework, every subject is defined through **Course Outcomes (COs)**, which represent specific knowledge and skills students are expected to acquire, and **Program Outcomes (POs)**, which map to broader professional capabilities such as problem-solving, teamwork, communication, and ethical responsibility. Accreditation bodies such as NBA in India and ABET globally mandate CO/PO attainment analysis to ensure that higher education institutions deliver quality education aligned with industry and societal needs.

The importance of this problem is twofold. From an **industry perspective**, employers increasingly demand graduates who possess not only theoretical knowledge but also demonstrable competencies. From a **societal standpoint**, transparent and data-driven educational practices help guarantee that learners from diverse backgrounds receive equitable opportunities to develop essential skills. From a **research perspective**, automating and personalizing attainment analysis opens avenues for applying advanced methods such as Bayesian knowledge tracing, item response theory, and adaptive learning, thereby advancing educational data science.

Despite its importance, current practices in most universities remain **manual and fragmented**. Faculty rely heavily on spreadsheets, where marks are entered for tests, assignments, and lab exams. Each question is mapped to one or more COs and POs, and attainment is calculated against predefined thresholds. This process is error-prone, time-consuming, and limited in scope:

- **Granularity**: Attainment is often calculated only at the end of the semester, obscuring module-wise or student-wise gaps.

- **Timeliness**: Late detection of weaknesses prevents corrective action during the course.

- **Scalability**: Managing large datasets for multiple sections and subjects becomes overwhelming.

- **Personalization**: Existing systems lack mechanisms to recommend targeted resources to students.

Current trends in educational technology—such as intelligent tutoring systems, adaptive assessments, and analytics dashboards—highlight the growing role of automation and AI in bridging these gaps. However, few systems integrate **CO/PO generation, automated mapping, competency tracking, and personalized recommendations** into a unified solution tailored to Indian university frameworks like VTU. Addressing this limitation has direct relevance to improving educational quality, ensuring compliance with regulatory standards, and advancing **Sustainable Development Goal 4 (Quality Education)** by promoting inclusive, fair, and effective learning outcomes.

3. Problem Statement

Outcome-Based Education (OBE) frameworks demand that institutions systematically measure and demonstrate student attainment of **Course Outcomes (COs)** and **Program Outcomes (POs)**. While the principle is sound, the **current practice of attainment calculation is predominantly manual**, especially in universities following VTU regulations. Faculty typically depend on spreadsheets to enter student marks, map each question to relevant COs and POs, and compute attainment percentages based on threshold values. This process, though functional, suffers from several limitations that hinder its effectiveness and scalability.

The core issue lies in the **lack of automation, granularity, and adaptability** in existing systems. Attainment data is usually compiled only at the end of the semester, providing a **cumulative picture** but failing to identify **module-level weaknesses** or **student-specific gaps** in learning. Consequently, corrective actions such as remedial classes, targeted practice, or curriculum adjustments are delayed, limiting their impact. Furthermore, the reliance on manual entry introduces a high risk of **human error** in mapping, calculation, and reporting, reducing the reliability of the results.

Another significant gap is the **absence of intelligent support systems**. Current spreadsheet-based approaches cannot dynamically analyze patterns, highlight critical trends, or provide **personalized recommendations** to students. Neither do they empower faculty with actionable insights such as heatmaps of weak modules, attainment progress over time, or curriculum-level gaps. While educational technologies exist in the market, most are either too generic or misaligned with the **CO/PO-specific compliance requirements of Indian accreditation systems**.

In summary, the problem is that **existing attainment tracking methods are manual, error-prone, delayed, and non-personalized**, creating barriers to timely intervention and continuous improvement in teaching and learning. The gap lies in the absence of a unified, automated system that integrates **CO/PO generation, mapping, attainment computation, and recommendation** into a seamless workflow. Addressing this gap is essential to support faculty, empower students, and strengthen institutional compliance with OBE, thereby contributing to **quality education at scale**.

4. Objectives of the Project

The project aims to build an intelligent and automated system to simplify and enhance the CO/PO attainment process in higher education. The objectives are as follows:

- **Objective 1: Design an automated framework for CO/PO generation and mapping**
  The first objective is to design a module capable of extracting and summarizing course content from different file formats such as PDFs, Word documents, and PPTs. This module will generate concise Course Outcomes (COs) and Program Outcomes (POs), ensuring that they are clear, measurable, and aligned with Bloom's Taxonomy. Additionally, the system should support the mapping of examination and laboratory questions to corresponding COs/POs, thereby minimizing manual effort and ensuring consistency across assessments.

- **Objective 2: Develop and implement a competency engine for attainment analysis**
  The second objective is to build a computational engine that processes student assessment data from Excel sheets. This engine will calculate attainment levels at multiple dimensions — per module, per student, and overall — by aggregating data across tests, assignments, and laboratory evaluations. The system will also handle edge cases, such as unattempted questions, while maintaining accuracy and transparency in the calculations.

- **Objective 3: Analyze attainment gaps and implement an adaptive recommendation system**
  The third objective is to analyze attainment outcomes to identify gaps at both the individual and class level. Based on these insights, a recommendation module will provide targeted suggestions, such as practice exercises, additional study resources, or remedial modules. This ensures timely intervention for students and helps faculty make informed instructional adjustments.

- **Objective 4: Develop faculty dashboards and institutional reporting tools**
  The fourth objective is to design dashboards and reporting modules that visualize attainment trends, heatmaps of weak modules, and student performance distribution. This provides faculty and administrators with actionable insights, supports evidence-based decision-making, and simplifies compliance with accreditation requirements.

Together, these objectives establish a comprehensive, data-driven system that strengthens both the teaching–learning process and institutional outcome monitoring.

5. Scope of the Project

The scope defines the boundaries of the project by clearly describing what the system will accomplish, what it intentionally excludes, and the potential domains where it can be applied. Establishing this scope ensures focused development, avoids scope creep, and highlights the relevance of the solution to real-world educational challenges.

5.1 What the Project Will Cover

1. **Automated CO/PO Generation and Mapping**
   The project will include mechanisms to extract content from course materials such as syllabi, lecture notes, PPTs, and reference documents. Using summarization techniques, it will generate concise and measurable Course Outcomes (COs) and Program Outcomes (POs). These outcomes will be aligned with Bloom's Taxonomy levels, ensuring that they represent varying cognitive skills. Furthermore, the system will support the mapping of assessment questions (internal exams, labs, assignments) to the respective COs and POs, reducing the manual burden on faculty and ensuring consistent compliance with OBE practices.

2. **Assessment Data Processing**
   A critical component of the scope is the ingestion of Excel-based student performance data. Each assessment question will already be tagged with relevant CO/PO identifiers. The system will read this dataset, process student scores, and prepare structured inputs for attainment calculations. It will standardize the processing across multiple exams, lab evaluations, and assignments, ensuring consistency across diverse assessment types.

3. **Competency Engine and Attainment Calculations**
   The scope includes building a robust computational engine capable of calculating attainment at multiple levels. This involves module-wise attainment (per unit/topic), student-level attainment (personal performance against defined COs), and overall course-level attainment (aggregated scores). The system will also handle special cases, such as students not attempting certain questions, by assigning appropriate values (e.g., treating them as zero). Such automation ensures accuracy, fairness, and repeatability of results.

4. **Recommendation and Feedback System**
   The project will cover an adaptive recommendation engine that uses calculated results to highlight learning gaps. Students will receive targeted resources, such as remedial exercises or suggested readings, while faculty will gain insights into weak modules and recurring difficulties across the cohort. This feature aims to improve learning outcomes by providing actionable feedback during the course rather than after it ends.

5. **Visualization and Reporting Tools**
   The scope also includes dashboards and reporting features for faculty and administrators. These will present performance data through visualizations such as attainment graphs, heatmaps of weak areas, and progress trends. Additionally, downloadable reports will support evidence-based decision-making and facilitate compliance with accreditation bodies that require CO/PO attainment documentation.

5.2 What the Project Will Not Cover

1. **Creation of Teaching Content or Question Banks**
   The system will not generate full-fledged lecture notes, textbooks, or question banks. Its role is limited to outcome generation and mapping, not complete content authoring.

2. **Integration with External LMS Platforms**
   While the system will process assessment data from Excel and internal tools, it will not integrate directly with third-party Learning Management Systems such as Moodle, Blackboard, or Canvas in this phase.

3. **Advanced Predictive Analytics**
   Although the system will provide recommendations, it will not perform complex predictive modeling such as dropout prediction, employability forecasts, or long-term performance predictions.

4. **Full Accreditation Workflow Automation**
   The project will assist accreditation indirectly through reports but will not automate the end-to-end process of accreditation documentation and submission.

5.3 Possible Application Domains

1. **Universities and Colleges** – Institutions can use the system to streamline CO/PO mapping and attainment analysis across courses, reducing faculty workload and improving consistency in reporting.

2. **Faculty Development Centers** – Trainers and educators can use the system to demonstrate OBE practices and train faculty in outcome-based pedagogy.

3. **Skill Development Institutes** – Vocational and professional training centers can apply the system to track competencies in practical and applied domains.

4. **Educational Data Analytics Research** – Researchers can use the system as a foundation to experiment with adaptive learning, data-driven assessments, and educational data mining.

6. Proposed Methodology

The project methodology is designed to replace the manual CO/PO attainment process with an automated, intelligent, and scalable system. The approach integrates Natural Language Processing (NLP), structured data ingestion, outcome mapping, and competency modeling. The methodology can be divided into the following components:

6.1 Techniques, Algorithms, and Models

1. Document Processing & CO/PO Generation

- **Techniques:**
  - OCR for scanned PDFs
  - NLP-based keyword extraction
  - Clustering and summarization
- **Models:**
  - Transformer-based summarization models (BART, T5) to convert course materials into concise CO/PO statements
  - Bloom's Taxonomy classifier (rule-based + ML) to assign appropriate cognitive levels
- **Goal:**
  Convert raw syllabus/teaching material into **5–7 Course Outcomes (COs)** and **8–11 Program Outcomes (POs)** per course.

2. Data Ingestion & Mapping

- **Techniques:**
  - Parsing Excel/CSV sheets using Python's **pandas** and **openpyxl**
- **Mapping:**
  - Each question tagged to COs/POs
  - Data normalized across modules, labs, and assignments
- **Goal:**
  Ensure uniform, structured input for downstream calculations.

3. Competency Engine (Attainment Calculation)

- **Techniques:**
  - **Rubric Evaluation** – fixed thresholds (e.g., 60%) for attainment
  - **Bayesian Knowledge Tracing (BKT)** – probabilistic modeling of mastery at the module level
  - **Item Response Theory (IRT)** – weighting based on difficulty of questions
- **Goal:**
  Generate both **student-level mastery** and **cohort-level attainment metrics**.

4. Recommendation Module

- **Techniques:**
  - **Rule-based recommendations** – e.g., if student < threshold in CO, suggest remedial modules
  - **Multi-armed bandit / Reinforcement Learning (future scope)** – adaptive learning exercises
- **Goal:**
  Provide **personalized student feedback** and **faculty teaching improvement suggestions**.

5. Visualization & Dashboards

- **Techniques:**
  - Interactive dashboards
  - Heatmaps and radar charts
- **Frameworks:**
  - **Frontend:** React.js
  - **Charts:** Recharts, D3.js
  - **Backend:** Flask / FastAPI APIs
- **Goal:**
  Present insights for **students, faculty, and accreditation compliance bodies**.

6.2 Tools, Frameworks, and Technologies

- **Programming Languages:** Python (backend, NLP), JavaScript/TypeScript (frontend)
- **Frameworks:** React.js (UI), Flask/FastAPI (API), TensorFlow / PyTorch (ML)
- **Libraries:** Pandas, NumPy, OpenPyXL (Excel parsing), NLTK, Spacy, HuggingFace Transformers (NLP)
- **Databases:** PostgreSQL (structured data), MongoDB (optional – unstructured logs)
- **Cloud Services:** Google Cloud Storage (document storage), Vertex AI (ML hosting)
- **Visualization:** Recharts, D3.js, Plotly
- **Deployment:** Docker (containerization), Kubernetes (scaling and orchestration)

6.3 Workflow / Architecture (Step-by-Step)

1. Input Stage

- Course materials (PDF, Word, PPT) → Processed by **NLP engine** to generate COs & POs
- Assessment results (Excel) → Standardized by **data ingestion pipeline**

2. Processing Stage

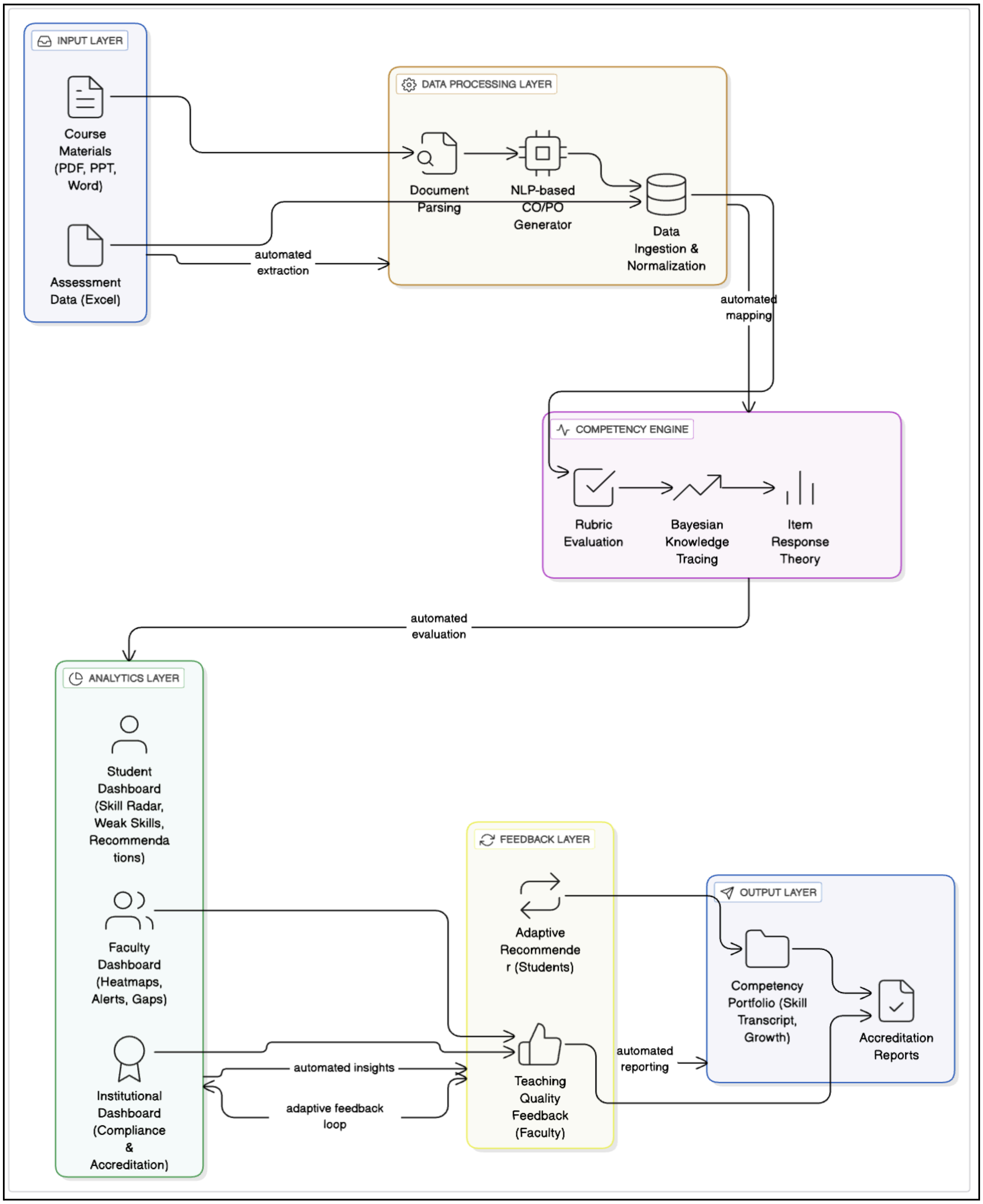
- **Mapping engine** links: Question → CO/PO → Module
- **Competency engine** applies attainment calculations (Rubric, BKT, IRT)

3. Analytics & Feedback Stage

- **Student Dashboard:** Skill radar, weak areas, personalized recommendations
- **Faculty Dashboard:** Heatmaps of CO/PO attainment, curriculum gaps
- **Admin Dashboard:** Accreditation-ready reports and summaries

4. Output Stage

- **For Students:** Personalized skill transcripts & growth trajectory
- **For Faculty:** Feedback for improving teaching quality
- **For Institutions:** Accreditation compliance dashboards



7. Expected Outcomes / Deliverables

1. **Automated CO–PO Mapping**
   The system automates the mapping of Course Outcomes (COs) to Program Outcomes (POs) by analyzing question papers, lab assessments, and learning materials. This reduces manual effort and ensures consistency in outcome mapping.

2. **Centralized Data Integration**
   Question papers, lab records, and assessment scores from multiple formats (PDF, Word, PPT, Excel) are standardized and merged into a single system, enabling seamless data handling across courses and modules.

3. **Dynamic Attainment Calculation**
   The model computes CO and PO attainment dynamically based on assessment results (internals, labs, and final exams). Complex calculations are automated, minimizing human error and ensuring transparency.

4. **Granular Student-Level Insights**
   The system not only evaluates course-level attainment but also generates student-level analytics, helping identify individual learning gaps and suggesting areas for improvement.

5. **Module-Wise and Lab-Specific Evaluation**
   CO attainment is tracked per module, while labs are evaluated with a slightly different strategy but still integrated into the same framework for balanced results.

6. **Skill Development and Feedback**
   By analyzing student performance against COs and POs, the system provides actionable insights for both learners and instructors, ultimately improving skills and course outcomes.

7. **Scalability and Reusability**
   The framework is designed to be flexible and scalable, making it applicable across multiple courses, batches, and departments with minimal modification.

8. **Enhanced Quality Assurance**
   The automated and data-driven approach ensures compliance with academic accreditation standards (like NBA/NAAC) while improving the overall quality of education delivery.

8. Significance / Applications

The proposed system holds substantial significance by addressing one of the most pressing challenges in higher education: the manual and error-prone process of **CO–PO mapping and attainment analysis**. Traditionally, faculty members spend hours compiling assessment data, mapping questions to outcomes, and calculating attainment levels. This process not only consumes valuable academic time but also risks inconsistencies and inaccuracies. By automating this workflow, the system reduces **manual workload**, enhances **accuracy**, and allows **real-time analysis** of student performance across both theory and laboratory components.

Academically, the project advances the implementation of **Outcome-Based Education (OBE)** by seamlessly integrating assessment, mapping, and attainment within a single automated pipeline. This ensures transparent and evidence-based evaluation while also enabling **student-level insights**. Such granular feedback supports **individualized teaching strategies**, curriculum refinement, and targeted interventions for weak learners. The project, therefore, strengthens the reliability of OBE practices while also contributing to research in data-driven education analytics.

From an industrial and commercial perspective, the system demonstrates strong potential as an **educational technology solution**. It can streamline accreditation processes such as **NBA/NAAC compliance**, provide universities with institutional-level dashboards, and assist training organizations in monitoring competence development. Moreover, its adaptability allows it to be applied in **corporate training ecosystems**, where outcome-based evaluation is essential for workforce development and upskilling.

At a societal and environmental level, the system promotes **quality education and lifelong learning** by aligning academic assessments with industry-relevant competencies. It further supports sustainability by reducing dependence on paper-based assessments and administrative documentation, thereby conserving resources and minimizing environmental impact.

In essence, the significance of this project lies in its ability to **bridge academic rigor, technological innovation, industrial applicability, and societal responsibility**—delivering a comprehensive solution that strengthens education systems while promoting sustainable practices.

9. Literature Survey

National Papers Reference

Sl #	Paper Title	Author details	Year	Methodology	Limitations
1	Automating Outcome Based Education for the Attainment of Course and Program Outcome*s*	Rajak, Shrivastava (conference/technical report record)	2018–2020 (conf/rep)	Algorithmic automation of CO/PO attainment calculation; spreadsheet-to-algorithm conversion and rule-based mapping. (Semantic Scholar)	Focus on automating calculation rules; limited NLP for CO generation; limited handling of student-level, module-wise personalization.
2	Automated Mapping of Course Outcomes to Program Outcomes using NLP & ML	Conference paper (authors vary) — ASPCON/IEEE workshop entry	2023	NLP pipeline to match course learning outcomes to program outcomes using embeddings and classifier. (ResearchGate)	Requires high-quality CO text; mapping confidence variable; human review still needed.
3	Automated Learning Outcome Extraction Systems (ALOES)	Indian research group (ResearchGate entry)	2021–2022	Syllabus parsing + extraction using keyword/NER + rule-based summarization. (ResearchGate)	Works best on well-structured syllabi; struggles with noisy slides and varied formats; limited evaluation on large curricula.

4	Outcome-based Education: Calculating Attainment of Programme Outcome through Course Outcome	Institutional study / whitepaper	2023	Spreadsheet-based formalization with algorithmic steps to compute CO→PO attainment. (ResearchGate)	Mostly formalization of existing practice; limited automation of ingestion or NLP generation.
5	Automating the Mapping of Course Learning Outcomes to Program Learning Outcomes using NLP for Accurate Program Evaluation	Regional conference / research group	2022–2023	NLP similarity measures + validation pipeline for mapping LO→PO. (ResearchGate)	Evaluation mainly on small datasets; does not integrate assessment ingestion or recommendations.
6	Automated Extraction of Learning Goals and Objectives from Syllabi (LDA + Neural Nets)	Indian academic preprint	2019	Topic modeling (LDA) + neural summarizer to extract learning goals. (Academia)	LDA coarse topics can miss fine-grained outcomes; heavy manual cleanup recommended.
7	Use of IRT/Statistical methods for attainment (regional study)	Institutional case studies (India)	2018–2022	Applies IRT/statistics to analyze question difficulty and student ability for program reports. (ResearchGate)	Requires large item-response datasets; many institutions lack sufficient data volume.

8	Practical approaches to OBE attainment automation (seminar report)	College-level implementation report	2020–2022	Spreadsheet macros + semi-automated scripts to compute CO/PO attainment, with manual overrides.	Practical but ad-hoc; not standardized or generalized across institutions.
9	AI-assisted learning objective authoring (GPT-based evaluation — regional)	Indian researchers evaluating transformers for LOs	2023	Uses GPT-family models to generate learning objectives and compare to human LOs. (arXiv)	LLM outputs need human curation; risk of phrasing mismatch with institutional templates.
10	Case study: Automating attainment calculation in VTU-style curricula	Departmental project report (VTU college)	2021	Mapping + scripted aggregation to produce attainment dashboards (local).	Scope limited to single college; lacks generalizable CO/PO NLP module.

International Paper Reference

Sl #	Paper Title	Author details	Year	Methodology	Limitations
1	An Introduction to Bayesian Knowledge Tracing with pyBKT	O. Bulut et al. (MDPI)	2023	Tutorial & application of BKT for student knowledge-state estimation; includes pyBKT usage. (MDPI)	BKT assumes binary correctness and independent skills; limited to per-skill models.

2	*BKT-LSTM: Efficient Student Modeling for Knowledge Tracing*	Sein Minn (arXiv)	2020	Hybrid BKT + LSTM model combining interpretability with sequence modeling. (arXiv)	Increased complexity; needs more compute and careful tuning.
3	*Back to the Basics: Bayesian extensions of IRT outperform neural nets*	Wilson et al.	2016	Compares Bayesian IRT variants vs DKT; hierarchical IRT showed strong performance and interpretability. (arXiv)	IRT needs strong item calibration and sufficient data per item.
4	*GIKT: Graph-based Interaction Model for Knowledge Tracing*	Yang et al.	2020	Graph-based model incorporating question–skill relations using GCNs for KT. (arXiv)	High model complexity; data-hungry; interpretability reduced compared to BKT/IRT.
5	*Predictive, scalable and interpretable knowledge tracing on structured domains (PSI-KT)*	Zhou et al.	2024	Hierarchical Bayesian KT combining interpretability and scalability. (arXiv)	New model — requires careful hyperparameter and domain mapping.
6	*Comparing prediction performance of IRT vs other methods*	Park et al. (PLoS/PMC)	2022	Empirical comparison of IRT/explanatory IRT vs ML methods for prediction. (PMC)	Domain-specific; performance depends on dataset characteristics.

7	*Automated Learning Outcome Extraction Systems*	International review / systems paper	2021	Reviews methods (LDA, NER, transformer summarizers) for LO extraction. (ResearchGate)	Many systems evaluated on small corpora; generalization unclear.
8	*Automating Mapping of Course LOs to PLOs using NLP*	International conference paper	2022–2023	Embedding-based similarity + classifier for LO→PLO mapping. (ResearchGate)	Needs human-in-the-loop for final validation.
9	*Using GPT-4 to Support Authoring of Learning Objectives*	Sridhar et al. (arXiv)	2023	Empirical evaluation of GPT-4 for LO generation—quality comparisons to human-authored LOs. (arXiv)	LLM hallucination risk; require faculty review and institutional style alignment.
10	*AI-based learning content generation and personalization*	Diwan et al. (ScienceDirect)	2023	Generates auxiliary content fragments and weaves into learning pathways. (ScienceDirect)	Content quality varies; human curation needed; ethical considerations for generative AI.
11	*Automated Extraction of Learning Goals from Syllabi (LDA + neural nets)*	International preprint	2019	Topic modeling + neural summarization pipeline. (Academia)	Topic models coarse; needs dataset-specific tuning.

12	*Parametric Constraints for BKT from First Principles*	Shchepakin (arXiv)	2023	Theoretical constraints for BKT parameter space improving identifiability. (arXiv)	Theoretical; requires empirical validation in real course data.
13	*Fairness Evaluation with Item Response Theory*	Xu et al. (arXiv)	2024	Investigates fairness and bias using IRT frameworks. (arXiv)	Focus on fairness metrics; needs curricular/ethnic/linguistic covariates for full assessment.
14	*Comparative study: IRT in educational assessment*	Research overview	2015–2022	Review and case studies on IRT application for tests/assessments. (ResearchGate)	Emphasizes need for calibrated items and large samples.
15	*DKT and modern knowledge tracing models comparisons*	Multiple authors (review/arXiv)	2018–2023	Compares deep KT (DKT, DKT-LSTM, GIKT) vs classical models; notes trade-offs. (arXiv)	Deep models achieve high accuracy but reduce interpretability and increase data needs.

The novelty of this project lies in automating CO–PO mapping and attainment analysis, removing reliance on manual, error-prone spreadsheets. Using natural language processing for outcome generation and advanced models like Bayesian Knowledge Tracing and Item Response Theory.the system enables precise and dynamic evaluation. Interactive dashboards provide clear insights for students, faculty, and institutions, while coverage of both theory and lab components ensures holistic assessment.With accreditation-ready reporting and adaptive feedback, the system offers a unified, intelligent, and scalable improvement over conventional Outcome-Based Education practices.

10. Work Plan / Timeline & Finances:

Phase	Task	Duration	Deliverables
Phase 1	Literature survey & problem finalization (review CO/PO mapping practices, OBE methodology, Bloom's taxonomy, existing automation tools)	2 weeks	Survey report with problem definition
Phase 2	Design & methodology development (system architecture, database schema, NLP/ML pipeline design, CO/PO generation method, competency engine design)	3 weeks	System design document & methodology framework
Phase 3	Implementation & testing (file ingestion, Excel parser, CO/PO generator, competency engine, recommendation engine, dashboards, manual overrides, testing on sample datasets)	6 weeks	Functional prototype & preliminary results
Phase 4	Evaluation & documentation (run on multiple courses, validate results with faculty, fine-tune formulas, prepare final documentation, report & presentation)	3 weeks	Final report & demonstration system

Estimated Expenditure :

Sl. No	Description	Amount (INR)
1	Hardware (laptop/desktop upgrades, GPU access if needed for embeddings/LLMs)	N/A
2	Software & Cloud Expenditures (Google Cloud SQL, Cloud Storage, Vertex AI APIs, Vector DB, Streamlit/React hosting)	4500-5000
3	Printing & Stationery	600-800
4	Miscellaneous	100-200
Total		5200-6000 INR

11. Resources Required

Hardware: Laptop/desktop with minimum 16 GB RAM, i5/i7 processor; optional GPU for faster embeddings/LLM tasks.

Software: Python (pandas, scikit-learn, langchain), PostgreSQL/MySQL, React, Google Cloud/AWS services.

Dataset: Course materials (PDF, Word, PPT), Excel assessment sheets (AAT, CIE, Labs, SAE), reference library.

Special lab requirements (if any): Cloud credits, departmental server access for deployment/testing.

12. References

- [1] Katona, Jozsef & Katonane Gyonyoru, Klara Ida, “Integrating AI-based adaptive learning into the flipped classroom model to enhance engagement and learning outcomes,” Computers and Education: Artificial Intelligence, 2025.

- [2]J. Smith, A. Brown, “Competency-based assessment tools for engineering problem-solving in higher education,” Cogent Education, 2024.

- [3]E. Castelló, J. García-Martínez, A. Valls, “Towards competency-based education in the chemical engineering degree,” Education for Chemical Engineers, 2023.

- [4] N.P. Subheesh, “Learning through Assessment and Feedback Practices: A critical review of engineering education literature,” EURASIA Journal of Mathematics, Science and Technology Education, 2020.

- [5] K. Mahboob, V. Venkatasubramanian, “Investigating learning outcomes in engineering education using a data-driven approach,” Computer Applications in Engineering Education, 2020.