Understanding Academic Resilience Through Motivational Profiles and Self-Efficacy: A Cluster and Logistic Regression Analysis

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Exploring the Role of Motivational Profiles and Self-Efficacy in Predicting Academic Resilience: A Cluster and Logistic Regression Analysis

Abstract

This research paper study investigates the relationship between motivational profiles, self-efficacy, and resilience in undergraduate engineering students using cluster and logistic regression analyses. Data were collected over a single semester from 151 students enrolled in a Statics course at a Southeast university in the United States. Clustering revealed four distinct motivational profiles: Adaptive High Achievers, Competitive Strivers, Mastery-Oriented Improvers, and Low-Performance Avoiders. Findings highlight the critical role of self-efficacy in predicting resilience, with students demonstrating high self-efficacy being nearly three times more likely to exhibit resilience. This empirical research paper provides practical insights into fostering academic success and resilience through tailored interventions.

Introduction

Studying psychological variables in higher education provides valuable insights into students' cognitive and behavioral development, shaping their adult personality and academic success [1]. While many students transition through college education smoothly, others face challenges that undermine their motivation and commitment, often leading to disengagement or even school dropout[2].These challenges are influenced by personal, contextual, and psycho-educational factors, as well as the absence of effective strategies to cope with academic demands [3]. Students' ability to manage these challenges plays a pivotal role in fostering a positive learning experience [4].

Achievement Goal Theory offers a framework for understanding the motivations behind higher education students such as students' academic behaviors, explaining how individuals approach tasks and strive for success. Achievement goals theory categorizes goals into mastery (learning and self-improvement) and performance (demonstrating competence in relation to others) goals [5, 6]. Mastery-oriented individuals prioritize personal growth and the process of learning, while performance-oriented individuals seek external validation and comparison. Elliot [7] expanded this framework by introducing approach and avoidance dimensions, where avoidance goals reflect a desire to evade failure or negative judgments. More recent models, such as Elliot and McGregor's [8] 2x2 framework provides a nuanced understanding of how students pursue positive outcomes or avoid undesirable ones [9].

To capture these variations, this study employs cluster analysis to group students into distinct motivational profiles based on their achievement goals. These profiles provide a richer understanding of how mastery and performance orientations combine in students' motivational tendencies. For instance, research indicates that adaptive profiles emphasizing mastery-approach orientations are linked to higher academic performance and engagement, while maladaptive profiles are associated with negative learning outcomes [10-12].

Self-efficacy also plays a central role in goal pursuit, as individuals who believe in their capabilities are more likely to approach challenges with confidence and determination[13]. Defined as one's belief in personal competence, self-efficacy influences goal choice, task preference, and resilience in the face of adversity[14]. High self-efficacy fosters persistence, optimism, and adaptability, enabling individuals to set and achieve higher goals [15]. Resilience, closely related to self-efficacy, reflects the ability to cope with stress and rebound from adversity. It encompasses personal resources such as optimism, coping strategies, and social support [16, 17]. Together, self-efficacy and resilience form a dynamic interplay that helps individuals navigate academic and life challenges [18-20].

This study builds on these theoretical foundations to investigate how achievement goals shape motivational profiles and their impact on self-efficacy and resilience among undergraduate engineering students. By employing cluster analysis, we identify distinct motivational profiles that reveal nuanced patterns in how students balance mastery-oriented growth and performance-focused aspirations. These profiles are then examined in conjunction with self-efficacy to predict resilience, highlighting the factors that foster persistence and adaptability in challenging academic environments. This approach further uncovers connections between mastery, performance, and avoidance goals, providing a comprehensive understanding of the interplay between motivation, self-belief, and resilience. By addressing these dynamics, the study contributes valuable insights into strategies for enhancing students' academic success and personal growth in engineering education.

Theoretical Framework

Achievement Goal Theory provides a foundational framework for understanding the diverse objectives individuals pursue in academic settings. It categorizes goals into mastery and performance orientations, which differ significantly in focus and the criteria for success. Mastery goals emphasize the development of competence, with success measured through personal growth and self-referenced standards, fostering intrinsic motivation [21, 22]. In contrast, performance goals aim to demonstrate competence relative to others, often contingent on gaining external validation or surpassing peers [23]. Balancing these goal orientations has been linked to improved academic outcomes, with research suggesting that mastery-approach and performance-approach goals can drive positive academic achievements, while avoidance goals tend to yield weaker or null results [24]. Moreover, studies distinguish performance goals into appearance-based and norm-focused categories, with norm-focused goals showing more adaptive outcomes when pursued autonomously [23].

Elliot's [7] extension of Achievement Goal Theory further refines this framework by integrating approach and avoidance dimensions, offering a trichotomous model that includes mastery, performance approach, and performance-avoidance orientations. This nuanced approach reveals how motivations to achieve success differ from those aimed at avoiding failure. Research consistently validates this model, demonstrating the theoretical coherence among the 2x2 achievement goal orientations and their consistent correlations across academic contexts[25]. Comparative studies show overlaps between constructs such as task goals and mastery goals, as well as ego goals and performance-approach goals, while also highlighting their unique contributions [26]. Beyond academia, Elliot's work has extended discussions on approach-avoidance motivation, enriching our understanding of goal-directed behavior across various domains[27].

Self-efficacy, central to academic success, reflects individuals' confidence in their ability to perform specific tasks and shapes how students engage with learning. Schunk [14] emphasizes that self-efficacy beliefs are influenced by personal experiences, success attributions, and contextual factors, serving as critical predictors of motivation and learning [28]. Empirical studies show that interventions like goal setting, feedback, and role modeling significantly enhance self-efficacy, fostering positive academic outcomes [14]. Furthermore, self-efficacy interacts with self-regulated learning processes, mediating academic achievement and underscoring its adaptability in education[28].

Research consistently highlights the positive relationship between self-efficacy and academic success, with stronger self-efficacy beliefs motivating students to overcome challenges and maintain engagement. For instance, self-efficacy serves as a resilience factor for marginalized groups, such as Black male students in community colleges, helping them persist in the face of barriers [29]. Experimental evidence also shows that fostering successful experiences can elevate self-efficacy, leading to improved academic outcomes, particularly among male students [30]. A robust correlation exists between general self-efficacy and academic performance across diverse populations [31]. Furthermore, self-efficacy's impact on academic achievement is mediated by causal attributions: internal attributions enhance performance, while external attributions may hinder it [32]. These findings affirm self-efficacy’s pivotal role in fostering academic resilience. Resilience, defined as an individual’s ability to adapt and recover from adversity, is closely linked to both self-efficacy and motivational profiles. Drawing from Positive Psychology and Lazarus and Folkman’s Transactional Model of Stress and Coping [33], resilience is conceptualized as a dynamic process involving emotional intelligence, problem-solving skills, and the capacity to thrive under pressure. Research indicates that students with mastery-approach goals and high self-efficacy are better equipped to develop resilience, enabling them to persist in demanding academic environments [34]. The interplay between these variables reflects a synergistic relationship, where motivational goals provide direction, self-efficacy reinforces capability, and resilience ensures adaptability.

In this study, Achievement Goal Theory specifically guided the clustering of students based on their achievement goal orientations, allowing us to identify distinct motivational profiles. Social Cognitive Theory, through the lens of self-efficacy, informed the use of logistic regression analysis to predict students' academic resilience based on their confidence in learning performance. Finally, the concept of resilience, drawn from Positive Psychology and the Transactional Model of Stress and Coping, framed resilience as the key outcome variable, representing students' ability to adapt to academic challenges. Together, these theoretical perspectives shaped the study’s design: Achievement Goal Theory provided the basis for categorizing motivational types, Self-Efficacy Theory explained the mechanism through which motivation might influence resilience, and Resilience Theory contextualized the adaptive outcomes we aimed to understand. This integrated approach ensured that both the classification and prediction aspects of the study were grounded in robust psychological theory. Accordingly, the study explores two main research questions:

1. How do distinct motivational profiles derived from achievement goal orientations influence academic resilience in engineering students?
2. To what extent does self-efficacy for learning performance predict resilience within these motivational profiles?

Method

Participants and procedures

A convenience sample of 151 undergraduate students from a core engineering statics course at a Southeast university in the United States participated in this study. The sample consisted of 64.90% males and 35.10% females, with ages ranging from 17 to 26 years. Approximately 47% of participants were between 17 and 19 years old, and another 48% were between 20 and 22 years old. A small proportion (5%) of students were 23 years or older. Participants were second- and third-year engineering students. Data collection was conducted through an online questionnaire administered using Qualtrics, ensuring ease of access and efficient data management. The study received Institutional Review Board (IRB) approval, adhering to ethical research standards and ensuring participants' rights and confidentiality were protected.

Measures

Achievement goal questionnaire

Students' achievement goal orientations were measured using the 12-item Achievement Goal Questionnaire (AGQ) developed by [8]. The AGQ assesses four achievement goals: mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance, with three items for each subscale. Participants rate items on a scale from 1 (never or only rarely true of me) to 5 (always or almost always true of me). Higher scores on each subscale reflect stronger orientation toward that particular achievement goal. Example items include "I am striving to understand the content of this course as thoroughly as possible." (Mastery-approach) and "My aim is to perform well relative to other students." (Performance-avoidance). The measure has demonstrated strong internal consistency and a clear four-factor structure in previous studies [8]. The reliability of each subscale, as measured by Cronbach's alpha, was as follows: mastery-approach ($\alpha = 0.863$), mastery-avoidance ($\alpha = 0.673$), performance-approach ($\alpha = 0.781$), and performance-avoidance ($\alpha = 0.878$). These values indicate acceptable to high internal consistency for the scales in the current study.

Self-efficacy for learning performance

The Self-Efficacy for Learning Performance (SLP) subscale from the Motivated Strategies for Learning Questionnaire (MSLQ) [35] was used to assess students' self-efficacy in this study. This 8-item subscale measures students' confidence in their ability to successfully complete academic tasks and achieve success in the course. Participants rated each item on a 5-point Likert scale, ranging from 1 (never or only rarely true of me) to 5 (always or almost always true of me). Higher scores indicate a stronger belief in their capacity to succeed academically. Example items include, "I believe I will receive an excellent grade in this class" and "I'm confident I can learn the basic concepts taught in this course." In this study, the SLP subscale demonstrated strong internal consistency (Cronbach's alpha = 0.927), and its scores were found to correlate with academic performance, consistent with findings from previous studies e.g., [36], which also demonstrated a strong link between self-efficacy and academic outcomes.

Resilience

In this study, students' resilience in the face of academic challenges was assessed using the Connor-Davidson Resilience Scale (CD-RISC) (Connor & Davidson, 2003), a widely recognized tool for evaluating individuals' ability to cope with adversity and stress. The CD-RISC consists of 25 items, which measure various dimensions of resilience, including personal competence, tolerance for negative emotions, and adaptability to change. Participants rated each item on a 5-point Likert scale, with responses ranging from 0 (not true at all) to 4 (true nearly all of the time), where higher scores indicate stronger resilience. Example items from the scale include: “I am able to adapt when changes occur” and “I can handle unpleasant feelings.” The CD-RISC has demonstrated robust internal consistency (Cronbach’s alpha = 0.89) and validity in previous research, making it a reliable measure for assessing resilience[37]. It has been widely used in studies exploring its relationship with mental health, well-being, and academic performance [38]. To examine how resilience predicted group membership, scores from the Connor-Davidson. Resilience Scale (CD-RISC) were categorized into high and low resilience using a median split. Scores at or above the median were categorized as high resilience, while scores below the median were categorized as low resilience. This binary categorization allowed for a focused examination of resilience as an outcome in the logistic regression analysis.

Data Preparation

Prior to cluster analysis and logistic regression, all continuous variables (achievement goals, self-efficacy, and resilience) were standardized using z-score transformation. This standardization procedure ensured that differences in variable scales did not disproportionately influence the clustering solution or regression estimates.
Cluster analysis was conducted using students’ achievement goal orientations (mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance) to form motivational profiles. Self-efficacy and resilience were not included in the cluster formation. Following clustering, binary logistic regression was employed to examine whether motivational profile membership and self-efficacy independently predicted resilience status.

Results

This study explored the relationship between motivational profiles, self-efficacy, and academic resilience in undergraduate engineering students through a combination of cluster analysis and logistic regression analysis. These methods were employed to address the study’s research questions while ensuring the dataset met the assumptions necessary for robust analysis. The dataset was examined to ensure the assumptions for both cluster analysis and logistic regression were met [39]. Normality and homoscedasticity were assessed using residual plots, with violations detected in homoscedasticity. Multicollinearity was ruled out using VIF values (<2), and Cook’s distance confirmed no influential outliers. The Durbin-Watson statistics indicated no violations of independence. No data points were removed, leaving a final sample size of 151 participants.

Correlational analyses

Correlations among the main variables are displayed in Table 1. Mastery-approach goals showed a moderate, positive, and significant correlation with mastery-avoidance, reflecting some overlap in approaching and avoiding mastery-related goals. Performance-approach goals were positively associated with both self-efficacy and resilience, highlighting their alignment with stronger perceived learning capabilities and adaptability. Performance-avoidance goals also showed a significant positive relationship with performance-approach goals, suggesting a dual focus on excelling and avoiding failure. Self-efficacy was positively correlated with resilience, reinforcing its role in promoting adaptive outcomes. Mastery-oriented goals, however, showed negligible correlations with self-efficacy and resilience. Surprisingly, no significant correlations were found between mastery orientations and resilience measures, though the patterns aligned with theoretical expectations.

Table 1. Correlation Matrix of Main Variables

No.	Variables	1	2	3	4	5	6
1	Mastery-approach						
2	Mastery-avoidance	0.48**					
3	Performance-approach	0.135	0.014				
4	Performance-avoidance	0.033	0.024	0.554**			
5	Self-efficacy for learning performance	0.002	-0.083	0.365**	0.054		
6	Resilience	-0.014	-0.086	0.187*	0.008	0.463**	

Note: **p < .01, *p < .05.

Cluster analyses

Cluster analysis was employed to identify motivational profiles based on achievement goal orientations. A combination of hierarchical and k-means clustering methods was used. The hierarchical clustering process, based on Ward’s method, generated a dendrogram, which was used to evaluate potential solutions. The Elbow Method indicated a clear inflection point at 3 or 4 clusters as shown in Figure 1. While both solutions were considered, a four-cluster solution was selected as it provided sufficient granularity while maintaining interpretability. The decision to select four clusters aligns with prior literature, which suggests that solutions with 3 to 5 clusters are optimal for balancing detail and clarity [40, 41]. Recent studies have also validated the robustness of using hierarchical and k-means methods for psychological profiling, particularly in educational research [42, 43]. The four clusters were labeled Adaptive High Achievers, Competitive Strivers, Mastery-Oriented Improvers, and Low-Performance Avoiders, based on their z-scores for mastery, performance, and avoidance goals. Welch's tests revealed significant differences in goal orientations across clusters, as detailed in Table 2 below.

Table 2. Descriptive Statistics and Welch's Test Results for Goal Clusters

Variables	**Cluster 1 (n = 56)**	**Cluster 2 (n = 33)**	**Cluster 3 (n = 41)**	**Cluster 4 (n = 21)**	**Welch F**	**p**
Mastery-approach goals	4.76(0.31)	3.73(0.75)	4.49(0.37)	4.06(0.73)	26.152	< .001
Mastery-avoidance goals	4.61(0.31)	3.00(0.67)	3.60(0.52)	3.87(0.69)	75.607	< .001
Performance-approach goals	4.39(0.48)	4.59(0.44)	3.62(0.51)	2.67(0.74)	56.893	< .001
Performance-avoidance goals	4.23(.75)	4.58(0.57)	3.55(0.77)	2.24(0.74)	55.715	< .001

Given the violation of the homogeneity of variances assumption, the use of Welch's test was used to provide a robust solution, ensuring the reliability of these results. The Welch's test results revealed significant differences across all goal scores (Mastery-approach, Mastery-avoidance, Performance-approach, and Performance-avoidance) when examining the four clusters. These findings highlight the existence of distinct groups within the sample, each demonstrating varying levels of achievement motivation.

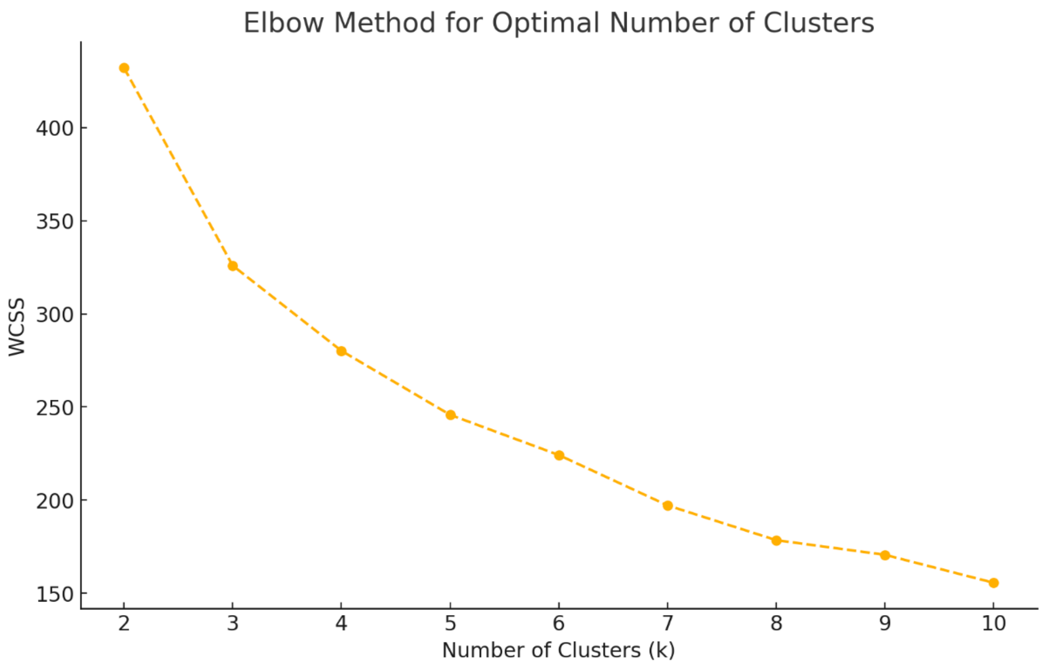

Fig1: An Elbowmethod showing the number of clusters.

The cluster analysis identified four distinct groups of students based on achievement goal orientations: Adaptive High Achievers, Competitive Strivers, Mastery-Oriented Improvers, and Low-Performance Avoiders.

Cluster Naming and Description

Based on the cluster centroids (mean scores), the following labels were assigned to each cluster:

Cluster 1 (n = 56): Adaptive High Achievers

Students demonstrated very high mastery-approach, mastery-avoidance, and strong performance goals. These students showed motivation across multiple domains, balancing personal growth, mastery concerns, and competitive performance. These individuals combine strong intrinsic motivations with a desire to avoid failure and excel relative to others. Their balanced goal orientations foster adaptability, engagement, and resilience [8, 44], aligning with research highlighting the academic success of well-rounded motivational profiles.

Cluster 2 (n = 33): Competitive Strivers

Students exhibited very high performance-approach and performance-avoidance goals, with lower mastery orientations, reflecting a strong emphasis on outperforming others and avoiding failure relative to peers. This group thrives in competitive environments but may be vulnerable to stress and anxiety [23]. Their heavy reliance on external validation for motivation [44] can drive both high achievement and increased risk of burnout.

Cluster 3 (n = 41): Mastery-Oriented Improvers

Students prioritized mastery-approach goals while maintaining moderate concerns about performance, suggesting a focus on personal improvement with some attention to external outcomes. These students emphasize learning and personal growth while moderately considering performance, demonstrating persistence and resilience consistent with findings on mastery-driven learners[5, 45]

Cluster 4 (n = 21): Low-Performance Avoiders

Students showed moderate mastery-approach but low performance goal orientations overall, reflecting disengagement from competitive achievement and lower concern for outperforming others. This group exhibits low motivation across domains, minimizing risks and disengaging from challenging tasks[35]. Research highlights that such low motivational engagement often limits academic growth and achievement potential[21]. Building on the cluster analysis, we further explore the relationship between motivational profiles, self-efficacy for learning performance (SLP), and resilience. Resilience, a critical attribute for thriving despite academic and personal challenges, is hypothesized to vary significantly across the identified clusters. Highly Motivated students are expected to demonstrate the highest resilience due to their balanced approach to achievement goals. SLP is anticipated to play a pivotal role in predicting resilience across all clusters. To examine these relationships, logistic regression was conducted, with resilience categorized as high or low. This approach will allow for a detailed analysis of how motivational orientations and SLP collectively influence resilience outcomes. Because resilience was conceptualized as an outcome variable rather than a clustering feature; logistic regression was used to assess the predictive role of motivational profiles and self-efficacy on resilience.

Table 3. Model Fit and Classification Accuracy

Logistic Regression

Measure	Value
Chi-square (χ2)	32.696
Degrees of Freedom (df)	4
p-value	<.0001
Cox & Snell R^2	0.195
Nagelkerke R^2	0.260
Hosmer-Lemeshow ppp-value	0.464
Classification Accuracy (%)	69.7

A binary logistic regression was conducted to examine the predictive relationship between motivational clusters, self-efficacy for learning performance (SLP), and resilience. Resilience was dichotomized into high and low categories, with SLP as a continuous predictor and motivational clusters (Adaptive High Achievers, Competitive Strivers, and Mastery-Oriented Improvers) as dummy variables, using Low-Performance Avoiders as the reference group. The model was statistically significant (χ2=32.696, df=4, p<0.001), explaining 19.5% to 26.0% of the variance in resilience (Cox & Snell R^2 = 0.195, Nagelkerke R^2 = 0.260). The Hosmer-Lemeshow test (χ2=7.693, P =0.464) indicated a good model fit, with an overall classification accuracy of 69.7%, as shown in Table 3.

SLP was a significant predictor (B=1.076, p<0.001, Exp(B)=2.933) showing that a one-unit increase in SLP nearly triples the odds of high resilience. None of the motivational clusters significantly predicted resilience (p>0.05). However, the Mastery-Oriented Improvers cluster (B=1.036, Exp(B)=2.806, P=0.103) showed a trend toward higher resilience, though not statistically significant. These findings highlight the critical role of self-efficacy in fostering resilience. Detailed results for all predictors, including coefficients, standard errors, and odds ratios, are presented in Table 4.

Table 4. Logistic Regression Results for Predicting Resilience

Predictor	B	SE	Wald	p	Exp(B)
SLP	1.071	0.239	20.107	< 0.001	2.919
Adaptive High Achievers	0.289	0.608	0.226	0.635	1.335
Competitive Strivers	-0.418	0.668	0.392	0.531	0.658
Mastery-Oriented Improvers	1.036	0.633	2.678	0.102	2.819
Constant	-0.292	0.528	0.305	0.581	0.747

Discussion

The findings of this study provide valuable insights into how motivational profiles and self-efficacy interact to predict resilience in undergraduate engineering students. By employing statistical methods, including cluster analysis and logistic regression, the study underscores the nuanced interplay between achievement goals, self-efficacy, and resilience in shaping academic adaptation and success.

Motivational Profiles and Resilience

The cluster analysis identified four distinct motivational profiles: Adaptive High Achievers, Competitive Strivers, Mastery-Oriented Improvers, and Low-Performance Avoiders. These profiles align with prior research on achievement goal orientations, offering a meaningful framework for understanding student motivation. Adaptive High Achievers demonstrated a balance of mastery and performance goals, aligning with findings that balanced motivational orientations foster resilience and adaptability [8, 44]. In contrast, Low-Performance Avoiders exhibited minimal engagement with both mastery and performance goals, which is consistent with studies showing the detrimental effects of avoidance goals on academic outcomes [21]. However, logistic regression results indicated that motivational profiles did not significantly predict resilience, with the exception of a non-significant trend observed for the Low-performance Avoiders. This finding suggests that while motivational profiles provide useful categorization, they may not independently drive resilience outcomes. This divergence from theoretical expectations could reflect the complexity of motivational constructs or potential overlap among clusters, which might dilute their predictive power. Future research should explore these dynamics further, perhaps by incorporating qualitative methods to uncover deeper insights into students' motivational experiences.

The Role of Self-Efficacy

Self-efficacy emerged as a strong and significant predictor of resilience, with a one-unit increase in self-efficacy nearly tripling the odds of high resilience (Exp(B) = 2.933). This finding aligns with Bandura's (1997) theory of self-efficacy, which emphasizes its central role in fostering persistence, optimism, and adaptability in challenging contexts. The results also echo prior research demonstrating the critical role of self-efficacy in academic achievement and resilience [46, 47].

The prominence of self-efficacy relative to motivational profiles highlights the importance of interventions targeting belief systems. For instance, strategies such as goal setting, constructive feedback, and role modeling could enhance students' confidence in their abilities, thereby boosting their resilience. These findings underscore the necessity of equipping students with tools to strengthen their self-belief as a pathway to thriving in rigorous academic environments.

Practical Implications

The findings provide important guidance for educators and academic support professionals in engineering education. Identifying four distinct motivational profiles suggests that interventions should be tailored: Adaptive High Achievers may benefit from enrichment activities that sustain both mastery and performance goals, while Competitive Strivers require support managing performance pressure. Mastery-Oriented Improvers thrive with challenge-based learning and feedback, and Low-Performance Avoiders need early motivational coaching to reengage them academically. Furthermore, because self-efficacy emerged as a stronger predictor of resilience than motivational profile alone, programs should prioritize building students' confidence through mastery experiences, incremental feedback, and peer modeling. Combining motivational profiling and self-efficacy assessment can enable personalized support strategies at program entry, maximizing student engagement and persistence. A multi-layered approach—supporting both motivation and belief in capability—is crucial for fostering resilience and long-term success among engineering students.

Limitations and Future Directions

The reliance on self-reported data introduces the possibility of response biases, such as social desirability. Additionally, the cross-sectional design limits the ability to infer causality. Longitudinal studies could provide deeper insights into how motivational profiles and self-efficacy evolve over time and influence resilience. Future research should also explore contextual factors, such as peer networks and institutional support systems, to provide a more comprehensive understanding of resilience dynamics.

Additionally, the sample size of 151 participants fell short of the 372 recommended by a priori power analysis, potentially reducing statistical power and the ability to detect smaller but meaningful effects. This limitation may also affect the generalizability of the findings, highlighting the need for future studies to recruit larger samples to enhance robustness. Qualitative approaches, such as interviews or focus groups, could complement the quantitative findings by capturing students' lived experiences and offering richer insights into the motivational and self-efficacy mechanisms underlying resilience.

Conclusion

This study underscores the critical role of self-efficacy in fostering resilience among engineering students while highlighting the nuanced contributions of motivational profiles. By integrating robust statistical analyses with theoretical frameworks, the research offers valuable insights into the interplay between achievement goals, self-belief, and adaptability. These findings have practical implications for designing targeted interventions to optimize student motivation, resilience, and academic success in engineering education. Future work should build on these insights to refine strategies for fostering resilience and adaptability, ultimately enhancing outcomes in STEM education.

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