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Clustering Student Performance: A Data-Driven Approach to Monitor Academic Success

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Abstract: The goal of Educational Data Mining (EDM) is the exploration of hidden patterns and insights in educational data. Making use of the EDM approach of clustering, this research explores the analysis of variation in students performance across the course of an academic degree. We perform experiments on the data of 210 students belonging to the Department of Software Engineering in an attempt to discover patterns between three class of learners' – high performers, intermediate performers, and low performers. These patterns are not only analyzed across different learner classes but also across different genders. The research also makes use of heatmap analysis to highligh subject-wise performance and to better understand the subjects that students struggle in. The findings of the reseach highlight the subjects that students have difficulties in and show that although students in most instances performed well in theoretical courses, several students had difficulty in practical courses. A comparison between two batches revealed that Batch-02 had generally improved performance which was particularly evident in the sixth semester of the degree program. These findings provide an alternative understanding of the intricate interaction between academic performance and student behaviors, which can be invaluable in guiding educators and policymakers to devise interventions that could help students achieve better results and ultimately reshape the learning paradigm.

Keywords: K-Means Clustering; Student Performance Analysis; Data Mining in Education; Clustering Algorithms; RapidMiner

1. Introduction

In recent years, educational institutions have started using technological innovations in an attempt to offer quality education at a high rate. Recent research has highlighted the importance of digital technologies, including artificial intelligence and educational data mining (EDM), in the enhancement of educational practices [1]. Along with this evolution, learning institutions generate huge volumes of data that are often diverse and concealed. The study scores of students, classroom projects, test results, and even more and more traces of online courses, which are digital in nature, make up such educational data. Online learning, which was accelerated by the pandemic, has introduced new dimensions of academic information collection, such as online student registration and the provision of lecture notes and other forms of online assessments. Even though much of the education has shifted to traditional classrooms again, there are a lot of institutes where online learning tools are applied due to their convenience and flexibility [2, 3]. Institutional repositories hold a vast amount and complexity of educational data that is not fully utilized, and several insights into the data that could improve the quality of education and student performance have not been discovered yet [4].

It is difficult and time-consuming to extract meaningful information manually in such enormous amounts of data containing a great number of attributes and comprehensive records regarding students. This challenge has necessitated the use of EDM, an emerging discipline that is meant to determine valuable patterns in useful information on educational data and actionable information. Some of the data analysis techniques employed by EDM have been utilized to transform raw academic data into knowledge that can be harnessed by the teaching process and also in the learning process of students [5]. Among the methods of EDM, Clustering, an unsupervised learning approach, has the advantage of grouping similar characteristics and patterns without the use of predefined labels. Clustering methods are efficient to identify the concealed structures and relationships in educational data to gain a more profound insight into the tendencies of student performance and behavior [6]. The focus of this research is on finding the patterns of student performance in the Department of Software Engineering, Mehran University of Engineering and Technology, Jamshoro. We analyze the academic history of two separate groups of students and attempt to unveil the nuggets on the academic development over the course of the degree program. This paper utilizes the results of clustering of performance groups, specifically K-Means clustering, and the metrics of evaluation used are Sum of Squared Errors (SSE), which are used to determine the quality of the clustering approach.

Section 2 of the paper is the review of the related literature on K-Means clustering concerning EDM. Section 3 presents the research methodology, the description of the data set of 2 batches of students, data integration, transformation, cleaning, and splitting, and the experimental setup with RapidMiner. Section 4 contains the results of the clustering, specifically this analysis focuses on finding how many students started as one group of clusters (high, medium, or low) and whether that number of students remains consistent or increase or decreases across multiple semesters to relate whether their performances remains consistent or changes with time and explains such significant findings as tendencies in student performance in theoretical and practical courses, the behavioral factors affecting the results, and the analysis of the results of the two batches. At last the analysis about gender based performances to find whether males or females tend to perform better and remain constant with their performances. The conclusions are presented next, which summarize the final findings and give recommendations for future studies and practical interventions.

2. Related Work

Over the last decade, EDM methods have been very useful in investigating a range of academic data and discovering useful information. Clustering has turned out to be one of those methods, however, due to its simple methodology of analyzing student achievements and creating meaningful patterns and interpretations. K-means clustering is one of the clustering methods that has become a mainstay in recent research on EDM to determine performance and engagement profiles of students. In [7], the researchers used K-Means on social studies grades at junior high schools with RapidMiner and formed three meaningful clusters, namely excellent, good, and moderate, which were found to be cluster valid by using the Davies-Bouldin index. On the same note, [8] used K-Means on the academic records of high school students, and it was able to classify the students into performance categories so as to assist in the application of specific teaching techniques. In vocational learning, [9] applied the K-Means algorithm in RapidMiner to cluster 125 students using academic and attendance information, and found the best number of clusters using the Davies-Bouldin index.

In study [10], blended learning patterns were studied with the help of K-means and hierarchical clustering as well as Gaussian Mixture Models. Results showed that K-Means yielded well-separated clusters that are cohesive based on Silhouette scores. Data from more than 6,600 records of university students in [11] were analyzed and clustered into high-achievers, average performers, and at-risk groups based on hours of study, attendance, and tutoring sessions, and were well validated by a Silhouette analysis. Wider algorithmic insights are obtained in [12] because the authors proposed an improved K-Means algorithm to represent the teaching-skill performance of English normal college students with the help of multi-dimensional performance indicators. K-Means and Calinski-Harabasz, and Silhouette measures were used to optimize the grouping of learners in adaptive tutoring, and [13] showed the flexibility of the algorithm in intelligent educational systems. Also, [14] suggested a probabilistic version of K-Means to classify courses, which combines PCA to reduce dimensions to enhance the accuracy of groupings.

These works all confirm the flexibility of K-Means in a wide variety of educational settings, including junior high school and university, and vocational campuses, with different kinds of data, such as test marks, school attendance records, and online performance indicators. They emphasize the usefulness of the method in the case of early intervention, individualized education, and monitoring performance. Our study is based on the existing literature, whereby K-Means clustering is implemented on two university-level batches based on midterm, sessional, and final marks to study the semester-wise performance change and positive performance indicators.

The current study aims to utilize K-Means clustering across four continuous semesters to uncover whether students shift from cluster groups as their degree progresses. These insights should be helpful for timely and targeted academic support. We consider two batches under same curriculum, and also utilize heatmaps to visualize student subject performance to highlight subjects where students are excelling and where they are struggling. Thirdly, this research extends to gender based cluster analysis, addressing which gender performed better in both batches.

3. Research Methodology

The study was conducted in a systematic step-wise approach as illustrated in Figure 1, in order to identify some of the significant trends in student academic data through clustering analysis. The essence of this procedure was to clean up the raw academic record and get it in a clean and structured format, so that it could be experimented with. This research employed the K-Means algorithm to accomplish clustering. We were highly attentive to data preparation, which we made consistent and clean prior to using this unsupervised learning. This enabled us to discover naturally defined groupings of students. Lastly, we appraised these resultant groups in order to understand the academic trends and certain student behaviors clearly. This whole procedure eventually managed to enable the derivation of actionable information without necessarily having to resort to any prior assumptions or pre-determined performance tags.

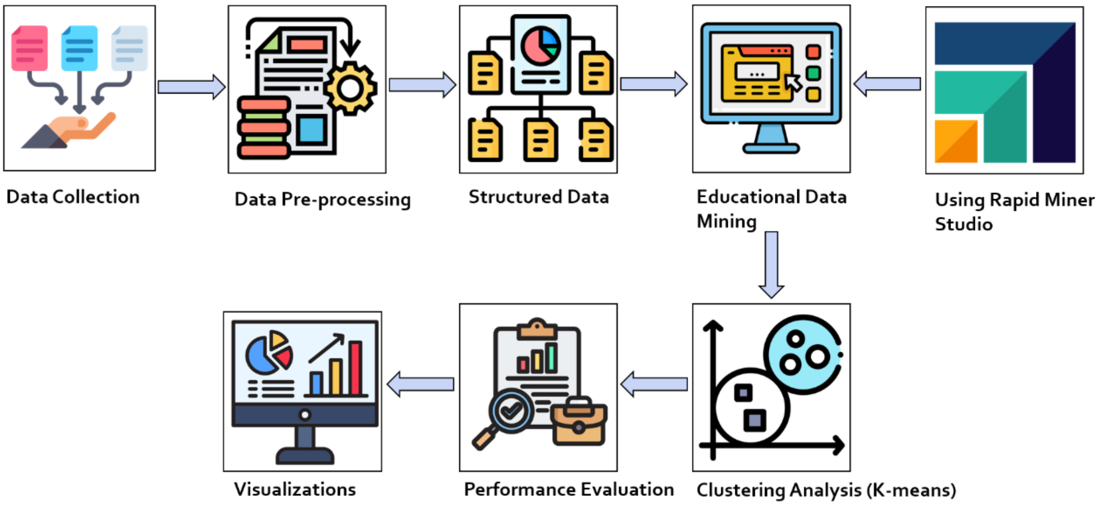

Figure 1. Research Methodology

3.1. Data Collection

The student data for this research were obtained through the Department of Software Engineering at Mehran University of Engineering and Technology. The data includes the academic record of 210 undergraduate students, and there were two successive batches from the same discipline: Batch-01 (B-01), comprising 90 students, and Batch-02 (B-02), comprising 120 students. Each student's academic records consisted of marks collected on four semesters (academic terms), like 5th, 6th, 7th, and 8th academic semesters, and in total from all semesters selected, there were 21 subjects: sessional assessments, mid-terms, and final examinations, as shown in Table 1. Basically, these records provide a full plan of student performance at the latter end of the degree program; hence, they are the best starting point of our clustering analysis.

Table 1. Subjects across Semesters or Academic Terms

Year	Academic Semester / Term	Subject	Abbreviation
3rd Year	5th Term	Communication and Presentation Skills	CPS
		Statistics and Probability	SP
		Software Construction and Development	SCD

		Human Computer Interaction	HCI
		Agent-based Intelligent Systems	ABIS
		Information Security	IS
		Discrete Structures	DS
		Data Science and Analytics	DSA
	6th Term	Data Science and Analytics (Practical)	DSAPR
		Mobile Application Development (Practical)	MADPR
		Software Re-engineering	SR
		Formal Methods in Software Engineering	FMSE
		Multimedia Communication	MC
	7th Term	Multimedia Communication (Practical)	MCPR
		Web Engineering	WE
4th Year		Web Engineering (Practical)	WEPR
		Simulation and Modeling	SM
		Cloud Computing	CC
	8th Term	Cloud Computing (Practical)	CCPR
		Software Quality Engineering	SQE
		Software Quality Engineering (Practical)	SQEPR

3.2. Data Preprocessing

Before we could run the clustering algorithm, the raw academic data needed a lot of preparation. We went through a series of thorough pre-processing steps to clean it up and make sure the quality was high enough for effective analysis.

3.2.1. Data Integration

To better understand student performance variation across genders, the gender data was merged with the existing academic records. This integration created a comprehensive dataset, enabling the examination not only of general performance patterns but also of gender distribution across the two batches. Connecting these variables gave us the necessary context to conduct detailed clustering and see how performance trends varied specifically between the male and female students.

3.2.2. Data Transformation

Assessment factors of class test marks and assignment marks were combined into a new field and named sessional marks. A combination of the sessional marks, midterm marks, and final examination marks forms a complete representation of the performance of each student.

3.2.3. Data Cleaning

We rigorously checked the dataset for any missing or null values, as even a few invalid entries can produce misleading results. We actively identified and corrected these issues to uphold the data's integrity and ensure the reliability of our analysis [15]. Once the data was clean, we carefully screened and refined the records. This filtering process successfully eliminated any irrelevant or unfinished records, resulting in a reliable final dataset. We completed the preparation with 200 full student records, all accurate and consistent, which formed the basis of our experiment, as detailed in Table 2.

Table 2. Division of students into batches

Batch Number	Student Count
B-01	84
B-02	116
Total	200

3.2.4. Data Splitting

For batch-wise analysis, the cleaned data was deliberately split into batch-wise data. This allowed us to study B-01 and B-02 separately, making it possible to compare performance trends across different cohorts. Additionally, we divided the records by academic semester to monitor student development over time. This segmentation would aid a comparative analysis on academic trends.

3.3. Experiment Analysis

EDM is a popular field that integrates different fields like data mining, machine learning, and statistical analysis to analyze datasets containing information on student academic performance. The primary goal of EDM is to identify hidden patterns within the data, offering meaningful insights for improving the quality of education in educational institutions [16]. Clustering, a fundamental unsupervised machine learning technique, is used to group data points that share similar properties or characteristics without any predefined information of labels in resultant classes. In a dataset, clustering seeks to find naturally occurring groups based on data points that are more similar to one another and can be merged into a group rather than to those in other clusters [17].

This research focuses on discovering unique patterns and insights from the academic performance of students from different batches in different semesters. The main objective was to compare how various academic batches developed over the course of an academic year and find the underlying trends in their educational performance. To make it possible, this research employed K-Means clustering as an experimental technique, which successfully identified specific, distinctive groups of student performance within the data.

3.3.1. K-*means* and Performance Evaluation

K-Means clustering is the most widely used unsupervised EDM approach designed to group a set of objects into unique clusters based on similarities within the objects or data points. The process involves grouping the data points objects into K clusters, where K is the number of clusters required. Each cluster is determined by its centroid, which is, in simple terms, the average value of all the data points the cluster contains [17]. The primary goal of the algorithm is to minimize the Sum of Squared Errors (SSE). This metric calculates intra-cluster variance. By increasing the number of iterations till it starts minimizing the SSE, we ensure that points within the same cluster are as close as possible to their cluster centroid, thereby maximizing homogeneity within clusters and maximizing differentiation between different clusters. The SSE is a key measure for evaluating the performance and quality of the clustering [18]. The mathematical equation for SSE is as follows:

$$SSE = \sum_{i=1}^{k} \sum_{x \in Ci} \|x - \mu i\|^2$$

Where n indicates the number of iterations, x_i is the value of the i^{th} iteration, and $\bar{x}$ signifies the mean of all iterations.

The working steps of the K-means algorithm are as follows. The first step is the random selection or selection of K centroids or by some heuristic. Subsequently, the data are clustered around the closest centroid. Centroids are then recalculated after the assignment as the average of the points in their cluster. This will be repeated until convergence is attained, which is usually when the cluster assignments essentially do not change greatly anymore or the decrease in SSE turns minimal. K-means has the advantage of being simple, scalable, and efficient, and more so with large datasets. It has been widely used in many fields, like image segmentation, market segmentation, but most importantly, learning educational data mining, where it is used to determine students' performance groups, learning behavior patterns, and other latent patterns in academic data.

Nevertheless, K-means is limited by the fact that it is sensitive to the initial centroid positions, requires the number of clusters to be specified in advance, and assumes that clusters are spherical and have the same size. Although there are such disadvantages, K-means is a classical algorithm used in grouping work because of its natural methodology and the ability to solve the problem quickly.

4. Experiment Results

In this section, the results of the use of the K-means clustering algorithm in the academic data are shown. The clustering approach revealed the performance patterns of students who had been studied in the two batches and provided a better insight into their learning behaviors and the development of the same with time. Investigating the composition of students in each cluster and analyzing the trends related to that, it was possible to obtain valuable information about the strengths and weaknesses of the academic processes and the level of engagement among students. The labels of the subjects are given as *Semester_SubjectAbbreviation_TypeOfAssessment*, so, for instance, if it is a subject of the fifth semester and we are observing the sessional marks, then the label for the subject CPS would be 5_CPS_S. Similarly, the midterms are abbreviated with the initial M, and the final examinations are abbreviated with the initial F. In this results section, the academic term can also be called a semester.

4.1. Experiment#1 - 5th Term

K-means was used in this research, and the performance data of 84 students in B-01 in the subjects of the 5th academic term are provided in Table 3. The result of the analysis, according to their scores in several different assessments, was three distinct clusters.

- Cluster 0: Students in this cluster achieved exceptionally high performance, particularly in final examinations such as SP_F, ABIS_F, and CPS_F. In addition, they consistently obtained higher scores in both mid-term and sessional assessments across most subjects.
- Cluster 1: This group demonstrated moderate overall performance. Their scores remained fairly consistent across subjects but did not reach the level of excellence seen in Cluster 0. For instance, results in CPS_F and SP_F were satisfactory yet below the top performers.
- Cluster 2: This cluster consisted of students with weaker or poorer academic outcomes or performance, especially in final examinations of subjects like CPS_F, SCD_F, and SP_F. Also, they had lower scores in other assessments, including sessional and mid-term marks, which identifies them as a group of students who need academic support from instructors.

Table 3. Fifth academic term subjects – students' B-01.

Subjects and Assessments	Cluster 0 (High Performers)	Cluster 1 (Intermediate Performers)	Cluster 2 (Low Performers
5_CPS_S	17.023	17.946	15.002
5_CPS_M	14.877	16.784	16.333
5_CPS_F	38.318	44.459	28.667
5_SP_S	17.045	19.405	15.667
5_SP_M	13.987	16.917	7.333
5_SP_F	33.864	51.324	31.000
5_SCD_S	8.497	9.343	8.333
5_SCD_M	6.456	8.945	6.000
5_SCD_F	19.176	25.197	14.516
5_HCI_S	17.410	18.589	15.457
5_HCI_M	15.872	18.148	12.107
5_HCI_F	16.312	19.509	13.781
5_ABIS_S	18.482	19.513	17.700
5_ABIS_M	14.862	16.022	12.012
5_ABIS_F	45.097	51.262	38.322
5_IS_S	14.032	20.056	18.012
5_IS_M	14.087	16.837	12.048
5_IS_F	16.023	17.469	15.169
Cluster %	52.4	44.0	3.6
Student Count		84	
Number of Iterations		9	
Sum of Squared Errors		0.470	

For analyzing B-02's fifth academic term performance of students, K-Means clustering was applied to the assessment data of 116 students, as shown in Table 4, and resulted in three unique clusters:

- Cluster 0: These students continuously demonstrated excellent performance in all assessments, but especially in final exams like IS_F, ABIS_F, and CPS_F. Their consistent performance shows they had a very clear understanding of concepts.
- Cluster 1: Most of the students with moderate performance were found in this group or cluster. They were having good scores in sessional and some finals, like IS_F, HCI_F, CPS_F, but had poorer marks in mid-terms (ABIS_M, SP_M), suggesting that they need to improve their learning in order to achieve high grades.
- Cluster 2: This group struggled across different assessments, particularly finals such as ABIS_F, SCD_F, CPS_F, and mid-terms like ABIS_M, HCI_M. Their low scores indicated that they need serious academic support from instructors and also need to improve their learning methods to move from poorer marks to good grades.

Across both batches, the three unique clusters show that educational hurdles are demonstrated in qualitatively different ways, while top performers Cluster 0 shows coherent excellence requiring enhancement rather than intervention, the struggling students fall into two educationally distinct categories: One group, named as Cluster 1, with particular weaknesses in particular assessment circumstances. The student in this cluster needs selective, skills-based support (study approach, assessment preparation). The other group is named Cluster 2, with major weaknesses and requiring concentrated curriculum-focused assistance starting earlier in the semester. Educators or instructors should use early sessional marks or performance as a distinguishing tool to identify at-risk students and differentiate teaching approaches accordingly, rather than waiting for mid-term results to activate remediation efforts.

Table 4. Fifth academic term subjects – students' B-02.

Subjects and Assessments	Cluster 0 (High Performers)	Cluster 1 (Intermediate Performers)	Cluster 2 (Low Performers
5_CPS_S	18.295	17.815	15.277
5_CPS_M	14.756	13.569	10.909
5_CPS_F	40.940	35.156	30.063
5_SP_S	18.750	17.310	16.207
5_SP_M	13.430	9.165	7.128
5_SP_F	39.510	30.659	29.554
5_SCD_S	9.705	8.534	7.014
5_SCD_M	8.130	6.609	5.037
5_SCD_F	23.350	19.855	15.645
5_HCI_S	19.130	18.776	17.634
5_HCI_M	16.452	12.086	8.854
5_HCI_F	40.501	34.354	31.455
5_ABIS_S	16.500	14.424	10.987
5_ABIS_M	14.527	9.452	3.846
5_ABIS_F	48.504	34.140	20.023
5_IS_S	19.000	18.000	17.055
5_IS_M	15.765	14.452	9.556
5_IS_F	52.600	48.100	40.450
Cluster %	34.5	56.0	9.5
Student Count		116	
Number of Iterations		9	
Sum of Squared Errors		0.442	

4.2. Experiment#2 - 6th Term

Focusing on the 6th-term subjects as shown in Table 5, the K-means clustering analysis for B-01 produced three distinct clusters with the following characteristics.

- Cluster 0: This cluster consisted of high-achieving students who excelled in the final examinations across all subjects. They also performed strongly in sessional assessments and mid-term exams.
- Cluster 1: Students in this cluster demonstrated moderate performance across all types of assessments, including sessionals, mid-terms, and final examinations.
- Cluster 2: This cluster comprised students with lower average scores, particularly in final examinations. However, they showed notable strength in MAD (Practical), outperforming even some of the intermediate-level students in this subject.

Table 5. Sixth academic term subjects – students' B-01.

Subjects and Assessments	Cluster 0 (High Performers)	Cluster 1 (Intermediate Performers)	Cluster 2 (Low Performers
6_DS_S	18.800	17.120	9.787
6_DS_M	18.607	15.008	14.717
6_DS_F	50.353	41.336	34.918
6_DSA_S	18.652	17.033	16.000

6_DSA_M	18.889	17.400	15.676
6_DSA_F	48.442	45.313	37.355
6_DSAPR_S	15.678	13.720	11.890
6_DSAPR_F	22.287	17.355	15.044
6_MADPR_S	17.612	14.378	12.899
6_MADPR_F	23.006	15.383	14.331
Cluster %	53.6	35.7	10.7
Student Count		84	
Number of Iterations		9	
Sum of Squared Errors		0.426	

Focusing on 6th-term subjects for B-02, which included 116 students, the following clusters were identified, as shown in Table 6.

- Cluster 0: This cluster is constituted of students who achieved high scores across the subjects. It includes students who perform well in both theoretical and practical subjects, demonstrating strong and steady academic excellence.
- Cluster 1: Students with moderate performance are grouped in cluster 1. These students have stable results above the minimum thresholds across the subjects.
- Cluster 2: Students in this group demonstrated lower scores across several subjects, with some marks falling significantly below average. These students require and would benefit from additional academic support or remedial interventions to improve their performance.

The contrast between B-01 and B-02 during the 6th semester highlights an important principle that struggling students do not have the same characteristics or are not a homogeneous group. In B-01, the low-performing students (Cluster 2) show that having low performance in theoretical subjects still have good practical competency, suggesting learning strategies mismatches rather than incompetence. However, B-02 Cluster 2, reveals wide academic challenges that require complete skill growth. This highlights the need for a distinct assessment that surpasses subject-specific assessment to discover whether low performance is caused by knowledge gaps, learning strategies, academic skill insufficiency, or motivational issues.

Table 6. Sixth academic term subjects – students' B-02.

Subjects and Assessments	Cluster 0 (High Performers)	Cluster 1 (Intermediate Performer)	Cluster 2 (Low Performers
6_DS_S	15.698	14.963	12.012
6_DS_M	15.156	10.727	10.157
6_DS_F	40.471	33.094	40.127
6_DSA_S	14.897	12.000	10.040
6_DSA_M	16.613	12.906	10.100
6_DSA_F	45.948	34.528	30.610
6_DSAPR_S	17.158	16.019	15.008
6_DSAPR_F	20.869	17.830	17.087
6_MADPR_S	18.066	16.094	14.000
6_MADPR_F	25.148	23.090	23.502
Cluster %	52.6	45.7	1.7
Student Count		116	
Number of Iterations		3	
Sum of Squared Errors		0.486	

4.3. Experiment#3 - 7th Term

Focusing on the 7th term subjects as shown in Table 7, the K-means clustering analysis for B-01 produced three distinct clusters with the following main features.

- Cluster 0: This cluster demonstrated moderate academic performance across various subjects.
- Cluster 1: This cluster is composed of students demonstrating lower academic performance, highlighting that they are facing difficulties in the subject.
- Cluster 2: This cluster consisted of those students who showed excellent performance, achieving good marks and grades in sessionals, mid-terms, and as well as final examinations in subjects.

Table 7. Seventh academic term subjects – students' B-01.

Subjects and Assessments	Cluster 2 (High Performers)	Cluster 0 (Intermediate Performers)	Cluster 1 (Low Performers
7_SR_S	16.920	15.541	14.360
7_SR_M	16.840	15.170	13.982
7_SR_F	45.358	34.658	25.313
7_FMSE_S	18.908	17.306	15.733
7_FMSE_M	17.020	14.030	10.612
7_FMSE_F	50.408	37.378	25.338
7_MC_S	18.880	17.738	16.400
7_MC_M	17.865	16.633	13.005
7_MC_F	50.840	42.049	33.300
7_MCPR_S	15.780	14.658	13.678
7_MCPR_F	23.980	22.608	21.076
7_WE_S	19.480	18.270	17.676
7_WE_M	17.890	14.610	10.807
7_WE_F	50.780	32.432	21.687
7_WEPR_S	19.770	18.925	15.333
7_WEPR_F	27.870	23.589	18.332
Cluster %	29.8	52.4	17.8
Student Count		84	
Number of Iterations		9	
Sum of Squared Errors		0.395	

Similarly, focusing on the 7th term subjects as shown in Table 8, the K-means clustering experiment for B-02 produced the following three unique clusters of performances.

- Cluster 0: Students with moderate marks in different types of assessments. They had acceptable marks in sessionals and mid-terms, but their final scores were not good and suggested room for improvement.
- Cluster 1: This cluster consisted of 61% of the students' batch, who had excellent performances in all subjects, but they had their best marks in the final exams of subjects including SR_F, MC_F, and WE_F.
- Cluster 2: The 12% of the students were found in this group and were identified as those students who had poorer performance in all types of exams or assessments and required serious observations in their studies.

Table 8. Seventh academic term subjects – students' B-02.

Subjects and Assessments	Cluster 1 (High Performers)	Cluster 0 (Intermediate Performer)	Cluster 2 (Low Performers
7_SR_S	17.648	15.066	14.529
7_SR_M	17.451	15.068	13.020
7_SR_F	35.549	31.914	25.143
7_FMSE_S	17.549	16.170	15.124
7_FMSE_M	14.570	12.198	10.008
7_FMSE_F	36.980	32.870	18.714
7_MC_S	17.787	16.209	15.047
7_MC_M	16.740	14.781	10.124
7_MC_F	39.955	35.542	24.760
7_MCPR_S	16.472	15.914	13.786
7_MCPR_F	16.833	14.492	13.500
7_WE_S	17.897	15.605	12.214
7_WE_M	13.743	10.832	8.757
7_WE_F	42.074	33.458	20.463

7_WEPR_S	18.789	16.510	12.786
7_WEPR_F	22.704	19.037	11.426
Cluster %	61.2	26.7	12.1
Student Count		116	
Number of Iterations		9	
Sum of Squared Errors		0.461	

4.4. Experiment#4 - 8th Term

Focusing on the 8th term subjects as shown in Table 9, the K-means clustering algorithm for B-01 identified three clusters of different performance of students as follows.

- Cluster 0: The students in this group had an average level of performance across all subject assessments.
- Cluster 1: Students in this group or cluster had poorer grades or marks and needed support in academic challenges.
- Cluster 2: The students in this cluster had excellent performances in all types of assessments in different subjects.

Table 9. Eighth academic term subjects – students' batch-01.

Subjects and Assessments	Cluster 2 (High Performers)	Cluster 0 (Intermediate Performer)	Cluster 1 (Low Performers
8_SM_S	18.150	17.795	14.400
8_SM_M	17.400	15.523	12.600
8_SM_F	52.850	47.841	37.800
8_CC_S	19.450	18.091	17.700
8_CC_M	18.550	12.977	11.100
8_CC_F	50.500	42.550	36.650
8_CCPR_S	16.500	15.091	14.100
8_CCPR_F	22.750	18.909	19.900
8_SQE_S	16.800	15.932	14.900
8_SQE_M	15.750	13.136	10.850
8_SQE_F	46.200	42.659	37.150
8_SQEPR_S	18.550	17.818	16.250
8_SQEPR_F	21.700	20.273	19.170
Cluster %	23.8	52.4	23.8
Student Count		84	
Number of Iterations		9	
Sum of Squared Errors		0.388	

Focusing on the 8th academic term subjects for B-02 as presented in Table 10, the K-Means comprehensive analysis once again produced three unique clusters with the following characteristics.

- Cluster 0: This group represents excellent and high performers in all assessments, but observing in depth then their final examination scores were outstanding. It means they had maintained their performance consistently in target of achieving good grades.
- Cluster 1: Students in this group showed poorer academic performance. Their consistently low scores across sessional work, mid-terms, and final assessments indicate their lower interest in studies or difficulty in grasping the concepts.
- Cluster 2: Students with average performances were found in this cluster. Their scores are neither exceptionally high nor drastically low, placing them squarely in the middle of the academic spectrum, but they still need to make improvements in order to achieve good grades.

Table 10. Eighth academic term subjects – students' B-02.

Subjects and Assessments	Cluster 0 (High Performers)	Cluster 2 (Intermediate Performer)	Cluster 1 (Low Performers
8_SM_S	15.537	13.189	11.033
8_SM_M	14.867	12.862	10.333
8_SM_F	49.278	36.868	18.044

8_CC_S	19.259	18.623	16.078
8_CC_M	16.500	15.012	13.556
8_CC_F	46.593	40.760	34.222
8_CCPR_S	16.630	15.151	14.333
8_CCPR_F	24.574	23.250	21.333
8_SQE_S	12.426	10.045	7.111
8_SQE_M	14.981	13.245	11.220
8_SQE_F	46.463	42.679	35.778
8_SQEPR_S	19.241	18.113	17.556
8_SQEPR_F	19.130	17.453	16.556
Cluster %	46.6	45.7	7.7
Student Count		116	
Number of Iterations		9	
Sum of Squared Errors		0.431	

5. Achievement Cluster Group Analysis

Figure 2 provides a comparison of the academic performance of the learners in B-01 and B-02 during the 5th, 6th, 7th, and 8th semesters, where they were ranked in High, Intermediate, and Low categories or clusters. In the case of Batch B-01, Intermediate clusters dominated most students at about 50 percent. Most importantly, however, the distribution demonstrates a definite decline in terms of performance throughout the academic year. This year, 44% of them were High performers and only 4 percent were in the Low category. Although High performers temporarily reached 53% during the 6th term, the overall picture changed quickly: as the 7th and the 8th terms approached, the percentage of High performers declined to 30% and 24%, respectively. Meanwhile, Low performers experienced a gradual growth, reaching 18% in the 7th term and reaching 24% in the 8th term. This trend shows that B-01 students experience some difficulties in terms of high academic performance, implying that there is a significant change in the top and middle performance brackets to the lower one in the last semesters.

In contrast, B-02 exhibits a more dynamic and unique pattern. In the 5th term, most students were in the Intermediate cluster while 34% were in the High and 10% belonged in the Low cluster. However, in the 6th term, there is a dramatic and unusual or unexpected spike in performance, with an overwhelming 97% of students achieving High performance and only minimal representation in the Intermediate (2%) and Low (1%) categories, indicating an unusual behavior in the academic records of students during the 6th term. This suggests that something specific during that semester or academic term, such as instructional methods, assessment styles, or student engagement strategies, may have had a highly positive impact on student outcomes. Interestingly, this exceptional performance did not completely persist in subsequent academic terms. In the 7th term, the proportion of High performers decreases to 61%, while Intermediate performers increase to 27% and Low performers rise to 12%. By the 8th term, performance levels stabilize, with an even split between High and Intermediate performers (46% each) and a smaller percentage (8%) in the Low category.

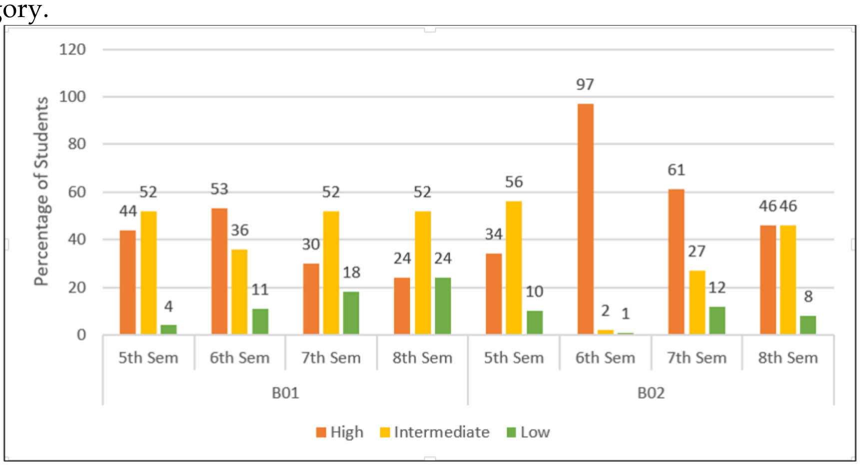

Figure 2. Percentage distribution of students in High, Intermediate, and Low performance categories across the 5th, 6th, 7th, and 8th semesters for Batches B-01 and B-02

6. Student Progression Across Semesters or Academic Terms

To monitor how individual students progressed during the final stages of their degree, clusters were formed at the end of each semester, and every student was grouped accordingly. Each cluster was defined by a centroid, which reflected the average mark of the students in that group across all subjects. To determine these centroids, the subject-wise averages within each cluster were first computed and then rounded off to the nearest whole number. For B-01, the Low cluster had a centroid value of 55, the Intermediate cluster had a centroid of 66, and the High cluster had a centroid of 76. For B-02, the centroids were 49 for Low, 61 for Intermediate, and 71 for High.

The marks of each student over the final four semesters were then combined, and their mean scores were calculated. Based on these semester-wise averages obtained, each student was assigned to one of the three clusters, Low, Intermediate, or high, for each semester, whichever was nearest to the centroid values of clusters in each academic term. This process resulted in an identifier for each student. The four valued identifier represented the centroid value of the cluster the student belonged to in each of the 4 semesters: 5, 6, 7, and 8. For example, a student who stayed in the Low cluster across all four semesters would be represented by the identifier [55, 48, 45, 53] for B-01 and the identifier [49, 21, 50, 55] for B-02. Similarly, a student who consistently performed well would be assigned the high cluster identifier of [76, 62, 71, 67] for B-01 and [71, 53, 57, 63] for B-02. These identifiers provide a compact summary of each student's academic journey during the last two years of their academic degree.

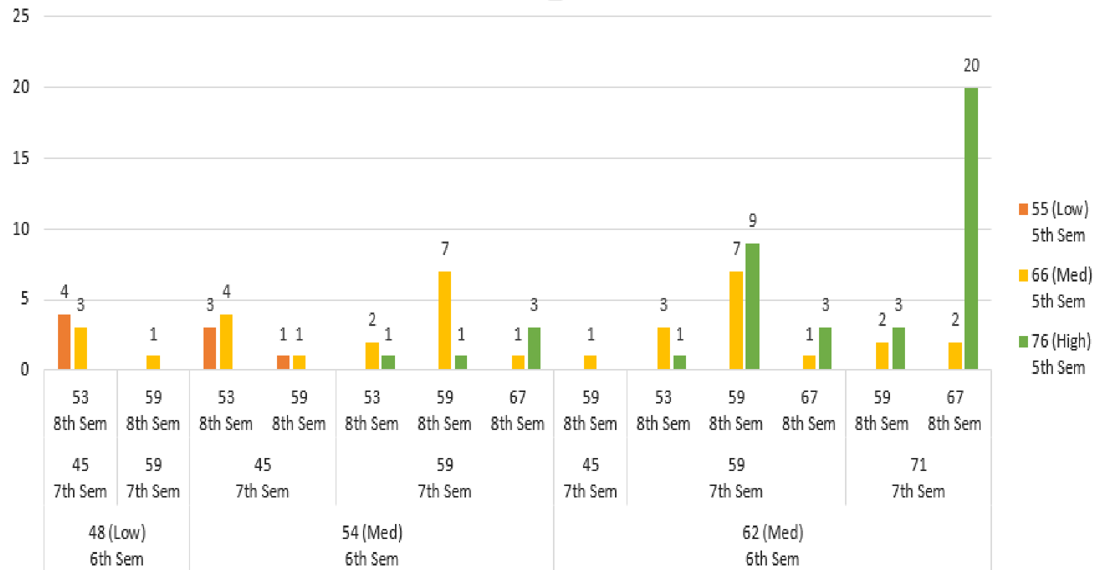

Figure 3. Aggregated performance visualization of B-01.

Once each student's cluster-based identifiers were established, their collective academic progression was illustrated through hierarchical histograms. Figure 3 presents the aggregated progression for B-01. In these figures, clusters corresponding to High performance are shown on the right side, whereas Low clusters are displayed on the left. The height of each bar represents how many students followed a particular path, while the color indicates the cluster to which they belonged in Semester 5. The base layer of the figure shows Semester 6 clusters (48, 54, and 62), each of which is then subdivided into Semester 7 clusters arranged from Low to High, and further split into Semester 8 clusters in the same order. A corresponding visualization for B-02 is presented in Figure 4, with base clusters representing Semester 6 centroids (21, 30, and 53). Together, these stratified visualizations provide a clear, understandable picture of how students' academic performance changed and discover shifts in academic assessments in different semesters. For B-02, only one student remained in the Low cluster across all semesters. Twenty students consistently stayed in the Intermediate cluster, and thirty-two students maintained High cluster status from Semester 5 through Semester 8. Moreover, thirteen students started in the Intermediate cluster in Semester 5 and advanced to the High cluster in Semester 6, remaining in the High cluster in Semesters 7 and 8.

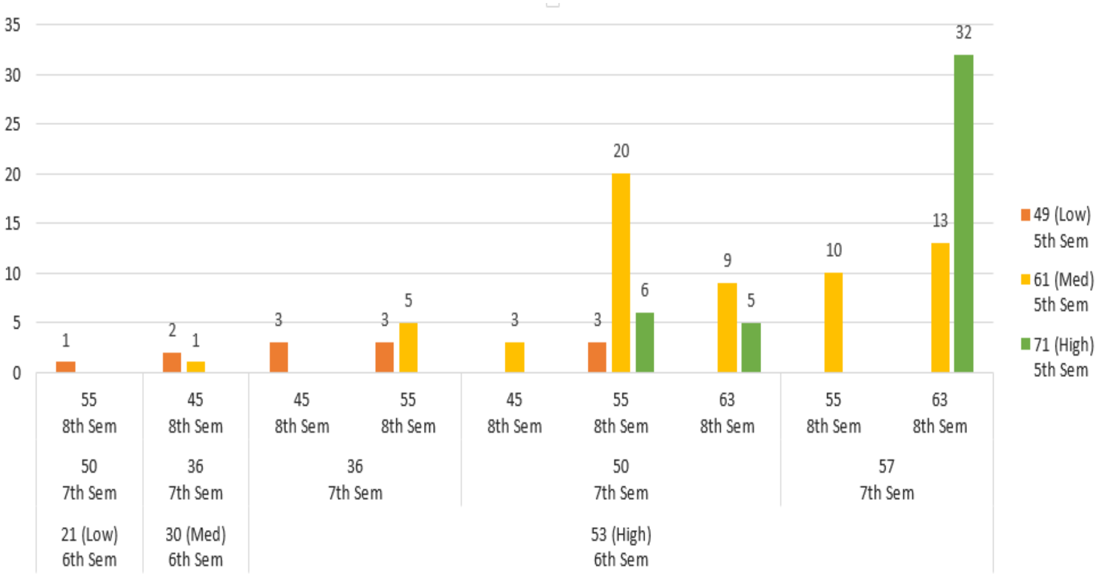

Figure 4. Aggregated performance visualization of B-02.

Overall, these findings indicate that most students tend to remain within the same cluster over time. A few students, however, show unusual patterns - some start with strong performance and later drop into lower clusters, while others begin in lower clusters and steadily improve into higher ones. The most noticeable changes in cluster membership occur by the end of Semester 6, after which most students' performance patterns remain stable.

7. Gender Wise Cluster Achievements

The two charts, shown in Figure 5 and Figure 6, represent a detailed gender-wise analysis of student performance for B-01 and B-02, categorized across different semesters and performance levels as Low, Medium, and High.

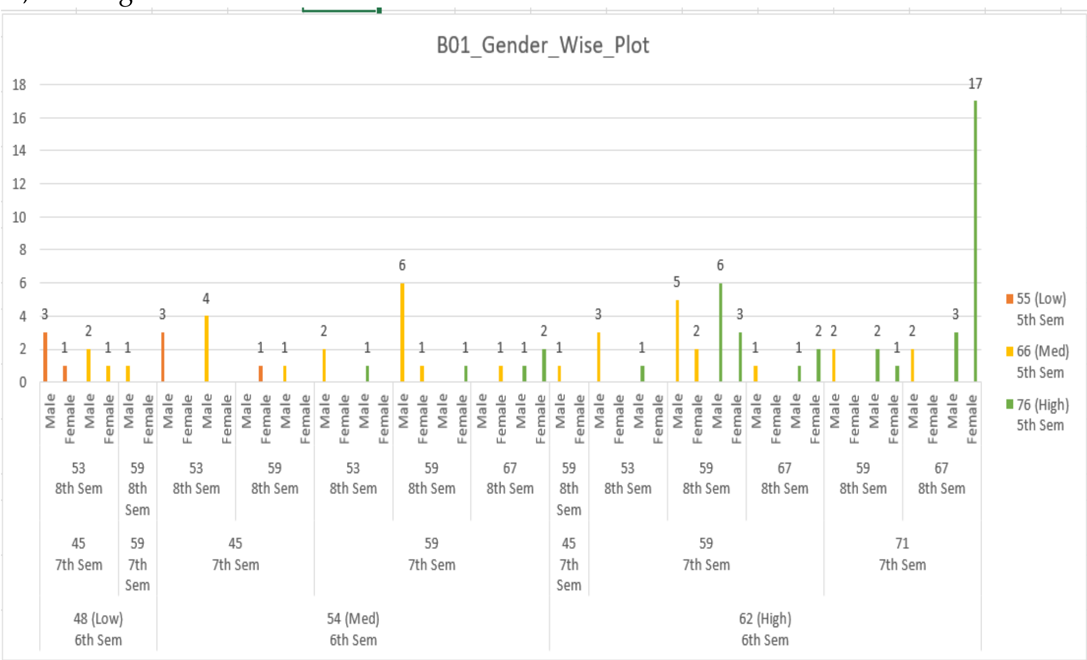

Figure 5. Distribution of Males and Females in each cluster of Batch 01.

In B-01, the majority of students fall within the medium performance category, indicated by yellow bars. This group shows a fairly balanced distribution between males and females, with male students having a slightly higher presence. The low-performing group, represented by orange bars, includes a larger proportion of male students, particularly in the 7th and 8th semesters, indicating that a subset of male students struggles academically in their final year. However, the most striking observation in B-01 is within the high-performance group. Here, there is a notable spike of 17 female students in the 5th semester, suggesting a highly and strong performance in all semesters during their study period. Overall, B-01 shows a modest performance distribution, with a strong standout group of high-achieving females but slightly concerning low scores among final-year males.

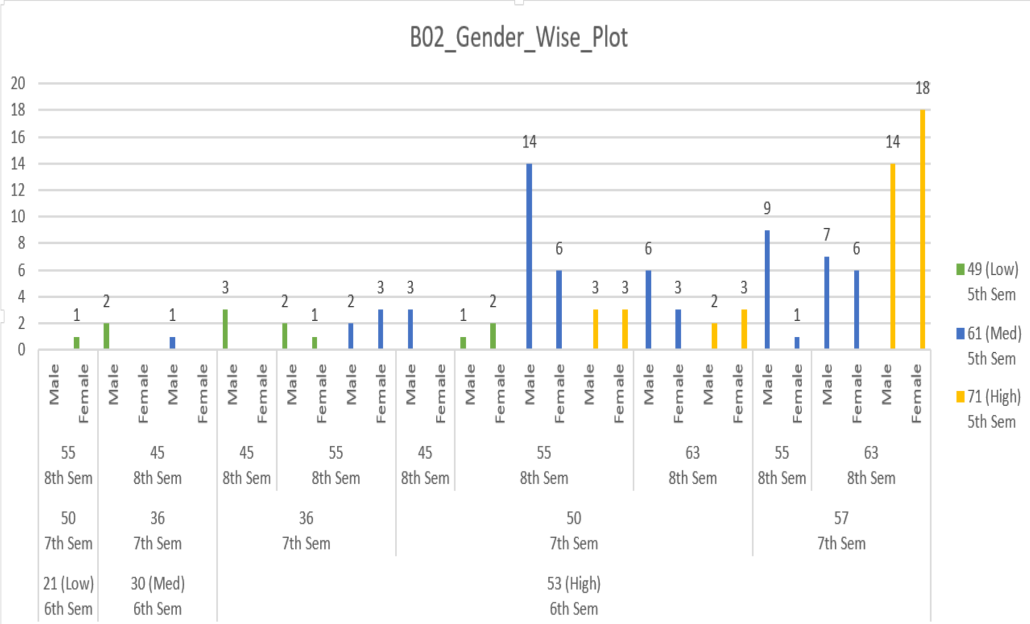

Figure 6. Distribution of Males and Females in each cluster of Batch 02.

In sharp contrast to B-01, B-02 showed a stronger and excellent overall academic performance. The Intermediate cluster performance group of students was the largest cluster in this batch, as the majority of students were found in this group, with male students particularly standing out, peaking with 14 students in the 8th semester. This study performance among males in the 7th and 8th semesters suggests a focused level of males in their studies as they neared graduation. Similarly, High performance seemed to be spread widely and remarkable in B-02. The excellence was balanced across genders early on, with a significant concentration and focus of 18 female and 14 male students from the 5th semester falling into the high-performance category. Also, B-02 had a lower number of Low performances. Only a few students were scattered across this category in any given semester, indicating that no specific semester or gender group struggled disproportionately, as there are some students who remain under lower performance as they have more focus on other activities instead of studying concentrated.

In summary, B-01 had a small number of excellent performing females in the 5th semester. Batch-02, in comparison, showed upper-level consistency across the intermediate and high performance clusters, with minimal low performance students, suggesting a fine academic base foundation in the 3rd academic year. Although both batches included high-performing female students, particularly in the 5th term, B-02 clearly maintained a more stable and powerful academic distribution between genders across all performance groups. This leads to the conclusion that B-02 not only outperformed B-01 but also achieved better consistency and greater gender balance in its academic outcomes. Comparing the performances of males and females across two batches, females have performed better than males and remained consistent in their performances across all semesters during their degree program.

8. Heatmaps Discussion

Heatmaps is a method of visually representing data trends and associations in datasets using a color map. They are particularly useful in EDM as a method of representing student performance trends across different subjects. Each cell in a heatmap corresponds to a specific value, such as a score in a subject, with the color intensity representing total marks obtained. Typically, pink indicates better performance, yellow indicates average or moderate results, and blue represents weaker performance [19]. Figure 7 presents heatmaps for the clusters examined in this study, including the 5th Term (top left), the 6th Term (top right), the 7th Term (bottom left), and the 8th Term (bottom right).

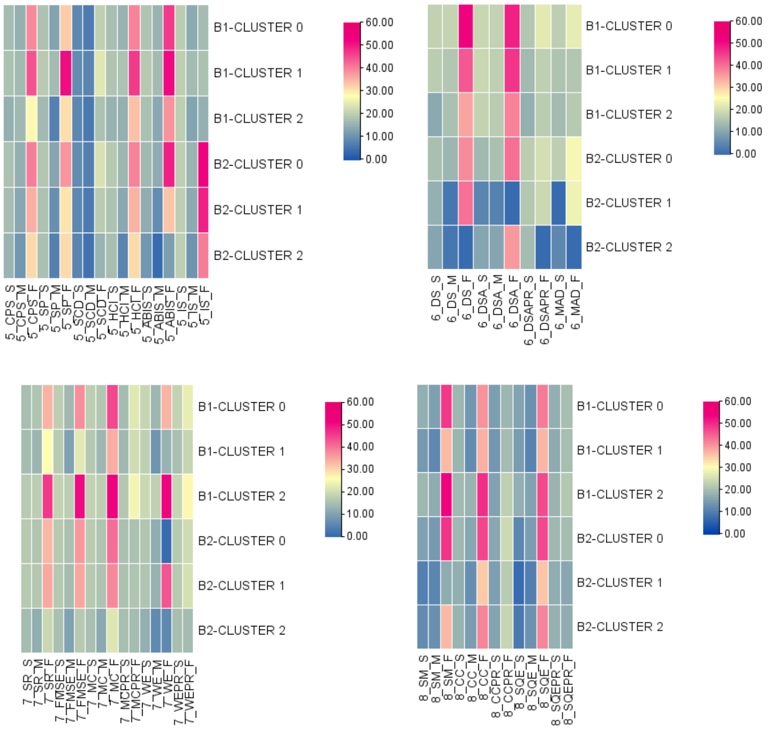

Figure 7. Heatmap Analysis Visualizations in Semesters: 5th, 6th, 7th, and 8th semester

An analysis of the heatmap uncovered that students performed well in the 5th semester, achieving good grades in the courses of CPS, SP, ABIS, and HCI; the best performance recorded was in the subject ABIS. There was severe variation in the performance between clusters in the subjects SP and HCI especially in the final exams indicating that students may struggle with these subjects. Similarly, the 6th semester shows strong performance, particularly in the subjects of DS and DSA; students have command on the subject DSA as all clusters have performed well in this subject. There is severe variation in the subject MAD with very few students attaining top scores across all clusters. The practical of MADPR also seems to require academic intervention. In the 7th semester, students exhibited strong academic performance in the subjects MC, with all other subjects showing moderate performance. Lastly, in the 8th semester, students excelled in subjects like SM, CC, and SQE. These findings highlight the need to improve teaching methods in practical subjects so students can grasp the concepts clearly, as performing well in theory and having poorer performance in practical parts indicates a huge gap between both components. We can also clearly identify the subjects that students have weaker performance in and can be suggested for improvement.

9. Conclusions and Future Works

This research identifies the differences in student performance across the identified clusters in four academic semesters. These informative insights are valuable for educators and administrators. They underscore the need for developing effective support strategies for students who are struggling and launching initiatives for high-performing students. Such actions can positively transform educational planning and help in producing students with better academic achievements.

The primary focus of this study was on 3rd and 4th year students from two different batches in the Department of Software Engineering. We specifically targeted their performance in upper-level courses to pinpoint both areas of student strength and subjects where they faced significant challenges. We had to restrict our scope due to data limitations in earlier academic years. Specifically, some inconsistencies and incomplete subject-wise mark distributions occurred as some subjects were opted in one batch while not in the other, and we specifically targeted those subjects that were the same in both batches. These critical, inconsistent data necessitated the study on the last two years' academic records, which were available from the 3rd to the 4th year, thereby guaranteeing the validity and accuracy of our research findings.

To boost the practical use and influence of this work, similar research experiments should be extended to other departments or disciplines of undergraduate programs in educational institutions by implementing the same methodology to guide and provide academic interventions and support to students, for improving students' academic outcomes and performances.

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