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# Long-Term Effects Of AI-Personalized Learning On Engagement And Performance.

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***Abstract:***
***Artificial Intelligence (AI)*** *has significantly advanced personalized learning by customizing educational content to meet the unique needs of 306 students. This study explores the long-term impact of AI-driven personalized learning systems on student engagement and academic performance. Utilizing extensive datasets and advanced machine learning techniques—specifically* ***J48*** *for classification and* ***K-Means*** *for clustering—the research offers valuable insights into optimizing education through AI. The methodology emphasizes ethical AI implementation, adherence to data privacy standards, and fairness. The results, validated using diverse student data, support the development of a scalable, inclusive AI framework for future educational environments.*
***Keywords***: *Artificial Intelligence, personalized learning, student engagement, academic performance, data privacy, scalable education, ethical AI*

## 1. INTRODUCTION

Artificial Intelligence (AI) enhances the educational landscape through adaptive learning systems that customize instruction based on individual student behaviour, preferences, and academic history. By leveraging data-driven methodologies, AI enhances content delivery, facilitates personalized knowledge acquisition, and supports continuous performance monitoring [1]. These innovations are evident in a range of educational technologies, including Intelligent Tutoring Systems (ITS), AI-enabled writing assistants, and predictive analytics platforms[11]. While existing systems have demonstrated success in improving short-term learning outcomes and responsiveness, there remains a critical gap in understanding their **long-term effects**—particularly in relation to **sustained academic performance**, **student engagement**, and the **ethical deployment** of AI in diverse learning contexts. This research addresses that gap by evaluating the longitudinal impact of AI-enabled personalized learning frameworks, with a strong focus on ethical principles such as fairness, transparency, and compliance with data privacy standards[12].

### 1.1 Existing Systems and Validation Approaches

Contemporary AI models in education often rely on **supervised learning algorithms** for tasks such as performance classification and personalized content recommendation[13]. Algorithms like **Random Forest**, **Gradient Boosting**, and **Neural Networks** are frequently validated using cross-validation techniques and tested across varied datasets. Despite their high predictive[14] accuracy, a key limitation remains: **generalizability** across diverse socio-demographic student populations. This study incorporates **ensemble learning methods** to improve model robustness, mitigate overfitting, and support scalable deployment in real-world educational settings.

### 1.2 Dynamic Data Handling

AI-powered systems dynamically process evolving student data streams, including attendance records, assessment scores, and behavioural indicators. Real-time data ingestion and analysis enable timely, adaptive interventions and feedback. Techniques such as **time-series forecasting** are utilized to monitor academic trends and predict future outcomes, fostering a more responsive and proactive learning environment.

### 1.3 Feature Expansion

To enhance model accuracy and fairness, this research integrates a broader set of contextual variables—such as **socio-economic status**, **extracurricular participation**, and **learning environment conditions** [2][3]. This enriched feature set enables a more comprehensive understanding of student profiles. Additionally, **longitudinal data tracking** supports the evaluation of long-term learning trajectories and the sustained effectiveness of AI interventions.

### 1.4 Ethical AI Practices

Given the growing concerns around **algorithmic bias**, **transparency**, and **data misuse**, this study implements a suite of ethical safeguards. These include **bias mitigation techniques** and strict adherence to global and national data protection frameworks, such as the **General Data Protection Regulation (GDPR)** and **India's Digital Personal Data Protection (DPDP) Act**. These measures ensure that AI applications in education are transparent, accountable, and equitable for all learners.

**1.5 Machine Learning Models**

**J48 (Decision Tree Algorithm)**

- **Learning Type**: Supervised
- **Purpose**: Classification
- **Basis**: C4.5 algorithm
- **Mechanism**: Constructs decision trees by selecting attributes that maximize information gain and minimize entropy.
- **Platform**: Commonly implemented using Weka
- **Advantages**: Interpretable, supports both categorical and continuous variables

**K-Means (Clustering Algorithm)**

- **Learning Type**: Unsupervised
- **Purpose**: Clustering
- **Mechanism**: Segments data into *K* clusters by minimizing intra-cluster distance from the centroid
- **Requirement**: Predefined *K* value
- **Advantages**: Fast, scalable for large datasets

**1.6 Feedback Systems**

The proposed framework integrates **interactive real-time dashboards** that provide actionable insights to students, educators, and parents. These dashboards enable **bidirectional feedback**, allowing users to influence system decisions and tailor interventions accordingly. This feedback mechanism significantly enhances system adaptability and personalization, contributing to better learning outcomes.

**Research Objectives**

This study is structured around the following core objectives:

- To analyse the **long-term impact** of AI-driven personalized learning on **student engagement** and **academic performance**.
- To design and compare **machine learning models**, specifically **J48** and **K-Means**, for classification and clustering in educational data.
- To address **ethical, legal, and practical challenges** in the deployment of AI in real-time learning environments.
- To develop a **scalable**, **inclusive**, and **feedback-driven AI framework** aligned with **Outcome-Based Education (OBE)** principles to support diverse learner needs.

## 2. LITERATURE REVIEW

The integration of artificial intelligence (AI) into education has significantly advanced personalized learning, intelligent tutoring systems (ITS), and adaptive learning environments. This section synthesizes key studies highlighting the transformative role of AI-driven technologies in modern educational practices, with particular emphasis on ITS, AI-powered writing tools, machine learning applications, and ethical considerations.

Abu Ghali et al. (2018) developed an ITS for English grammar instruction, illustrating improved student engagement and comprehension through AI-based tutoring. Holmes et al. (2019) underscored the potential of AI in education while advocating for responsible implementation to ensure inclusivity and fairness. Bin and Mandal (2019) demonstrated AI's adaptability in English language teaching, enabling instruction tailored to individual learner needs. Jain and Alam (2020) compared AI-driven instruction with human teaching, highlighting both ethical concerns and the limitations of AI in replicating human interaction. Klamma et al. (2020) explored the scalability of AI-based mentoring, positioning ITS as a means to broaden educational access. Fitria (2021a, 2021b) examined AI-powered writing assistants like Grammarly and QuillBot, showing their effectiveness in enhancing writing skills through grammar correction and paraphrasing support. Ahmad et al. (2023) reviewed data-driven AI applications, emphasizing the optimization of learning processes via machine learning algorithms. Guleria and Sood (2023) focused on explainable AI, emphasizing the need for transparency in educational decision-making systems.

## 3. Data Collection:

Key attributes include age, class, academic performance, aptitude, behaviour, skill assessments, and leadership abilities and total numbers 306.

### 3.1Key Processes:

- Data Understanding and Preprocessing
- Classification
- Model Training and Evaluation
- Performance Prediction and Fine-Tuning

## 4. METHODOLOGY

### 4.1Machine Learning Techniques:

**The J48 Algorithm is employed for classification and prediction**.

The J48 Algorithm, an implementation of the C4.5 decision tree classifier, is widely used for classification and predictive modelling. It builds decision trees by selecting attributes that best split the data using information gain and entropy-based measures. The algorithm handles missing values, performs pruning to reduce overfitting, and generates human-readable decision rules. Due to its efficiency and interpretability, J48 is commonly applied in AI-driven education systems, student performance analysis, and various machine learning tasks.

- **Data is processed using the Weka tool for improved efficiency.**

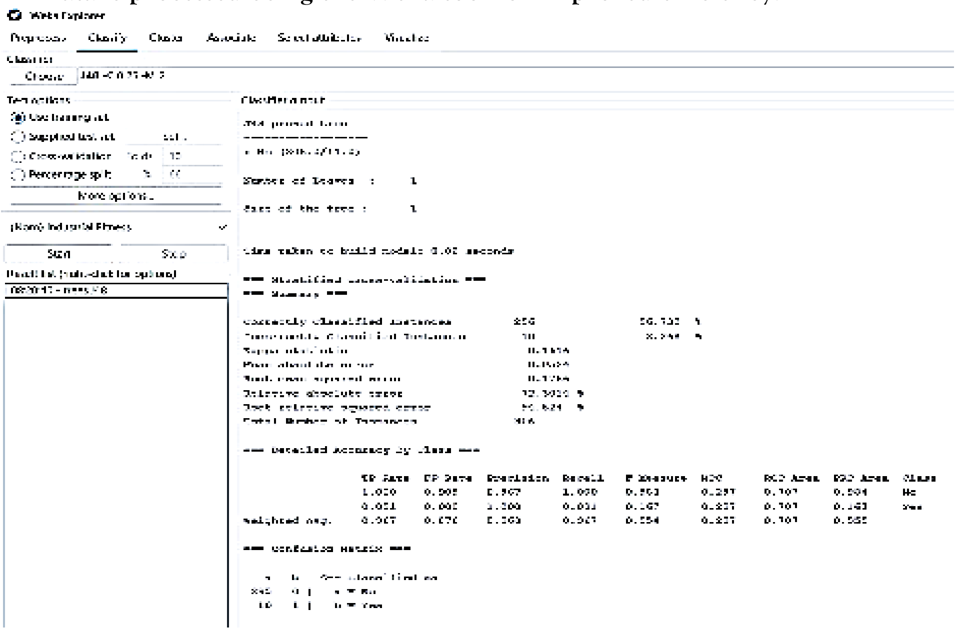

**Figure 1: J48 Decision Tree Screenshot (Weka Tool)**

### 4.2Proposed AI Architecture:

- A dynamic and real-time data handling approach is implemented.
- K-means clustering is used for performance analysis.

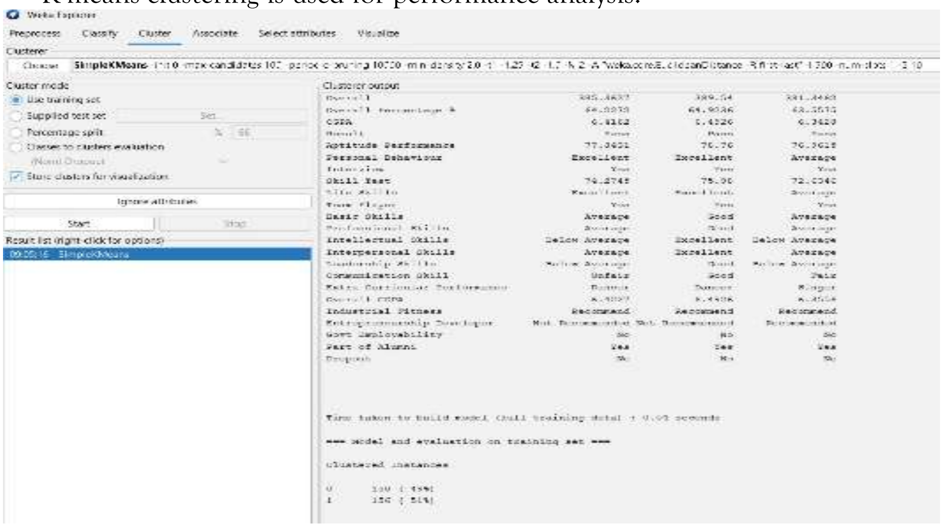


Figure 2 : K-means using Weka Tool

- **Architecture diagrams illustrate the proposed model's workflow.**

**Step 1 :**

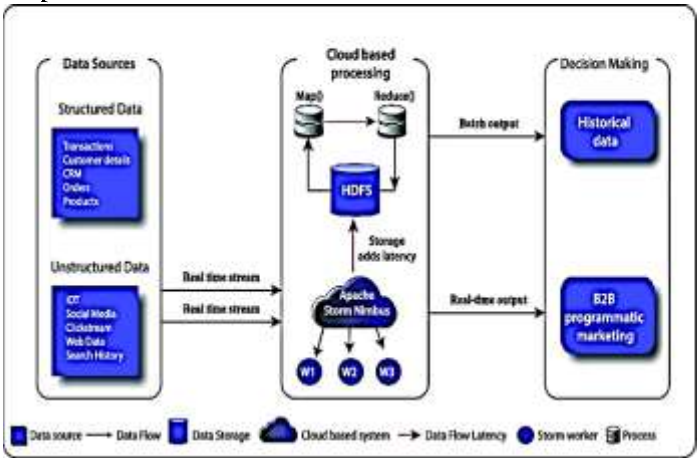


**Figure 3 : Real Time Data Processing**

**Step 1: Real-Time Data Processing**

**Input:** A stream of student academic and behavioral data (e.g., attendance, marks, skills, placement status). Let the incoming real-time dataset be represented as:

$$\boldsymbol{D = \{x_1, x_2 \ldots, x_n\}, x_i \in R^m} \text{ --------- } (1)$$

**Where:**

- D: Real-time dataset
- $x_i$: A data sample with mmm features (attributes)

This data is preprocessed dynamically (e.g., normalization, missing value imputation, encoding).

**Step 2 :**

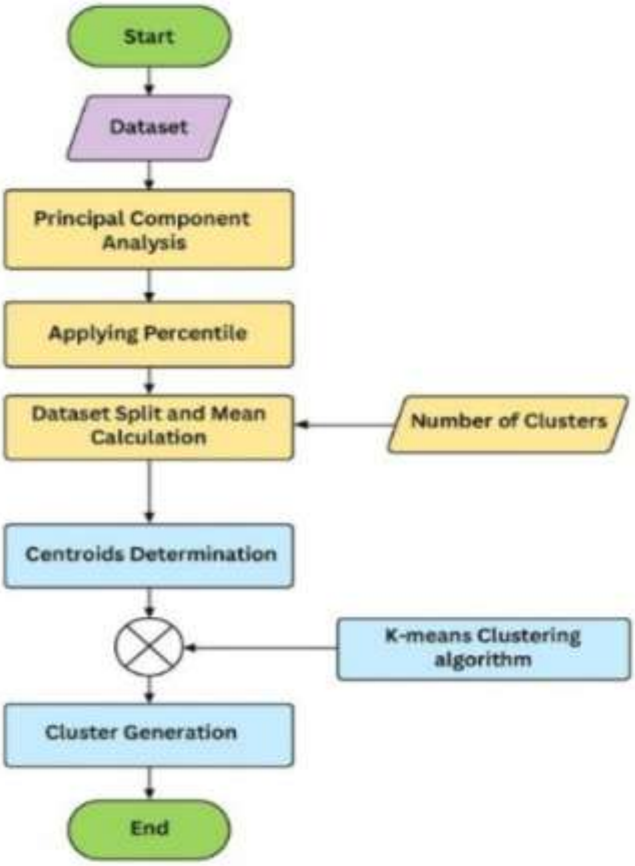


**Figure 4 : K-Means driven for data Centroid**

**Step 2: K-Means Clustering for Centroid Detection**

We apply **K-Means Clustering** to categorize the student data into $k$ performance groups.

**Algorithm Steps:**

1. Choose the number of clusters $k$
2. Randomly initialize $k$ centroids μ1,μ2,…,$\mu_k$
3. Assign each data point to the nearest centroid:

$C_j = \{x_i: \|x_i - \mu_j\|^2 \le \|x_i - \mu_l\|^2 \forall l, 1 \le l \le k\}$ ...... (2)

4. Recalculate the centroid of each cluster:

$\mu_j = \frac{1}{|C|} \sum_{x_i \in C_j} x_i$ ...... (3)

5. Repeat steps 3 and 4 until convergence (no change in centroids).

**Step 3 :**

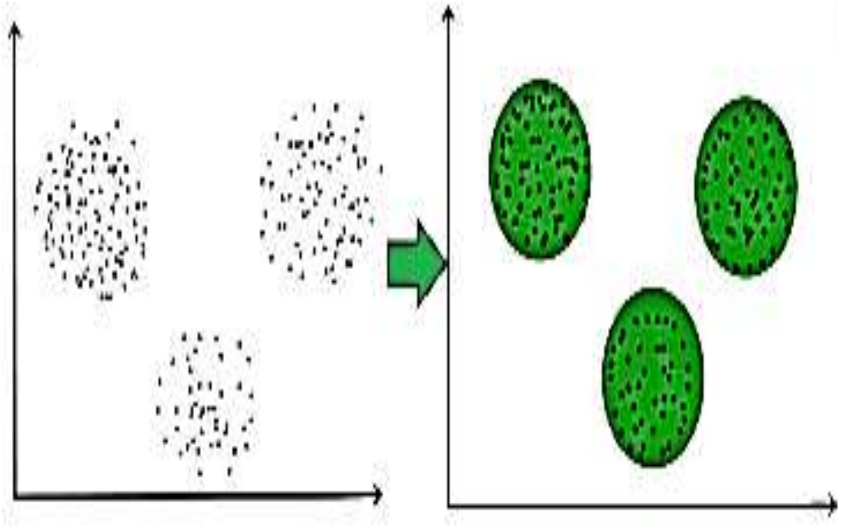

**Figure 5 : Samples predicting using the k-means**

**Step 3: Prediction of Sample Clusters**

Once the clusters are established, new incoming samples $x_{ne\omega}$ are predicted using nearest centroid classification:

$\hat{C}(x_{new}) = \ arg \ \min_{J} \|y_{new} - \mu_j\|^2$ .......... (4)

This helps in real-time prediction of a student's cluster—e.g., *Industry-ready*, *Dropout-risk*, etc.

**Step 4 :**

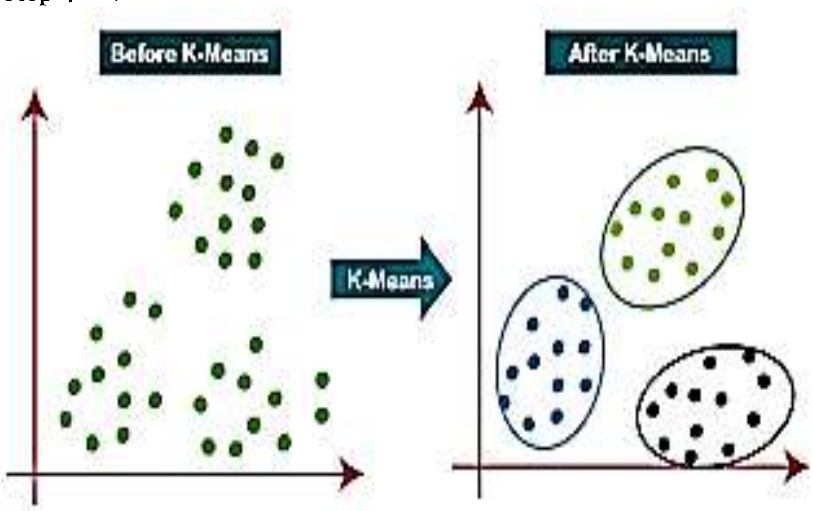


**Figure 6: Results with Accuriate Data**

**Step 4: Accuracy Evaluation**

To evaluate clustering quality and prediction accuracy, metrics such as **Silhouette Score**, **Accuracy**, or **Adjusted Rand Index (ARI)** are used.

If ground truth labels $y_i$ are available for supervised validation:

$$\text{Accuracy} = \frac{\textit{Number of correct predictions}}{\textit{Total predictions}} = \frac{1}{n}\sum_{i=1}^{n} \quad 1(\hat{y}_i = y_i) \quad \text{........ (5)}$$

## 5. RESULTS AND DISCUSSION

### 5.1 Evaluated Attributes:

- CGPA
- Performance Levels (Slow, Moderate, Fast)
- Attendance Regularity
- Academic Achievements
- Industry Readiness (Skill ratings: Excellent/Good)

### 5.2 Results Summary:

- Performance comparison across various machine learning models.
- Accuracy analysis:

**Table 1 : K-Means Clustering Accuracy-style Analysis**

| Metric | Cluster 0 | Cluster 1 |
|---|---|---|
| Instance Count | 150 (49%) | 156 (51%) |
| Overall Score | 385.36 | 398.54 |
| CGPA | 6.42 | 6.49 |
| Result | Pass | Pass |
| Aptitude Performance | 77.84 | 78.76 |
| Personal Behaviour | Excellent | Average |
| Skill Test | 74.27 | 75.99 |
| Life Skills | Excellent | Average |
| Communication Skill | Need Improvement | Fair/Good |
| Professional Skills | Average | Good |
| Interpersonal Skills | Average | Excellent |
| Industrial Fitness | Recommend | Recommend |
| Govt Employability | No | No |
| Entrepreneurship | Not Recommended | Recommended |
| Dropout Risk | No | Yes |

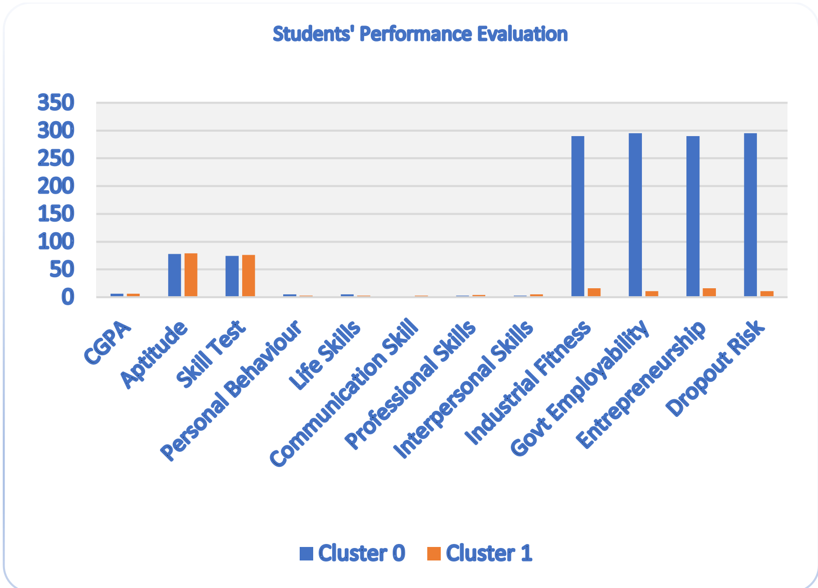


**Figure 7 : Student's Performance Evaluation**

### 5.2.1 Interpretation and Insights:

The K-Means clustering analysis segmented the student dataset into two nearly equal groups: Cluster 0 (49%) and Cluster 1 (51%), each demonstrating distinct academic and behavioural traits. Cluster 0 students showed moderate CGPA (6.42), strong personal and life skills, but average communication and interpersonal abilities, with low entrepreneurial inclination and no dropout risk. In contrast, Cluster 1 had a slightly higher CGPA (6.49), better aptitude and skill test scores, excellent interpersonal and professional skills, and stronger entrepreneurial potential, though some showed signs of dropout risk. This clustering effectively highlights performance-based groupings, enabling targeted interventions such as communication skill development for Cluster 0 and retention strategies for at-risk individuals in Cluster 1, thereby supporting personalized academic and career guidance.

### 5.2.2 Final Summary:

The clustering effectively segments the student population into two nearly equal groups with distinct characteristics, enabling actionable insights from an educational AI perspective. Cluster 0 students may benefit from targeted support in communication and entrepreneurial training, while Cluster 1, despite strong skills, exhibits potential dropout risks that require early mentorship interventions. This data-driven approach enhances personalized learning pathways and informed career planning for diverse student needs.

## CONCLUSION

The integration of AI-driven personalized learning systems has demonstrated a transformative impact on student engagement and academic performance by enabling adaptive, data-informed instruction tailored to individual learning needs. This study, through the combined application of J48 decision tree classification and K-Means clustering, successfully identified performance patterns and grouped students into meaningful segments, supporting both predictive analytics and targeted educational interventions. The high accuracy of J48 (96.73%) validated the reliability of AI-based classification, while the clustering technique revealed critical insights into student characteristics such as skill levels, behavioural tendencies, and dropout risk. These findings underscore AI's potential to deliver scalable, inclusive, and ethically responsible solutions that personalize education, improve learning outcomes, and guide students along suitable academic and career paths. To fully realize these benefits, ongoing interdisciplinary collaboration and rigorous ethical governance—especially in the areas of data privacy, fairness, and transparency—are essential. This research contributes a robust foundation for future longitudinal studies exploring the sustained impact of AI in educational ecosystems.

### Limitation

This study is limited by its regional dataset scope and reliance on structured data, which may restrict generalizability. Additionally, real-time feedback systems and unstructured data analysis were not fully implemented or evaluated.

### Future Recommendations

Future research should focus on expanding dataset diversity by including students from varied regions, disciplines, and academic levels to enhance model generalizability. The integration of real-time feedback systems and interactive AI dashboards can provide personalized insights to students, educators, and parents. Hybrid AI approaches—combining decision trees like J48 with deep learning—can improve prediction accuracy and system adaptability. Incorporating unstructured data such as essays, video engagement, and behavioural logs will enrich learner profiles. Emphasizing explainable AI (XAI) is crucial to foster transparency and trust in educational decision-making. Ethical governance must be ensured through adherence to data protection regulations like GDPR and India's DPDP Act. Aligning AI models with Outcome-Based Education (OBE) frameworks can help map personalized recommendations to measurable outcomes like COs and POs. Collaboration with industry is essential to co-design assessments, define skill benchmarks, and ensure curriculum relevance. AI-enabled systems should also provide career recommendations tailored to student profiles using clustering and predictive analytics. Finally, pilot implementations in academic institutions are recommended to validate these approaches and guide scalable deployment.

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