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Diagnosing and Prescribing Solutions for Perceived Amotivators in Engineering Education Using Learning Analytics

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ABSTRACT

Amotivation, as a construct of the Self-Determination Theory (SDT), represents a critical barrier to student engagement and success in engineering education. While a lot of study has concentrated on intrinsic and extrinsic motivators, there has been little focus on diagnosing and addressing amotivators within this context. This study explores the perceived amotivators among second-year (third-semester) engineering students registered in a formal program, utilizing learning analytics to derive actionable insights. A survey consisting of five statements related to amotivation was administered, with responses measured on a 5-point Likert scale.

Key analytical methods employed include Pearson's correlation analysis to evaluate the relationships between survey statements, k-means clustering to identify patterns of amotivation based on survey responses, and further clustering analysis to figure out the association between mean amotivation scores and cumulative grade point averages (CGPA). The findings reveal distinct clusters of students with varying levels of amotivation and academic performance, providing a sophisticated comprehension of the interplay between perceived amotivators and student outcomes.

The current study contributes to the existing body of knowledge by diagnosing amotivators in engineering education and prescribing targeted interventions. The outcomes emphasize the significance of addressing both cognitive and emotional barriers to enhance student engagement, improve academic performance, and foster a more supportive learning environment. These revelations provide a basis for educators and administrators to develop data-driven strategies to mitigate amotivation and promote student success

Keywords—Learning Analytics; Amotivation; Intrinsic Motivation; Exintric Motivation; Self Determination Theory; K- Means Clustering; Prescription;

INTRODUCTION

The economic growth and technological advancement of nations is predominantly linked to their engineering education policies. In order to fulfill the increasing demand for specialized skills, the education system must prepare students to meet these challenges with creativity, critical thinking, and technical expertise. However, a pressing concern in engineering education today is the prevalence of amotivation—a state where students lack the drive or purpose to engage actively in their learning. Amotivation is not merely an individual problem but a systemic issue that undermines the overall effectiveness of education, potentially leading to increased dropout rates and inadequate academic performance, and reduced readiness for professional challenges [1].

Factors contributing to this phenomenon range from uninspiring instructional methods and curriculum misalignment to external pressures such as societal expectations and financial constraints. Understanding the underlying causes of amotivation in engineering education requires a multifaceted approach [2]. These perceived amotivators vary widely across student populations and institutional contexts, making it crucial to adopt a data-driven methodology to diagnose, predict, prescribe and address them.

The emergence of learning analytics offers a transformative solution to this challenge. Learning analytics involves the collection, analysis, and interpretation of data related to students' learning behaviors, academic performance, and engagement patterns [3]. By leveraging this data, educators and administrators can gain actionable insights into the factors that hinder student motivation and engagement. Moreover, diagnostic analytics can identify at-risk students early, enabling timely interventions that address specific issues before they escalate [4].

This study focuses on diagnosing and prescribing evidence-based solutions for perceived amotivators in engineering education using learning analytics. The primary aim is to uncover patterns and trends that reveal the root causes of amotivation, provide insights to identify vulnerable students, and devise tailored solutions promoting engagement and success.

The significance of this study lies in its potential to enhance student outcomes and institutional effectiveness in engineering education. Addressing amotivation is not only critical for individual student success but also for ensuring that the engineering workforce of the future is equipped to tackle complex global challenges. Through the application of learning analytics, this research aims to contribute to the development of more inclusive, adaptive, and effective educational environments that foster motivation and resilience among engineering students.

In the following sections, this paper will provide a comprehensive investigation of the literature on student motivation and learning analytics, outline the methodology used to collect and analyze data, present the findings on key amotivators, and propose evidence-based interventions. By doing so, it seeks to offer a holistic approach to addressing one of the most pressing issues in engineering education today.

RELATD WORKS

This section discusses the methods, resources, and research that are currently available in both the areas of learning analytics and student motivation.While research on intrinsic and extrinsic motivators dominates the literature, few investigations concentrated on diagnosing amotivation and addressing its underlying causes, particularly in engineering education. Amotivation, a state identified by a lack of intention to act or absence of motivation, has been thoroughly investigated within the framework of Self-Determination Theory (SDT). J. Lee and D. Kim [5] have designed a learning analytics dashboard informed by Self-Determination Theory (SDT) and to investigate university students' experiences with it. The findings suggest that such dashboards can enhance student engagement by supporting autonomy, competence, and relatedness.A. Bustamante-Mora [6] emphasizes the role of autonomy, competencies, and psychological needs in effective learning models, highlighting the importance of addressing demotivators in engineering education.

One study explores engineering students' motivation for learning and studying through the lens of Self-Determination Theory and identifying factors that act as demotivators and suggesting strategies to enhance intrinsic motivation in project-based learning environments [7]. Redesigning a course taught to first year engineering students, using Self Determination Theory principles explored how addressing amotivators can improve student engagement and learning outcomes related to autonomy, competence, and relatedness [8]. Identifying gap between SDT principles and real engineering classroom environments helps in identifying amotivators and offer recommendations for orienting teaching practices to escalate student motivation [9]. S. Weydner-Volkmann and D. Bär [10], explored the design of learning analytics tool to support student autonomy, an essential component of SDT, and reduce demotivators in the learning process.

In learning analytics, it is possible to diagnose learning problems and inform effective student management strategies. For example, by building data analysis model for educational evaluation using the K-means clustering, they have uncovered patterns in students' comprehensive evaluation data focused to words diagnosing and student management strategies [11]. One of the research presents use of predictive model to align learners' expectations and performance to support self regulated learning in higher education [12]. Self-Determination Theory differentiates between intrinsic motivation (engaging in activities for inherent satisfaction), extrinsic motivation (engaging for external rewards), and amotivation, that unfolds when individuals identify no link between their behaviors and results [13]. Rigid and intensive curriculum, restrictions of autonomy in course selection, poor self-confidence in

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abilities, not knowing the relevance of their studies, disconnect between theory and real world applications, and little academic support can manifest as amotivation [14]. Attending to these issues is critical, as engineering programs have the objective to support graduates for technical proficiency as well to solve complex problems.

In learning analytics, the aggregation and examination of educational data to optimize learning environments, offers a promising avenue for diagnosing and addressing amotivation. These instruments yield sensible insightsinto the factors contributing to amotivation and enable tailored interventions. Cawkwell, Paul, and Jazayeri [15] conducted a study at the University of Calgary focusing on second-year electrical engineering students. Utilizing Theory of Self-Determination as a framework, they analyzed student reflections to gain insights into motivation levels. The results clearly indicate the value of creating supportive learning environments to foster intrinsic motivation and imply that integrating SDT principles into classroom practices can improve student engagement and lower amotivation. It is essential to fulfill the psychological requirements as explained in SDT, these interventions can reduce amotivation feelings in engineering programs and increse determination. One study claims that learning analytics may be used to monitor and enhance student engagement, which may result in more effective educational outcomes through targeted interventions [16]. K–means clustering was used as a tool for effective identification of distinct learning patterns in engineering education [17]. To advance academic success, support struggling students and enhance teaching methods, applying learning analytics would lead to actionable insights across different clusters. Effective Identification of learners at risk based on poor academic performance for providing valuable insights and early targeted interventions is accomplished through Clustering. To reveal distinct groups of learners based on similar academic outcomes and academic behavior can be achieved through clustering [18].

Most studies focus on intrinsic and extrinsic motivators, leaving a gap in understanding how to address the unique challenges posed by amotivation. Research on using learning analytics specifically for amotivation is still lacking, despite these developments.

This research aims to bridge that gap by applying learning analytics to diagnose perceived amotivators in engineering education and prescribe evidence-based solutions to address them.

In this investigation, a survey comprising five Likert-scale statements was used to assess perceived amotivators among second-year engineering students. Identifying trends and clusters that point to important areas of concern is achieved by correlating survey responses with academic performance data (CGPA).

METHODOLOGY

Learners for this research were chosen from second- year engineering of a particular program. Participants were selected based on their enrollment to third semester of their program. It was ensured that they had completed a set of foundational set of engineering courses and were beginning to encounter more advanced courses. This phase of their academic journey was thought to be crucial for assessing motivation and its potential impact on academic performance.

The groups of participants were diverse and included students who were admitted via two different pathways:

i. *Common Entrance Test (CET):* Students admitted based on performance in a standardized entrance examination, reflecting merit-based selection.
ii. *Non CET:* Students admitted based on institutional discretion or other non-merit-based criteria.

This mix of admission categories allowed for a more comprehensive analysis of the relationship between admission pathways, perceived amotivation, and academic outcomes.

A. Sampling Method

The survey adopted a convenience sampling approach, where all third-semester students present during the survey period were invited to participate. Participation was voluntary, and pupils received assurances that their answerswould remain anonymous and confidential. This method ensured high response rates while minimizing potential sampling bias.

*Ethical Considerations***:** Prior to conducting the survey, the following ethical protocols were adhered to:

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Informed Consent: Every participant was made aware of the study's objectives, the nature of the questions, and how their data would be used. Consent was soughtbefore participation.

Confidentiality: Participants' identities were anonymized, and unique identifiers (e.g., student IDs) were used solely for matching survey responses with academic performance data.

*Data Collected:*The survey responses were complemented by academic performance data, includingSemester Grade Point Averages (SGPA**)** for Semesters 1 and 2.The cumulative grade point average (CGPA) at the completion of Semester 2.Whether the student had failed any courses (indicated by an "F" grade).

This holistic data collection approach provided a robust basis for diagnosing and addressing perceived amotivation among engineering students.

Data Collection: Data for the study was gathered using a survey and compiling academic performance records to explore the connection between perceived amotivation and academic outcomes among second-year engineering students.

B. Survey Administration

*Survey Design***:**

The survey instrument consisted of *five Likert-scale statements***,** designed to assess perceived amotivation. Each statement required students to rate their level of agreement from 1***(Strongly Disagree)*** to **5** ***(Strongly Agree)***. The survey's statements were created utilizing well-established motivation research frameworks and modified for use in engineering education. A greater level of perceived amotivation was indicated by a higher score on each given statement.

*Survey Procedure***:**

The purpose of the survey was explained to the students, and they were reassured that their responses would remain anonymous. To guarantee maximum participation, the survey was administered during regular class hours. There were no incentives offered, and participation was completely voluntary. An internet platform was used to administer the surveys.

*Survey Sample***:**

The survey was sent to all third-semester students in the program and a total of 120 students completed the survey out of those enrolled.

C. Likert-Scale Statements

The statements were designed to explore students' beliefs, attitudes, and emotions related to their motivation for pursuing engineering education. The specific statements included:

1. *"I don't see the relevance of my engineering education to my future goals."*

This statement measures students' apparent disconnect between their academic work and their goals for their personal or professional lives.

2. *"I often feel like I am wasting my time studying engineering."*

This explores feelings of purposelessness and whether students perceive their efforts in engineering education as worthwhile.

3. *"I struggle to find reasons to put effort into my coursework."*

This statement assesses the difficulty students' face in finding intrinsic or extrinsic motivation to engage with their studies.

4. *"I feel incapable of succeeding in engineering subjects, which makes me less motivated."*

This captures students' self-perceived competence and how it impacts their motivation levels.

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5. *"I feel unmotivated to complete my assignments or attend classes because I don't see the point."*

This explores students' overall sense of engagement and on the importance of finishing coursework.

The statements were crafted to cover various facets of amotivation, including relevance, purpose, effort, perceived competence, and overall engagement. The statements were written in simple and clear language to ensure that students understood them easily without ambiguity.

*Rating System***:** The survey used a *5-point Likert scale* to capture the degree to which students agreed or disagreed with each statement. The scale was defined as follows:

1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

A higher degree of amotivation with regard to the specific statement was indicated by a score that was closer to 5

Survey Administration Notes: Participants were encouraged to respond honestly and assured that there were no right or wrong answers. They were instructed to rate each statement independently based on their personal experiences and feelings toward their engineering education.

D. Analysis Methods

Machine learning and statistical techniques were used to analyze the survey and academic performance data. These methods aimed to diagnose perceived amotivation, identify patterns, and understand its impact on academic outcomes.

1. Descriptive Statistics

The main characteristics of the dataset were compiled using descriptive statistics, combining the survey responses and academic performance indicators.

Measures of Central Tendency: Mean and median were calculated for Likert-scale responses to understand the average levels of perceived amotivation for each statement.

Measures of Variability: Standard deviation was brought in to investigate the spread of responses and variability among students.

Frequency Analysis: Response frequencies for each Likert-scale option were analyzed to identify the distribution of agreement or disagreement with the statements.

Descriptive statistics provided a foundational interpretation of the data and helped highlight patterns in perceived amotivation levels among students.

2. Correlation Analysis

Pearson's correlation analysis was performed to measure the strength and direction of relationships between survey responses and the survey statements

*Variables Analyzed:*Correlations between the answers were computed to the five Likert-scale statements.

Interpretation: A positive or negative correlation indicated whether higher perceived amotivation scores were associated between the statements. Correlation analysis identified the inter relationship among the statements, showing the dimensions of perceived amotivation, providing information on important areas for intervention.

3. Clustering Analysis

K-Means clustering was applied to group students based on their responses to the Likert-scale statements.

Cluster Determination: The optimal number of clusters was identified using the elbow method, where the within-cluster variance was minimized.

Output: In order to depict various motivational profiles, students were divided into discrete clusters, such as highly motivated, moderately motivated, and highly amotivated.

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Purpose: Clustering provided insights into subgroups of students with similar patterns of perceived amotivation, allowing for targeted interventions tailored to each group.

RESULTS AND DISCUSSION

A. Descriptive Analytics

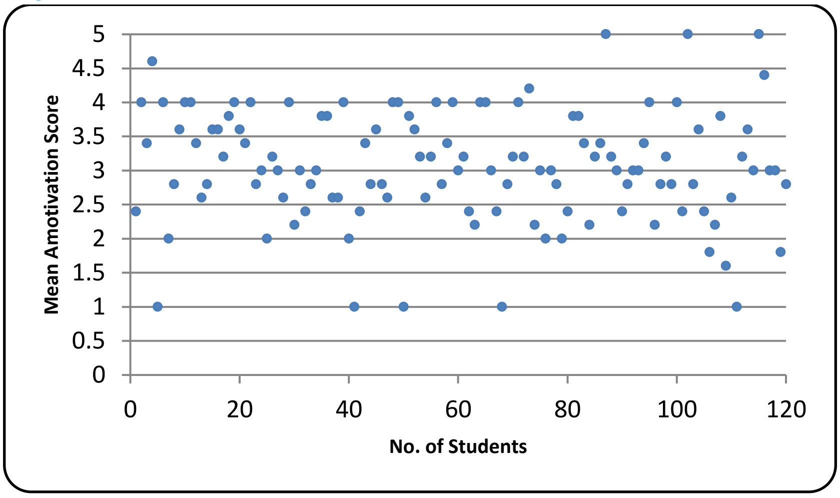

Figure 1. Scatter plot showing spread for students against mean amotivation score

Mean of the survey response scores for each student, across 5 statements was calculated and a scatter plot was drawn (Figure 1) to visualise the spread of students with respect mean amotivation score. It is evident from the plot that majority of students fall above the average mean amotivation score 2.5, showing the tendency to words moderate or high amotivation.

Table 1. Survey Responses and their Mean Scores

Survey Statements	Student Responses					Statement wise Mean Scores
	1	**2**	**3**	**4**	**5**	
S1	6	20	33	50	11	3.33
S2	16	38	29	32	5	2.77
S3	5	17	43	48	7	3.29
S4	11	28	39	38	4	2.97
S5	14	32	29	31	14	2.99
Mean of Mean						3.07

Survey responses were tabulated indicating the numbers student response for each of the statement on the likert scale of 5. Mean scores of the responses for both categories of admission and the overall statement wise mean score were calculated as show in Table 1. Mean score for a statement indicates the tendency of amotivation.

Statement wise key observations are as follows

S1: *"I don't see the relevance of my engineering education to my future goals"*

A total of ***50 students (41.7%)*** agreed and ***11 students (9.2%)*** strongly agreed, indicating that ***over 50%*** of the respondents find limited relevance of their engineering education to their future goals. ***33 students (27.5%)*** were neutral, suggesting some level of uncertainty or mixed feelings among a significant proportion of respondents. This could indicate a lack of clarity about how their education connects to their future.The mean score of **3.33** leans

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slightly toward agreement, indicating that, on average, students perceive a disconnect between their education and future goals.

S2:*"I often feel like I am wasting my time studying engineering."*

A combined ***37 students (30.8%)*** agreed or strongly agreed with the statement. This suggests that nearly one-third of students feel their engineering education is not a valuable use of their time.***29 students (24.2%)*** selected neutral, indicating a notable proportion of students are unsure or possess diverse views with regard to the significance of their studies.The mean score of **2.77** suggests a slight leaning toward disagreement, indicating that most students find value in their engineering education, but there is a considerable minority who feel otherwise.

S3: *"I struggle to find reasons to put effort into my coursework."*

A total of*48 students (40%)* agreed with the statement, and ***7 students (5.8%)*** strongly agreed.Together, ***55 students (45.8%)*** reported some level of difficulty in finding motivation for their coursework.A large proportion, ***43 students (35.8%),*** selected neutral, indicating uncertainty or mixed feelings about their effort and motivation.The mean score of **3.29** reflects a slight inclination toward agreement, indicating that motivation challenges are common but not overwhelming for the majority.

S4: *"I feel incapable of succeeding in engineering subjects, which makes me less motivated"*

A total of*38 students (31.7%)* agreed, and ***4 students (3.3%)***strongly agreed, indicating that about ***35%*** of respondents feel their lack of confidence negatively impacts their motivation.***39 students (32.5%)***selected neutral, suggesting many students are uncertain about how their perceived incapability affects their motivation.The mean score of **2.97** shows a slight tilt toward neutrality, with no overwhelming trend toward agreement or disagreement.

S5:*"I feel unmotivated to complete my assignments or attend classes because I don't see the point."*

In all,*31 students (25.8%)* agreed, and ***14 students (11.7%)*** strongly agreed, meaning about ***37.5%*** of respondents feel unmotivated because they don't see the point of their coursework. ***29 students (24.2%)*** selected neutral, reflecting a significant number of students who feel indifferent about their motivation in relation to seeing the purpose of their assignments and classes. The mean score of **2.99** reflects an almost perfect neutrality, indicating that opinions are nearly evenly distributed between agreement and disagreement, with no strong overall trend.

B. Pearson's Correlation Analysis

The purpose of this investigation is to look at the linear relationships between the survey statements (variables) that represent perceived amotivators among engineering students.

The formula for calculating Pearson's correlation coefficient (**r**) is as shown in equation (1)

$$r = \frac{n\sum(x_i y_i) - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2} \cdot \sqrt{n\sum y_i^2 - (\sum y_i)^2}} \qquad (1)$$

Where

- n is sample size
- x_i, y_i are individual sample points

The **Pearson correlation coefficient (r)** was calculated (Table 2) for each pair of variables to quantify the strength and direction of their linear relationship. The coefficient ranges from **-1** (strong negative correlation) to **+1** (strong positive correlation), with **0** indicating no linear relationship.

Table 2. Pearson's Correlation Coefficient Matrix

	S1	**S2**	**S3**	**S4**	**S5**
S1	1.00	0.70	0.66	0.62	0.48

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S2	0.70	1.00	0.53	0.72	0.64
S3	0.66	0.53	1.00	0.66	0.54
S4	0.62	0.72	0.66	1.00	0.66
S5	0.48	0.64	0.54	0.66	1.00

Key Observations from Correlation Coefficient matrix:

1. *S1 and S2*: A correlation of **0.70** indicates a strong positive relationship, meaning students who perceive less relevance of engineering education to future goals (S1) are also likely to feel they are wasting time studying engineering (S2).

2. *S2 and S4:* A high correlation of **0.72** suggests that students who feel they are wasting time (S2) are also likely to feel incapable of succeeding in engineering subjects (S4).

3. *S1 and S3*: A correlation of **0.66** suggests a moderate relationship between struggling to find reasons for coursework effort (S3) and not seeing the relevance of engineering education (S1).

4. *S4 and S5*: A correlation of **0.66** shows that students feeling incapable of success (S4) often also feel unmotivated to complete assignments or attend classes (S5).

5. *S1 and S5*: A correlation of **0.48** indicates a weaker, yet positive relationship between S1 and S5. While still related, the link between failing to recognize the value of engineering and lack of motivation for assignments is less pronounced.

6. All correlations are positive, suggesting a consistent pattern where various forms of amotivation (e.g., perceived irrelevance, wasted effort, and lack of success) tend to reinforce each other among students.

C. Clustering Analysis on Survey Statement Responses

Using K-means clustering, the survey responses were categorized into three distinct groups based on students' levels of amotivation. The clustering is interpreted using the Likert scale ratings. The clusters reflect students' perceptions regarding their motivation in engineering education. After convergence, the algorithm identified the following three clusters (Table 3).

Table 3. Statement wise Clusters

Attribute	Cluster 0 (43 instances)	Cluster 1 (22 instances)	Cluster 2 (55 instances)
s1	2.30	4.23	3.78
s2	1.95	2.41	3.55
s3	2.65	2.95	3.93
s4	2.49	2.14	3.67
s5	2.33	1.95	3.93

1. Cluster Interpretation:

i. Students in **Cluster 0** have a low perception of relevance between their engineering education and future goals, while **Cluster 1** strongly perceives adisconnect. **Cluster 2** moderately agrees with this statement.
ii. **Cluster 0** students strongly disagree that they feel like they're wasting time. **Cluster 1** slightly disagrees, and **Cluster 2** moderately agrees with this statement.
iii. **Cluster 0** shows low difficulty in finding motivation for coursework, whereas **Cluster 2** has significant difficulty.

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iv. **Cluster 0** and **Cluster 1** students do not feel incapable of succeeding in engineering, but **Cluster 2** struggles more with this perception.

v. **Cluster 0** and **Cluster 1** do not feel strongly unmotivated to complete assignments, but **Cluster 2** strongly agrees that they feel unmotivated.

2. Description of Clusters with Prescriptions

Cluster 0 (43 students, 36% of instances): Low Amotivation

Key Characteristics: Students in this group generally report low levels of amotivation across all statements.

Interpretation: These students are generally motivated, feel competent, and recognize some relevance in their education. While not completely disengaged, they could benefit from opportunities to further connect their coursework with their professional goals.

Prescriptions:[19],[20]

i. Provide opportunities for skill enhancement and applied learning to maintain their positive engagement
ii. Focus on showcasing real-world applications to sustain their moderate motivation.

Cluster 1 (22 students, 18% of instances): Moderate Amotivation

Key Characteristics: This group exhibits moderate levels of amotivation, particularly regarding the perceived relevance of their education.

Interpretation: These students' main challenge is the perceived lack of relevance of their education (s1), even though they don't necessarily feel incapable or entirely disengaged. They may benefit from more career-focused interventions, such as real-world applications or mentorship programs that align academic content with their professional goals.

Prescriptions:[21]

i. Focus on aligning coursework with career aspirations through project-based learning and industry exposure.
ii. Conduct career counselling to help students bridge the gap between their studies and future goals.

Cluster 2 (55 students, 46% of instances): High Amotivation

Key Characteristics: Students in this group report high levels of amotivation across all statements.

Interpretation: These students are highly disengaged, feel less competent, and struggle to see the value of their education. The lack of both intrinsic (s3) and extrinsic (s1, s2) motivation, as well as feelings of incompetence (s4), make this group particularly vulnerable. They require targeted interventions such as academic support, personalized mentorship, and curriculum adjustments to boost engagement.

Prescriptions:[22],[23]

i. Implement personalized support such as mentoring and counselling to address feelings of incompetence.
ii. Revamp the curriculum to include more interactive, hands-on projects and career-oriented objectives.

D. Clustering Analysis on Mean Amotivation Score and Cumulative Grade Point Average (CGPA)

The scatter plot (Figure 2) visualizes the relationship between students' *mean amotivation scores* (on a Likert scale of 5) and their *CGPA* or Cumulative Grade Point Average (on a scale of 10).

We used k – means clustering, the clustering results classify students into ***three clusters*** based on their ***mean amotivation scores*** and ***CGPA*** (Table 4).

1. *Description of Clusters with Prescriptions*

Cluster 0 *(Moderately Amotivated, Below-Average CGPA - 27% of Students)*

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Students in this cluster have a ***moderate*** *level of amotivation* (mean = 3.48).Their CGPA is below the overall average **(6.97 vs. 8.03)**.This suggests that moderate amotivation may negatively impact academic performance for these students. Table 5 shows the evidence based prescriptions for **cluster 0**.

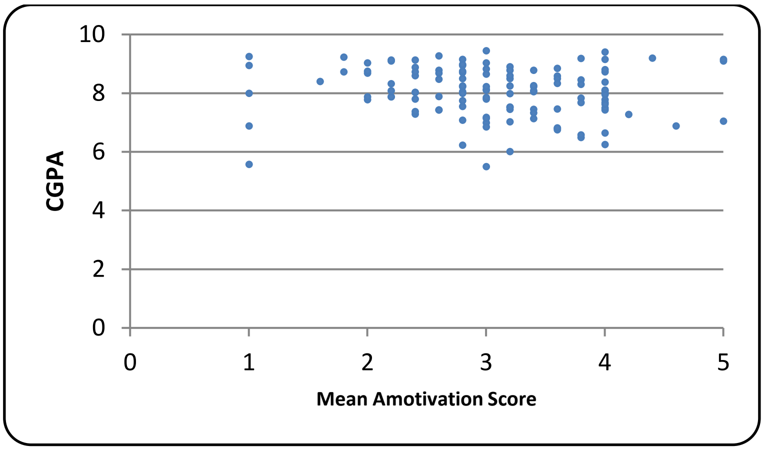

Figure 2: Scatter Plot showing the relationship between Mean Amotivation Score and CGPA

Table 4. Clusters based on Mean amotivation score and Mean CGPA

Cluster	Mean Score (Amotivation)	Mean CGPA	Number of Students	Interpretation
0	**3.48**	6.97	32 (27%)	**Moderately** amotivated, below-average academic performance
1	**2.37**	8.33	51 (43%)	**Least** amotivated, above-average academic performance
2	**3.68**	8.55	37 (31%)	**Highly** amotivated, high academic performance

Table 5. Prescribed Solutions for **Cluster 0** (Moderately Amotivated, Low CGPA)

Prescription	***Action***	***How It Works***
Workshops on Study Skills and Intrinsic Motivation [24]	Conduct workshops to teach effective study strategies, time management, and goal-setting to boost self-efficacy and motivation.	Teaching practical skills and fostering a growth mindset can help students overcome feelings of inadequacy and engage more deeply with their studies
Mentorship Programs [25]	Pair students with senior peers or faculty mentors who can provide guidance, share strategies for success, and offer emotional support.	Mentorship helps students build confidence and find relevance in their studies by learning from the experiences of others.
Curricular Relevance Enhancement[26]	Revise coursework to include more real-world applications, group projects, or problem-solving tasks related to industry challenges.	Students are more motivated when they can see how their studies connect to real-world outcomes, making their education feel less abstract.

Cluster 1*(Least Amotivated, High CGPA - 43% of Students)*

This is the largest group (43% of students).These students exhibit the ***lowest amotivation levels***(mean = 2.37) and have a ***high CGPA*(8.33).**This indicates that low levels of amotivation are associated with better academic

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performance, as students in this cluster appear to be highly engaged and motivated. Evidence based prescriptions for **Cluster 1** are shown in Table 6.

Table 6. Prescribed Solutions for **Cluster 1** (*Least Amotivated, High CGPA*)

Prescription	Action	How It Works
Recognition and Reward Programs [27]	Introduce systems to acknowledge and reward academic excellence, such as merit certificates, scholarships, or public recognition	Recognition sustains motivation by validating students' efforts and encouraging them to continue performing at a high level.
Goal-Setting and Vision Workshops [28]	Offer workshops that focus on long-term goal planning, helping students align their current academic efforts with career aspirations.	These workshops keep students focused and motivated by providing a clear sense of purpose.
Leadership and Advanced Learning Opportunities [29]	Encourage these students to take on leadership roles in academic or extracurricular activities, such as mentoring juniors or participating in advanced projects.	Providing leadership opportunities ensures these students remain challenged and engaged, fostering personal growth.

Cluster 2 *(Highly Amotivated, High CGPA - 31% of Students)*

Students in this cluster have the **highest amotivation scores** (mean = 3.68) but also the **highest CGPA (8.55).**This suggests that despite high amotivation, these students manage to achieve strong academic outcomes. Extrinsic motivators (e.g., rewards, pressure from parents/teachers) might explain their performance. Table 7 presents the evidence based prescribed solutions for **cluster 2**.

Table 7. Prescribed Solutions for **Cluster 2** (Highly Amotivated, High CGPA)

Prescription	Action	How It Works
Purpose-Driven Learning [30]	Introduce assignments and projects that address societal challenges or innovative solutions in engineering.	Purposeful engagement helps students find meaning in their studies, reducing feelings of amotivation.
Stress and Well-Being Programs [31]	Provide workshops or counselling sessions focused on managing stress, avoiding burnout, and fostering a healthy work-life balance.	High-performing students often face pressure to maintain their success, which can lead to emotional fatigue and diminished motivation.
Career Exploration and Mentorship [32]	Pair these students with mentors or arrange industry exposure activities to help them see the connection between their studies and potential career paths.	Clear career alignment reduces feelings of purposelessness and re-engages students with their education.

CONCLUSION

The study titled "*Diagnosing and Prescribing Solutions for Perceived Amotivators in Engineering Education Using Learning Analytics*" provides an in-depth investigation into the factors contributing to amotivation among second-year engineering students. Rooted in Self-Determination Theory (SDT), this research shifts the focus from intrinsic and extrinsic motivators, which have been carefully considered, to the relatively underexplored domain of motivation. By leveraging learning analytics, the study identifies, categorizes, and prescribes evidence based solutions for perceived amotivators in engineering education.

Key conclusions drawn from this study, offer significant knowledge concerning the interaction between student motivation, academic performance, and perceived relevance of their educational experience. Pearson's correlation analysis among the five survey statements, designed to measure different dimensions of amotivation, revealed critical interrelationships. Trends of low academic confidence, unfavorable attitudes toward coursework, and a lack of belief in the engineering curriculum's applicability were revealed in these associations.

Furthermore, k-means clustering analysis of survey responses enabled the segmentation of students into three distinct clusters based on their amotivation levels. Cluster 0: (Least Amotivated) represented the most motivated group, demonstrating confidence in their abilities and a positive outlook towards their education. Cluster 1: (Moderately Amotivated) included students exhibiting a mix of positive and negative perceptions, suggesting potential for improvement with targeted interventions. Cluster 2: (Highly Amotivated) comprised students with high mean amotivation scores, reflecting significant disengagement and dissatisfaction. The diversity in student experiences and the necessity of tailored interventions was well highlighted through this clustering approach.

The clustering analysis that included mean amotivation score with CGPA uncovered an important connection between the academic achievement and motivation. The adverse impact of amotivation on learning outcomes has been proven by the lower CGPAs of students in Cluster 0. On the contrary, students in Cluster 2 not only revealed higher levels of motivation, but they also performed better academically. Such findings underline the need it is to address amotivation in order to improve performance and engagement.

The diagnostic process adopted in this study's has substantial implications for engineering education. Educational settings may initiate targeted efforts to address the underlying causes of disengagement. Interventions for highly amotivated students might involve restructuring curriculum to better suit their interests, offering more academic assistance, and cultivating a feeling of belonging and purpose. Mentorship programs, more access to career-focused workshops, and opportunities for experiential learning could be beneficial for students who are moderately amotivated. It is necessry for motivated students to remain engaged in challenging yet rewarding learning environments.

In summary, this study advances our theoretical knowledge of amotivation in engineering education, additionally it also suggests practical strategies to lessen its impacts. Applying learning analytics to identify and address perceived amotivators, educational institutions may create a more encouraging and stimulating environment that will ultimately improve students' academic performance and general well-being.

The findings of this research offer a guide for future efforts geared to nurture an engineering student population that is more resilient and motivated.

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