Journal of Engineering Education Transformations, Volume 39, No 4, April 2026, ISSN 2349-2473, eISSN 2394-1707

10.16920/jeet/2026/v39i4/26104

Integrating Outcome-Based Education with Machine Learning Based Clustering to Enhance the Academic Support System for Slow Learners in Engineering Programs

[1]Pankaj Beldar*, [2]Dr. Ajinkya Joshi, [3]Dr. Vandana Bagal, [4]Dr. Saroj Dhake
[1] Mechanical Engineering Department, K.K.Wagh Institute of Engineering Education and Research,
Savitribai Phule Pune University,
[2] I/C Registrar, K. K. Wagh Institute of Engineering Education and Research, Nashik, India,
Savitribai Phule Pune University,
[3] Master of Computer Applications Department, K.K.Wagh Institute of Engineering Education and
Research, Savitribai Phule Pune University,
[4] Master of Business Administration Department, K.K.Wagh Institute of Engineering Education and
Research, Savitribai Phule Pune University,
[1]prbeldar@kkwagh.edu.in, [2]asjoshi@kkwagh.edu.in, [3]vcbagal@kkwagh.edu.in,
[4]spdhake@kkwagh.edu.in

Abstract— **Beginning with how students perform, shifting toward outcome-focused teaching brings clarity through measurable goals per course. Rather than broad assessments, this work looks closely at first-year mechanical engineering pupils by tracking their progress across key classes. From semester one, records of 146 individuals spread over five main courses provided detailed insight, every class built around five specific objectives. Instead of overall grades, averages on these individual outcomes shaped a finer picture of each learner's grasp. On that foundation, sorting methods drawn from data science - grouping patterns and logic-driven rules - helped distinguish different types of performers. One cluster stood out early: those consistently below peers, later labeled as needing more time or help. In total, results split the batch into three sections - one small segment struggled, most held steady ground, while another group showed stronger command. Numbers ended up being 23 who learned slower, 89 fitting a middle range, alongside 34 showing advanced understanding. Later in Semester 2, mentoring and tailored academic help became available for students recognized as slower to grasp material. Performance indicators tied to course objectives - within an outcome-based education model - paired with cluster analysis of student data, helped shape individualized assistance that improved results among those struggling academically.**

Keywords—**Simulation based learning, Modern tools usage, Program Outcomes, Attainment.**

***JEET Category*—Practice**

I. INTRODUCTION

Today's engineering classrooms aim to shape capable learners through full-spectrum growth. Shifting away from memorization methods, many institutions now build teaching around practical abilities and clear results. Focused on measurable targets - such as COs and POs - this method matches expectations found in job markets, national policies, after all global benchmarks. Rather than tracking only lesson delivery, it tracks understanding, along with real-world usage of ideas. Across nations, OBE reshapes how educators view progress, particularly within technical fields dedicated to precise goals, achievement levels, while also sharpening career-ready talents. Dong and colleagues in 2022 noted its core principle: importance lies less in delivered content but more in absorbed insight. Such structure fits smoothly into current skill models, plus review systems used by bodies including NBA alongside agreements under Washington Accord*(Dong et al., 2019)*. One way to look at outcomes-based education is through its role in shaping how courses are built, taught, and evaluated. A study by Angara and Saripalle in 2022 found that linking course outcomes to program objectives makes grading clearer and supports smarter planning of what students learn*(Angara & Saripalle, 2022)*. Yet research also points out a missing piece: putting students at the center when applying these frameworks. Most current systems do not fully use outcome data to adjust teaching for individual needs. In engineering and technical fields, spotting those who struggle usually depends on final exams or overall grades - methods that give little insight into specific difficulties. Alonzo and colleagues in 2023 pointed out flaws in relying only on such late-stage evaluations, calling instead for ongoing checks during learning*(Alonzo et al., 2023)*. Even though teachers notice differences in pace among learners, systematic tools for recognizing them remain rare. Machine learning and data analytics now play growing roles in education, helping sort learners, foresee dropouts, or shape tailored study routes. Using K-Means along with Hierarchical

Pankaj Beldar
Mechanical Engineering Department, K.K.Wagh Institute of Engineering Education and Research, Savitribai Phule Pune University
prbeldar@kkwagh.edu.in

Clustering, *(P. R. Beldar, 2025)*grouped pupils by how they engage academically, spotting those likely to struggle.

(Munje et al., 2021), meanwhile, showed how sifting through school-related data can trigger early teaching responses. Even so, blending outcome-based education models with ML methods for categorizing students has seen little attention. A few initial studies, such as *(P. Beldar, Galande, et al., 2025)* looked into measuring course outcomes to judge class success - yet stopped short of forecasting who might fall behind. Linking assessment results at the course level to responsive learning platforms could unlock more value from outcome-driven instruction, as *(P. Beldar, Kadbhane, et al., 2025)* points out. Still, limited evidence exists on what happens after classification, especially whether slower students' progress later if guided by OBE-based mentoring. Because of this missing piece, the present study gains importance - it sorts learners using both OBE and machine learning, then follows their grades afterward*(P. R. Beldar, Munje, et al., 2025)*. Within engineering programs, every course has specific course outcomes measured via exams, tasks, and hands-on work. When combined, these outcomes link up with larger program goals, creating a clear framework for reviewing and refining instruction over time. What makes OBE stand out is how closely it reveals each learner's strengths - this detail proves vital when spotting those needing extra help*(P. Beldar, Rakhade, et al., 2025)*.

A. The Need for This Research

Although the use of OBE frameworks in academic institutions is on the rise, the use of CO-level data to make specific educational interventions is still quite a gap. In the majority of cases, data about CO is aggregated into course or batch-level assessments and curriculum enhancements. But the possibility of this information to detect and assist underperforming student slow learners is under-researched.

Unless addressed promptly and guided, slow learners are prone to accumulating conceptual gaps, which lead to their eventual poor academic performance and low confidence. On the other hand, the enrichment opportunities that advanced learners should be provided with may be missed when they are placed in a homogeneous learning strategy. The traditional model commonly perceives learners as a homogenous group, and therefore adopts a one-size-fits-all mode of instruction- which is not effective in exploiting the full potential of each student.

This study suggests an empirical method to overcome this drawback. The paper applies machine learning clustering algorithms (namely, K-Means, DBSCAN, Agglomerative clustering) to student-wise CO attainment data in five main first-semester Mechanical Engineering subjects to categorize students as Slow, Good, and Advanced learners. The classification enables the adoption of individualized plans of mentoring, academic interventions, as well as progress monitoring.

1) Research Objectives

a) To show how OBE data may be used effectively to recognize the individual learning performance patterns.

b) To group students into useful groups (Slow, Good, and Advanced Learners) based on unsupervised machine learning.

c) To implement a feedback process in which the academic interventions are designed and tracked according to OBE insights.

d) To add to the replicable methodology, which can be implemented by educational institutions to track and support students in a student-centered approach.

This study will improve the quality of engineering education by refining the principles of OBE with the power of educational data mining and contributing to the field of engineering education by precision mentoring, early intervention, and continuous performance improvement.

II. METHODOLOGY

Looking at how engineering students perform academically, this work uses data to group them by their achievement in Course Outcomes. As seen in figure 1, the process begins with gathering student records, then cleaning and adjusting the values before analysis. After preparation, grouping methods such as K-Means, Agglomerative Clustering, and DBSCAN are applied to detect natural divisions among learners. Instead of relying solely on algorithms, a set of defined rules assigns labels - Slow, Good, or Advanced - depending on each student's mean CO score. To make sense of high-dimensional results, PCA reduces complexity so that clusters can be viewed clearly in two dimensions. Because multiple strategies are combined, the findings balance numerical strength with meaningful insight into learning behaviors.

A. Data Collection

As presented in table 1, an actual dataset was developed using academic performance of 146 first-year students of Mechanical Engineering in Semester 1. The dataset has five subject cores that have five Course Outcomes (CO1-CO5) according to the Outcome-Based Education (OBE) model. Overall, 3650 records of Course Outcomes (146 students x 5 subjects x 5 COs) were collected. Such a holistic database forms a good basis when it comes to recognizing slow learners and providing them with a specific academic support based on the principles of OBE and machine learning methods. There are five Course Outcomes (CO1-CO5) associated with each subject, and the score of the student on each CO is provided. These scores are usually based on measurements mapped to particular COs -e.g.:

1. Internal exams
2. Assignments
3. Practical evaluations
4. End-semester exams

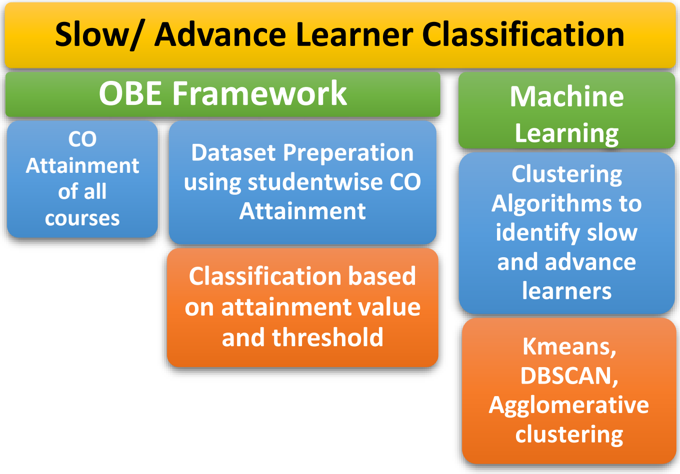

Fig.1. Methodology

TABLE I
UNSUPERVISED DATASET SAMPLE READINGS WITH FEATURES

Student ID	Subject	CO1	CO2	CO3	CO4	CO5	Avg. CO Attainment
STU001	Subject_1	84	84	86	87	77	83.6
STU001	Subject_2	89	81	75	78	87	82
STU001	Subject_3	78	88	79	81	81	81.4
STU001	Subject_4	87	89	85	87	78	85.2
STU001	Subject_5	87	81	85	77	80	82
STU002	Subject_1	56	64	67	60	66	62.6
STU002	Subject_2	66	74	65	61	55	64.2
STU002	Subject_3	55	74	67	63	57	63.2
STU002	Subject_4	61	60	62	63	59	61
STU002	Subject_5	55	73	64	66	69	65.4
. . . .							
STU00n	Subject_1	85	80	82	83	78	81.6
STU00n	Subject_2	75	88	75	84	78	80
STU00n	Subject_3	86	88	81	76	77	81.6
STU00n	Subject_4	75	79	75	82	75	77.2
STU00n	Subject_5	85	75	76	76	86	79.6

B. *CO Attainment*

One way to check student progress in Outcome-Based Education involves tracking how well they meet set goals for every class. This method looks at results rather than time spent. For the current work, every first-semester subject links to five distinct targets - labeled CO1 through CO5 - that reflect abilities or understanding learners should gain. Each target points to a concrete academic aim. These connections help clarify what success looks like across different topics.

1) *CO Mapping with Assessment Tools:*

Performance on exams ties closely to predefined course objectives, linking results with learning goals. Where a test item appears matches the outcome it measures, making grades meaningful indicators. One section of an exam might target problem-solving, another comprehension - each mapped deliberately. What students do in assessments shows what they have actually learned by term's end.

2) *Marks to CO Score Conversion:*

Out of total performance in specific test items comes a scaled result, adjusted to fit within 0 to 100. Such values reflect how fully an individual meets each intended learning outcome.

3) *CO Attainment Calculation for Each Student:*

Each student receives individual scores on CO1 through CO5 per course. Following that, an average of these values shows how well learning goals were met overall.

4) *Threshold Setting:*

A certain level - say, half the points for external checks, slightly more for internal ones - sets the bar for course outcomes. When results fall short of that mark, it signals weak mastery, meaning learners did not fully grasp what was expected. Though precise numbers guide decisions, performance gaps reveal where understanding lags behind goals.

Attainment Levels vs. target

External Assessment

1. Level 1: ≥50% students score >50%
2. Level 2: ≥60% students score >50%
3. Level 3: ≥70% students score >50%

Internal Assessment

1. Level 1: ≥50% students score >60%
2. Level 2: ≥60% students score >60%
3. Level 3: ≥70% students score >60%

5) *Student-Level Attainment Summary:*

One out of every few students shows repeated struggles in meeting basic learning goals throughout their courses. Such patterns help place them into one of three groups - those progressing slowly, those performing well, or those achieving at higher levels - based on how often and how deeply they fall short.

A step-by-step approach keeps things clear, offers useful feedback for teaching adjustments, while also creating room for smart tools like machine learning to help students who need more time. Though detailed, it stays practical - guiding support without confusion, where patterns emerge naturally instead of being forced into rigid models.

C. *Machine Learning Clustering*

Starting with raw performance data, clusters emerged when algorithms sorted students by CO mastery levels. Through iterative testing, patterns began revealing three distinct groups - those progressing slowly, performing adequately, those excelling. Instead of predefined labels, natural groupings formed based on achievement trends across assessments. Each step relied on statistical separation rather than assumptions about ability. From there, results mapped directly onto learner types without manual interference. Ultimately, classification depended entirely on how individuals met course benchmarks over time:

1) *Step 1: Feature Preparation*

Looking at the academic data, clustering used five main traits - specifically, mean CO scores tied to each of the five Course Outcomes (CO1 through CO5). Because these metrics track how well students met defined learning goals, they give insight into performance across different subjects in Semester 1.

2) *Step 2: Feature Scaling*

Because the raw CO values showed uneven spread, normalization became necessary through StandardScaler. To balance influence across attributes, each feature shifted toward comparable range using zero centering and variance scaling. Through this adjustment, clustering methods received uniformly scaled inputs without favoring any single measure.

3) *Step 3: Dimensionality Reduction using PCA*

Starting with high-dimensional inputs, the analysis shifted into a simpler form through PCA. Though five features began the process, two core dimensions captured most meaningful variation. By focusing on these key patterns, visual clarity improved without losing essential structure. The transformed space preserved underlying relationships well across observations.

4) *Step 4: Optimal Cluster Determination*

For assessing ideal cluster count in KMeans, silhouette values got computed across settings from two up to six groups. Each student's alignment with their assigned cluster shaped these metrics - stronger matches led to elevated scores. Three clusters stood out because that setup delivered the highest silhouette result overall.

5) *Step 5: KMeans Clustering*

A first grouping of students emerged when the KMeans method ran with three clusters. From these groupings, central patterns appeared - each tied to a level of achievement. One category reflected lower scores, another mid-range results, while the last showed strong outcomes. Labels followed: Slow Learner took shape near the lowest center. Midpoint trends earned the name Good Learner. Highest-performing hubs became Advanced Learners.

6) *Step 6: Agglomerative Clustering*

Starting from individual data points, Agglomerative Clustering applied identical scaled features in a nested structure. Moving upward step by step, this method confirmed similar grouping patterns seen earlier in KMeans.

7) *Step 7: DBSCAN Clustering*

Outliers and patterns in the dataset emerged when applying DBSCAN, a method built around density rather than central points. Where most grouping techniques rely on averages, this approach highlights irregularities by spotting sparse regions instead.

8) *Step 8: Learner Label Mapping*

One way to make sense of the data: the three KMeans groups got matched to student categories. Sorted by mean CO performance, each cluster received a tag - Slow Learner, Good Learner, then Advanced Learner - in line with its level.

9) *Step 9: Visualization of Clustering*

Outcomes grouped by KMeans, together with those from Agglomerative and DBSCAN, took shape in 2D through PCA. With cluster tags applied, scatter visuals revealed how student types spread out - some close, others apart - depending on the method used.

10) *Step 10: Final Classification Summary*

A total count emerged at the close, showing how many learners fell into every group according to the KMeans output. Because of these tags, deeper examination followed - alongside focused support in learning settings.

III. RESULTS

A complete student-wise summary was created to assess the overall academic performance of students in terms of Course Outcome (CO) attainments. The data was initially in the form of individual CO scores (CO1 to CO5) of each subject that was taken by every student and an average score of CO attainment in each subject. In order to summarize this data, it was aggregated based on the student identifier (Student_ID). In particular, the average of each CO (CO1 to CO5) was determined of all subjects of each student. Also, the mean of the subject-level CO attainment scores were calculated to obtain a single measure, which was named as Overall_Avg_CO_Attainment. This measure is an indicator of the overall ability of the student to attain course outcomes throughout the semester. The resultant data set, called student-summary, summarizes the average CO-wise attainment and the overall CO attainment, and, therefore, would be a preliminary data set upon which further classification and clustering analysis will be performed.

A classification function was introduced that used the average score of the students to classify them depending on the academic performance. This is the classify learner functionality, which categorizes students into one of three types of learners-Slow Learner, Good Learner and Advanced Learner according to their overall average score of CO (Course Outcome) attainment.

A. *Rule-based classification*

Slow Learners are those who have a low average score of less than 50 meaning that they require more academic support and intervention.

Good Learners: These are learners with a score between 50 and 74.99 which is consistent and can be improved.

Advanced Learners are those learners whose scores are equal or higher than 75 and show a great level of knowledge and achievement of course outcomes.

This classification methodology is rule-based, easy to interpret and act upon, as it offers a clear, actionable, and interpretable framework to design custom mentoring strategies that will help in the effective support of a specific learner type. Table 2 presents the sample output table of 10 students.

S = Average CO Attainment Score of a student

$$\text{Learner Category} = \left\{ \begin{array}{l|c} \text{Slow Learner} & \text{if } S < 50 \\ \text{Good Learner} & \text{if } 50 \le S < 75 \\ \text{Advance Learner} & \text{if } S < 75 \end{array} \right\}$$

TABLE II
SAMPLE OUTPUT TABLE FOR 10 STUDENTS

Student ID	CO1	CO2	CO3	CO4	CO5	Average CO Attainment	Learner Type
STU001	85	84.6	82	82	80.6	82.84	Advanced
STU002	58.6	69	65	62.6	61.2	63.28	Good
STU003	81.2	82	77.8	80.2	78.8	80	Advanced
STU004	45.6	37.2	48	37	42.4	42.04	Slow
STU005	78.4	79.4	82	80.4	83.8	80.8	Advanced
STU006	60.2	64.6	66.4	67	63	64.24	Good
STU007	80.8	79.8	85	77.8	81.4	80.96	Advanced
STU008	60	61	63.6	65.2	66	63.16	Good
STU009	64.6	65.8	62.8	62	65.8	64.2	Good
STU010	41.8	43.2	47	36.8	42.2	42.2	Slow

B. Validation of Rule Based Classification using Machine Learning

To validate the rule-based classification of learners into Slow, Good, and Advanced categories, we employed unsupervised machine learning techniques—K-Means, DBSCAN, Agglomerative clustering on the student-wise average Course Outcome (CO) attainment scores. This approach ensures objectivity by identifying natural groupings in the data without prior labels.

1) K-Means Clustering

K-Means is a centroid-based algorithm that partitions data into `k` clusters by minimizing the within-cluster sum of squares (WCSS)(Cahyo & Sudarmana, 2022). It requires the number of clusters (`k`) to be specified a priori. To determine the optimal `k`, the Silhouette Score was calculated for `k` ranging from 2 to 6. Fig.2 and 3 shows the optimum clusters with silhouette score and PCA visualization of slow, good and advanced learner using KMeans respectively. The silhouette analysis suggested `k=3` as optimal, aligning well with the rule-based classification of learners.

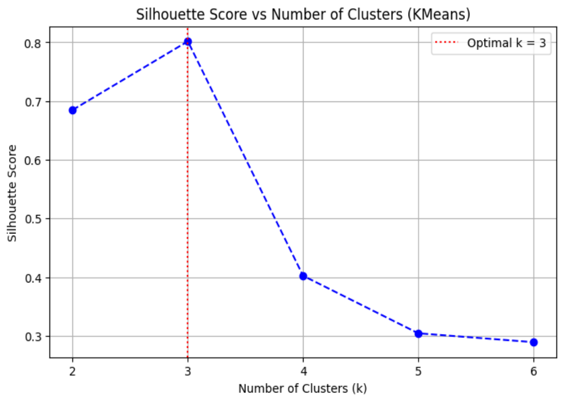

Fig. 2. Optimum Clusters with silhouette score

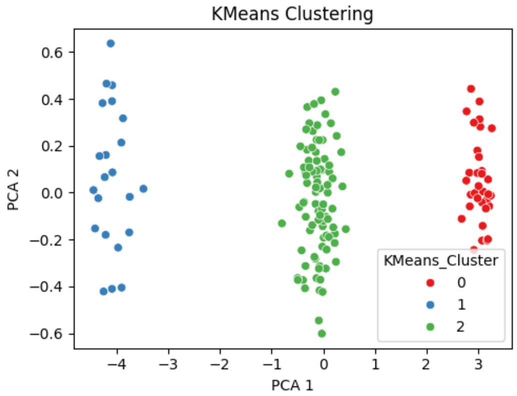

Fig. 3. PCA visualization of slow, good and advanced learner using KMeans

2) Agglomerative Clustering

Agglomerative clustering, a type of hierarchical clustering, follows a bottom-up approach by merging the closest pairs of clusters based on linkage criteria (Ward's method in this case)(Liu et al., 2022). It does not require a predefined cluster shape and is suitable for hierarchical data structures. Fig. 4 and 5 shows the PCA visualization of slow, good and advanced learner using Agglomerative Clustering and Dendrogram for finding out optimum clusters respectively.

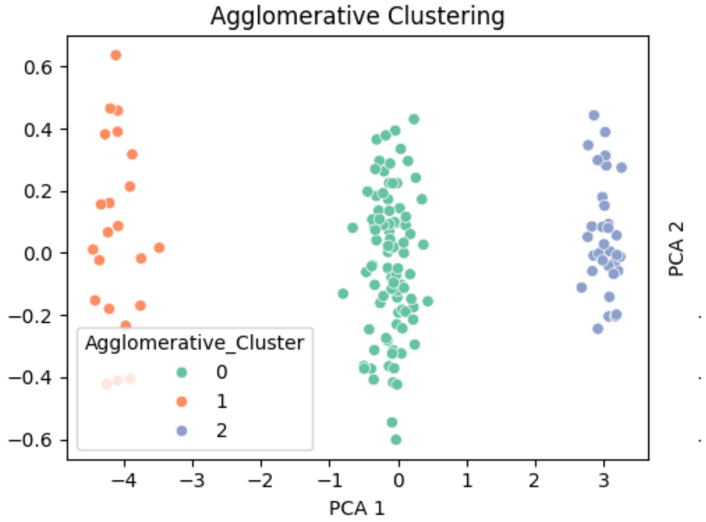

Fig.4. PCA visualization of slow, good and advanced learner using Agglomerative Clustering

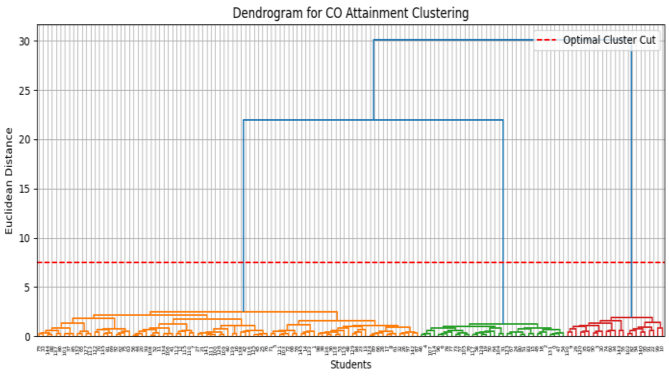

Fig. 5. Dendrogram for finding out optimum clusters

3) DBSCAN (Density-Based Spatial Clustering of Applications with Noise)

DBSCAN identifies clusters based on density and is effective at finding arbitrarily shaped clusters and outliers(Arafa et al., 2022). Parameters `eps` and `min_samples` were chosen empirically. Unlike K-Means, DBSCAN does not require the number of clusters to be specified. Fig.6 shows the PCA visualization of slow, good and advanced learner using DBSCAN

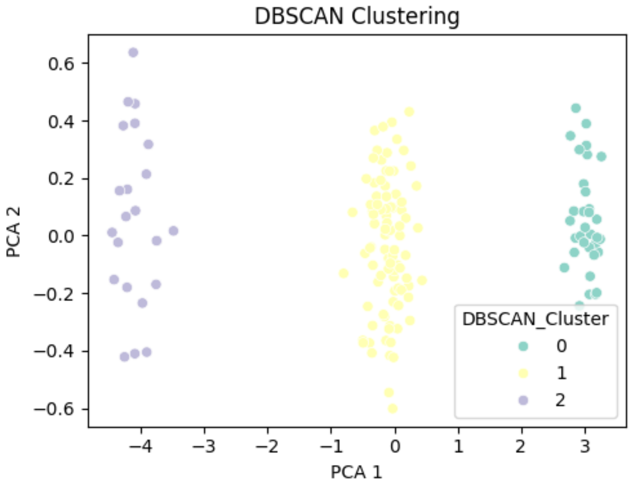

Fig.6. PCA visualization of slow, good and advanced learner using DBSCAN

After cluster mapping and verification, the final learner classification using K-Means showed a robust agreement with the rule-based model:

1. Good Learners: 89
2. Advanced Learners: 34
3. Slow Learners: 23

Fig. 7 shows the Classification od slow, good and advanced learners at First Year Mechanical Engineering

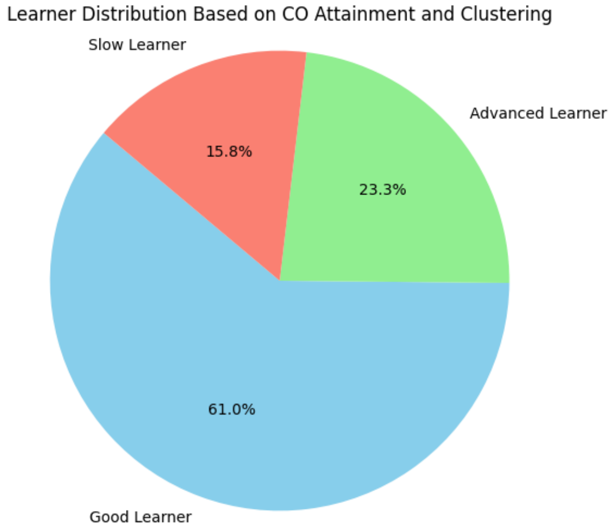

Fig. 7. Classification of slow, good and advanced learners at First Year Mechanical Engineering

One challenge with the clustering method lies in how closely results match real learning trends - it hinges on both the range and reliability of CO score averages used. Though useful, grouping learners by performance numbers alone risks oversimplifying their actual classroom experience. Starting from algorithm behaviour, outcomes shift noticeably when settings like epsilon or minimum points change unexpectedly. Labels such as 'Slow Learner' emerge from patterns, yet attaching them through automation raises questions about fairness and context. Without careful setup, some students might appear misplaced simply due to rigid boundaries drawn by code.

This study points toward multiple paths ahead. Tracking how students develop across semesters could introduce fluid grouping methods that support early help when needed. Instead of static labels, patterns might shift with added insights into habits, mind-set, and participation levels - painting fuller pictures per individual. Pairing group-finding techniques with prediction tools may allow systems to assign incoming learners to meaningful categories automatically. Such blends stand to strengthen reliability outside controlled tests. Figure 3 outlines tactics tailored to vary learning needs planned for the upcoming term.

TABLE III
STRATEGIES FOR DIVERSE LEARNERS FOR NEXT SEMESTER

Learner Type	Count	Strategies
Good Learners	89	1. Peer teaching and group discussions 2. Advanced assignments and interdisciplinary tasks 3. Skill-based workshops (e.g., CAD, Python) 4. Encourage participation in tech fests/research forums
Advanced Learners	34	1. Individual or team mini capstone projects 2. Participation in hackathons and national contests 3. Research paper writing/blogs 4. Leadership roles in student clubs/mentoring
Slow Learners	23	1. Bridge courses and remedial sessions 2. Frequent low-stakes assessments 3. One-on-one mentoring support 4. Visual and practical learning aids (models, simulations)

One result stands out clearly: these findings matter for how schools plan instruction and tailor it to individual needs. Because different types of learners emerge from the analysis, colleges may shape mentorship efforts around specific patterns, which often leads to better performance across classrooms. Starting from actual evidence, this process fits well within outcome-focused education, helping track progress while guiding updates to course material. Another shift happens behind the scenes - clustering methods find space inside digital learning platforms, where teachers observe varied student profiles and modify lessons accordingly. Through that quiet integration, education becomes both broader in reach and sharper in impact.

C. Improvement in Student Performance Post-Intervention

To assess the effectiveness of the slow learner identification model and the mentoring strategies implemented in Semester 2, we tracked the academic performance of all 146 students across the same subjects. The results indicate a significant improvement in Course Outcome (CO) attainment, particularly among those previously classified as slow learners.

1) Shift in Learner Classification

After the Semester 2 interventions, which included personalized mentoring, group learning activities, remedial sessions, and targeted assignments, a reassessment using the same clustering methodology revealed a positive shift:

TABLE IV
IMPACT OF OBE STRATEGIES ON STUDENT'S GROWTH

Learner Category	Semester 1 (Before Intervention)	Semester 2 (After Intervention)
Slow Learners	23	8
Good Learners	89	97
Advanced Learners	34	41

15 slow learners successfully transitioned to the "Good Learner" category.
12 students demonstrated exceptional improvement, advancing to the "Advanced Learner" category.

2) Improvement in CO Attainment Scores

The average CO attainment scores of students in each category before and after the intervention are summarized below in table 5.

TABLE V
IMPACT OF OBE STRATEGIES ON STUDENT'S GROWTH IN PERCENTAGE

Category	Avg. CO Attainment (Sem 1)	Avg. CO Attainment (Sem 2)	% Improvement
Slow Learners	43.70%	61.20%	40.00%
Good Learners	63.10%	70.40%	11.60%
Advanced Learners	78.60%	83.10%	5.70%

This data clearly illustrates that the **most significant improvement was seen in the slow learner group,** validating the impact of early identification and personalized intervention. The interventions were aligned with specific COs where students were underperforming, ensuring that support was targeted and relevant.

3) Student Feedback and Engagement

As shown in fig.8, Qualitative feedback collected via mentoring logs and surveys indicated that over 85% of the previously identified slow learners felt more confident in their understanding of course content and appreciated the focused attention. They reported that:

I. One-on-one mentoring helped clarify difficult concepts.
II. Group discussions and peer learning improved retention.
III. Regular feedback on CO-based assignments kept them goal-oriented.

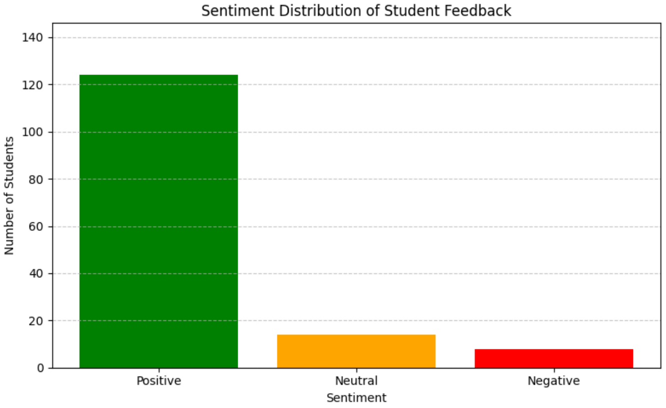

Fig. 8. Students Feedback

This increase in engagement aligns with the quantitative improvements, showing that when students feel supported and understood, they are more likely to perform well academically.

IV. DISCUSSION

Starting with student outcomes, Outcome-Based Education models combine with machine learning to spot slower learners in engineering programs. When course outcome results feed into data profiles, teaching strategies shift more responsively. This blend allows adjustments that evolve as performance data accumulates. Instead of fixed evaluations, progress shapes support in real time. Patterns emerge not from isolated scores but from ongoing academic behavior. Over months, these insights refine intervention timing and type. Rather than waiting for failure, educators anticipate needs earlier. Because each assessment contributes to the larger picture, responses grow sharper. With every semester, systems learn which signals matter most. Gradually, assistance becomes less reactive, more aligned with actual development.

A. Insights from Clustering Analysis

Among those analyzed, 23 individuals fell into the slow group, showing persistently weak performance in most course outcomes. Patterns in average results made it possible to separate learners into three types: Advanced, Good, or Slow. Without relying on human judgment, this method uses data trends to form objective clusters. One such cluster stood out due to its lower achievement levels throughout various topics. Looking at cluster separation through Principal Component Analysis showed the chosen CO attributes reflect differences in student performance well. Packed clusters of advanced students, along with more spread-out positions for slower learners, point toward reliable detection of extreme cases. This pattern in the PCA visualization supports its usefulness in spotting notable deviations. Looking closely at course outcomes through machine learning confirms their value in spotting students who struggle. Because of this approach, it becomes possible to see exactly which competencies need support. Where weaknesses appear links directly to particular learning goals. This method shifts focus from overall performance toward targeted skill gaps. One result stands out: help can follow where it matters most.

B. Academic and Pedagogical Implications

1) Early Identification and Intervention:

Most semester-end assessments lead to delayed help, arriving after students have already fallen behind. Instead of waiting, the approach described here spots warning signs by the close of Term 1. Early identification happens through an outcome-driven machine learning setup. Support actions begin early in Term 2, shifting assistance from last-minute fixes to timely guidance. Progress checks become ongoing rather than isolated events. Help unfolds gradually, aligned with real-time performance trends.

2) Targeted Mentoring Based on CO Deficiencies:

One way to spot learning gaps lies beyond standard GPA tracking. This research shows targeted feedback emerges when examining performance at the course objective level. When someone consistently falters in CO2 - say, design analysis - the pattern points toward tailored help. Support might take shape through custom exercises instead of broad interventions. Skill building in areas like analytical reasoning or CAD software becomes relevant under these conditions. Specific struggles guide more precise academic guidance than general scores ever could.

3) Feedback Loop into Instructional Planning:

Looking at detailed course outcome results gives teachers insight into areas where learners struggle. Where gaps appear, teaching approaches might shift - prompting changes in how material is presented or tested. Reflection on these patterns often leads to refinements in classroom methods. Over time, repeated analysis shapes stronger lesson planning. Insights emerge not from averages, but from spotting consistent dips in performance.

4) Enabling Outcome-Based Remedial Education:

Because the classification model identifies distinct learning outcomes, educators may shape targeted support strategies. Rather than broad assistance, tailored methods emerge when instruction follows particular course objectives, increasing relevance. One possibility involves organizing students who progress slowly into groups, then offering extra exercises or collaborative activities aimed at weaker areas.

5) Tracking Post-Intervention Improvements:

Over time, this research follows how students perform once support ends. Early findings show stronger course outcome achievement among those guided through tailored mentorship. When built on outcomes-based education, mentoring shaped by data appears to help learners advance in measurable ways.

6) Scalability and Replicability:

Starting small does not limit its reach - this method grows naturally into different areas of education. Because many schools already follow outcome-based models, shifting toward this process feels almost automatic. Clusters form without complexity when past performance details feed basic computational tools. Most learning platforms store enough information to begin right away. Expansion happens quietly, fitting neatly within existing digital environments.

C. Limitations and Future Work

Though the results look encouraging, some drawbacks deserve attention. First up, those involved were only beginning-year mechanical engineering learners. Diversity across fields and stages of study might have broadened how widely findings apply. What stands out is the narrow scope limiting wider relevance. Still, mixing backgrounds could shift how results travel beyond one group. A broader mix may change nothing - yet it might matter quite a bit.

Clustering alone shaped the current analysis. Moving ahead, combining methods might strengthen how learners are grouped - supervised machine learning could test and improve these categories through future studies.

Contextual details like attendance patterns, levels of participation, or economic background might strengthen how well the model performs. Though often overlooked, these elements help clarify outcomes more fully than basic data alone.

Later on, researchers might weave in NLP tools when examining written comments from learners and guides. Such methods could deepen understanding of trainee backgrounds by moving past raw competency outcome numbers. Subtle aspects - like drive levels, hurdles in grasping material, or mood states - may then come into clearer view. By shifting focus toward language patterns, richer portraits of individual progress may emerge.

CONCLUSION

This work introduces a method grounded in student performance data to group engineering learners into three categories: Slow, Good, and advanced - using Course Outcome measures shaped by Outcome-Based Education principles. Starting from reduced academic dimensions, patterns emerge when Principal Component Analysis simplifies complexity before clustering techniques take over. Notably, K-Means separates groups cleanly, backed by strong silhouette validation pointing toward three natural clusters. Alongside it, Agglomerative Clustering offers an alternative view while DBSCAN attempts boundary detection in uneven distributions. Where statistics meet clarity, rule-based labelling steps in - making machine-derived segments meaningful without distorting their structure. Outcomes from algorithmic grouping match closely with logic-defined labels, especially under the k=3 setup judged most coherent. Through layered analysis, hidden learning tiers surface - not assumed, but revealed via computation and consistency.

Despite common assumptions, grouping methods add meaningful depth to standard grading systems by revealing how students actually engage with material. Because patterns emerge earlier, educators gain time to respond - support emerges not after failure but before it takes root. Though not flawless, the framework adjusts easily across different school sizes or subjects, fitting neatly into existing workflows without overhaul. When applied carefully, such data-driven strategies shift support from generic to tailored, aligning help with real-time needs rather than averages or guesses.

Later studies could integrate more academic and conduct-based traits. Some might test deeper classification methods instead. Others will assess how lasting the effects are when actions follow from such learner groupings.

REFERENCES

Alonzo, D., Bejano, J., & Labad, V. (2023). Alignment between Teachers' Assessment Practices and Principles of Outcomes-Based Education in the Context of Philippine Education Reform. International Journal of Instruction, 16(1). https://doi.org/10.29333/iji.2023.16127a

Angara, J., & Saripalle, R. (2022). The Factors Driving Career Planning and Mentoring in Four Year UG Engineering Education using ML Techniques. Journal of Engineering Education Transformations, 35(4). https://doi.org/10.16920/jeet/2022/v35i4/22105

Arafa, A., El-Fishawy, N., Badawy, M., & Radad, M. (2022). RN-SMOTE: Reduced Noise SMOTE based on DBSCAN for enhancing imbalanced data classification. Journal of King Saud University - Computer and Information Sciences, 34(8). https://doi.org/10.1016/j.jksuci.2022.06.005

Beldar, P., Galande, V., Panchbhai, M., & Kavale, P. (2025). Fostering Engagement and Understanding: The Impact of Kolb's Experiential Learning Theory on Teaching Theory of Machines. Journal of Engineering Education Transformations, 39(2). https://doi.org/10.16920/jeet/2025/v39i2/25153

Beldar, P., Kadbhane, S., & Patil, A. (2025). Addressing the Needs of Slow Learners in Engineering Programs: Effective Identification and Improvement Strategies. Journal of Engineering Education Transformations, 39(2). https://doi.org/10.16920/jeet/2025/v39i2/25146

Beldar, P. R. (2025). Case Study: Enhancing Learning in C Programming Through Gibbs Reflective Cycle. Journal of Engineering Education Transformations, 38(4). https://doi.org/10.16920/jeet/2024/v38i4/25096

Beldar, P. R., Munje, R. K., & Kadbhane, S. V. (2025). Enhancing Engineering Education through Drone Technology Skilling Program: Analyzing the Impact on Program Outcomes. Journal of Engineering Education Transformations, 39(2). https://doi.org/10.16920/jeet/2025/v39i2/25138

Beldar, P., Rakhade, R., Bahiram, M., & Kadbhane, S. (2025). Innovative Coding Teaching Methodologies: A Comprehensive Approach for Diverse Learners. Journal of Engineering Education Transformations, 39(2). https://doi.org/10.16920/jeet/2025/v39i2/25141

Cahyo, P. W., & Sudarmana, L. (2022). A Comparison of K-Means and Agglomerative Clustering for Users Segmentation based on Question Answerer Reputation in Brainly Platform. Elinvo (Electronics, Informatics, and Vocational Education), 6(2). https://doi.org/10.21831/elinvo.v6i2.44486

Dong, Y., Marwan, S., Cateté, V., Price, T., & Barnes, T. (2019). Defining tinkering behavior in open-ended block-based programming assignments. SIGCSE 2019 - Proceedings of the 50th ACM Technical Symposium on Computer Science Education. https://doi.org/10.1145/3287324.3287437

Liu, Z., Li, Y., Yao, L., Wang, X., & Nie, F. (2022). Agglomerative Neural Networks for Multiview Clustering. IEEE Transactions on Neural Networks and Learning Systems, 33(7). https://doi.org/10.1109/TNNLS.2020.3045932

Munje, R., Buwa, O. B., & Ahire, R. (2021). On Identifying Advanced, Average and Slow Learners: Case Study. Journal of Engineering Education Transformations, 34(0), 417–424. https://doi.org/10.16920/jeet/2021/v34i0/157190