# Engineering Success: Identifying Key Predictors of GPA Trajectories Through Latent Class Trajectory Modeling

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# A Longitudinal, Person-Centered Analysis of Engineering Students' GPAs: Identifying Patterns and Predictors

## Introduction

This empirical full research paper discusses a person-centered analysis of engineering students' GPAs. Academic performance is frequently assessed using GPA in educational research, where it has been studied in connection with various factors (such as self-efficacy and motivation) and in a wide array of populations (for a systematic review and meta-analysis, refer to [1]). GPA is also often a crucial factor in determining the success of college and university students, especially in the field of engineering, where GPA is used to gate entry to specific majors, and students must complete many rigorous and competitive classes to graduate [2], [3], [4], [5]. Due to the competitive culture and a "meritocracy of difficulty" in engineering, GPA also is an indicator of identity, achievement, and belonging for engineering students [3], [6], [7]. These indicators may be particularly meaningful for marginalized students in engineering, for whom GPA can function as a salient signal of legitimacy and belonging in the face of microaggressions and hostile climates [8], [9].

Most studies that include GPA focus on a single timepoint (for examples, refer to [10], [11], [12]). There are some exceptions, such as Grove & Wasserman (2004) who compared averages from multiple groups (such as men and women or different majors)[13]. While this study provides valuable information about the patterns of GPA across a student's academic career, it also highlights the need to understand the latent groups concealed within the mass. Other studies have used hierarchical linear modeling and growth curve modeling to examine factors contributing to different GPA trajectories. For instance, Kreisberg & Hsin (2021) modeled the relationship between immigration status and GPA, allowing for a close examination of the differences in GPA trajectories of the targeted groups and accommodating the inclusion of other demographic variables [14]. Similarly, DuPaul et al. (2021) examined the GPA trajectories of students with ADHD (medicated and non-medicated) and a comparison group of non-ADHD peers [15]. Notably, none of these studies focus on engineering students specifically.

In this study, we use latent class trajectory modeling (LCTM) to study patterns in engineering students' GPAs over time. LCTM is a form of growth mixture modeling, a type of analysis that allows for the identification of latent or hidden groups within heterogeneous populations. Non-longitudinal forms of mixture modeling, like latent profile or latent class analysis, can identify latent groups of students whose scores cluster at a single time point (for an example refer to Grunschel et al.'s (2013) study of academic delayers [16]). LCTM identifies latent trajectories, e.g. clusters of participants whose scores vary across multiple time points in similar ways. LCTM has not been used often in engineering education research, with previous applications mainly focusing on criminology and health [17], [18], [19]. However, it is useful in any analysis in which 1) fluctuation over time is of interest, and 2) the identification of latent groups is linked to outcomes of interest. This directly relates to the study of GPA. Consistent with the first point, previous research suggests that there are consistent patterns of variation in engineering students' GPAs, such as the infamous 'sophomore slump' that often occurs in students' second year [20], [21]. Consistent with the second point, GPA is important to students' short-term and long-term success and wellbeing. Maintaining adequate performance is necessary to remain enrolled and to graduate, and as described above, it also impacts students' psychosocial wellbeing.

Because LCTM is a data-driven approach, in which latent groups are identified algorithmically instead of by researchers, it allows for the identification of groups while minimizing the potential impact of researcher bias. Once these latent groups have been uncovered, additional analyses can explore how other variables predict assignment to the previously-hidden groups. In this analysis, we will look for the emergence of latent trajectories across our entire student sample, and then investigate a series of non-cognitive and affective factors (such as personality, mindset, perceptions of faculty, identity, and belonging) as potential predictors of students' GPA trajectories.

## Method

*Participants*

This analysis used survey data from 883 students from two institutions (a public land-grant research university in the midwestern U.S and a comprehensive, state-supported university on the U.S. west coast) who enrolled in Fall 2017 and consented to participate in this study (refer to Table 1 for full demographic information). Race and gender distributions in the sample are reflective of the student population in engineering and at the participating institutions. First-generation status was derived from participant responses to two items asking about their primary caretakers' highest level of education.

**Table 1. Participation information**

| *Race/Ethnicity* | *Total* | *Percentage* |
|---|---|---|
| American Indian or Alaska Native | 10 | 1.13% |
| Asian | 191 | 21.63% |
| Black or African American | 20 | 2.27% |
| Hispanic, Latino, or Spanish Origin | 93 | 10.53% |
| Middle Eastern or North African | 22 | 2.49% |
| Native Hawaiian or Pacific Islander | 11 | 1.25% |
| White | 632 | 71.57% |
| Biracial/Multiracial * | 97 | 10.99% |
| No Response | 7 | 0.79% |
| *Gender* | | |
| Woman | 243 | 27.52% |
| Trans, Agender, Genderqueer, or Non-Binary | 6 | 0.68% |
| Man | 626 | 70.89% |
| No Response | 8 | 0.91% |
| *First-Generation Status* | | |
| Continuing Generation | 767 | 86.86% |
| First-Generation | 100 | 11.33% |
| No Response | 16 | 1.81% |

* Participants who selected two or more options

*Measures*

Participants' GPAs were derived from institutional records and were calculated on a 4.0 scale for all terms (including summer) from Fall 2017 to Summer 2020, i.e., the first three years of the students' enrollment. Non-grade reports, such as "W" for withdrawal or "I/IN" for incomplete, were not included in this analysis and did not affect the GPA calculation. Compiling all GPAs produced a dataset with a large amount of missing data, due to different calendar systems between the two institutions and irregular enrollment in summer terms. As a result of this missing data, multivariate outlier screening was not possible. Instead, participants' GPAs were converted to z-scores, and participants with two or more outlier GPAs were dropped from the dataset (n=9).

For the regression analysis, 30 variables (25 psychological constructs and 5 demographic variables) were analyzed in conjunction with the results from the latent class trajectory modeling. These variables were chosen as part of the SUCCESS survey (Studying Underlying Characteristics for Computing and Engineering Student Success), an examination of non-cognitive and affective factors that influence student success in engineering. The process for selecting, piloting, and evaluating these measures is summarized here for convenience and detailed in full in separate publications [22], [23]. The selection of constructs was theory-informed but intentionally broad, reflecting the premise that multiple motivational, personality, and contextual factors may shape success in engineering. The current study similarly adopts a preliminary, exploratory approach, examining which of these established constructs prospectively differentiate GPA trajectories rather than testing a narrowly specified model. Survey data was collected from Fall 2017 to Spring 2018, and measures those that performed as expected in the factor analysis (e.g., above recommended cutoffs and with the expected factor structure) were retained for this analysis.

*Analysis*

*Latent Class Trajectory Analysis.* The latent class trajectory modeling approach used in this paper was derived from two sources, [24], [25], and was performed using the *lcmm* package in R [26]. A preliminary analysis of a partial dataset and a detailed write-up of the process is also available [27]. In brief, there are five primary steps to the analysis: planning, determination of effects structure and polynomial terms, model testing, model confirmation, and model plotting and review. Classes with less than 5% of the population were considered potentially spurious, as they represent the possibility that trajectories are being fitted to random noise in the data [28]. A model with several small classes was thus considered poorer-performing than comparative models with more balanced classes. After evaluating models using the measures listed above, the best-performing models were selected for plotting and further review. The effects structure and polynomial terms were re-evaluated for each class of each model, and adjusted if needed for the final comparison. Ultimately, the model with the best parsimony and clearest interpretation was selected as the final model.

*Regression Analysis.* Once the trajectories were identified and cases assigned, a hierarchical multinomial regression was run to examine the relationship between a host of non-cognitive and affective factors and participants' GPA trajectories. For this analysis, a reference group was selected to act as the baseline that other groups were compared to, and odds ratios were generated detailing the probability that participants would be assigned to a selected class compared to the reference group. For example, an odds ratio of 1.5 would indicate that an increase on the specified variable increases the odds of being assigned to the target group instead of the reference group (an odds ratio below 1 indicates the opposite). Wald's test is used to evaluate the odds ratios and determine their statistical significance [29]. All standard regression assumptions were evaluated, including assessment of multicollinearity (via variance inflation factors), inspection of linearity, and screening for influential cases and outliers, and all diagnostics fell within acceptable ranges [30].

Variables were clustered into four groups (Demographic and Academic Predictors, Personality and Trait Predictors, General Academic Experience Predictors, and Engineering Experience Predictors) and entered into the model sequentially, allowing for comparison of the nested regression models and the evaluation of the value they add to the model overall. The order of entry reflected conceptual grouping and relative stability of the predictors. Demographic and prior academic variables were entered first because they represent the most longstanding characteristics. Personality and trait variables were entered next, as they are generally stable individual differences. General academic experience variables followed, reflecting students' early adjustment to the college environment. Engineering experience variables were entered last, as all variables were assessed early in enrollment and engineering identity/belonging is expected to change in response to students' engineering experiences. Because of the small size of one of the trajectory groups, two similar groups were combined for this analysis (more details in the Results section below).

*Race/Ethnicity Group Comparison.* Participants were also clustered into groups according to race/ethnicity and gender identity in order to examine the impact of structural barriers, racism, and institutional inequities in engineering education. The fine-grained data collected from our multiple-choice race/ethnicity option (described in more detail in Table 1) produced nine categories, most of which had less than 100 participants. To use race/ethnicity in our analysis we thus created larger categories to group students whose racial/ethnic identities had shared aspects: Asian and Middle Eastern, n=213; Black, Indigenous, and Hispanic/Latino, n=134; White, n=632; and Biracial, n=97 (participants who provided no race/ethnicity information were dropped from the analysis; n=7).

## Results

*Latent Class Trajectory Analysis.* Given our previous work with a subset of our current data, we expected there to be multiple nonlinear trajectories (a preliminary analysis identified four trajectories with a random effects common structure best fitting the data; [27]). The effects structure and polynomial terms were confirmed by testing a single-class, quadratic model with no random effects and examining the plotted residuals as per recommendations [24]. Multiple models ($k$=2 through 7) were tested using gridsearch (e.g., starting values selected randomly and each model tested 100 times, with the best performing model selected). Two models (5-class and 6-class) with the best fit indices and acceptable entropy. Both models had issues with small group sizes; the 5-class model had two groups with less than 3% of the population, while the 6-class model had one such group. Plotting and comparing the 5- and 6-class models revealed that they were very similar; however, the 6-class model identified an additional class without a significant penalty to entropy (.79 for the 5-class model, .78 for the 6-class model). Overall, these differences suggest that the 6-class model is a more nuanced interpretation of the data and exhibits a similar or better fit that warrants a slightly less parsimonious solution. This model was selected as the final product of this analysis. The resulting classes were:

1. *Consistently High Performers.* Students in this group began their academic careers with high GPAs, and maintained or slightly improved their grades over the next three years. This is the largest and most-populated group in the analysis (42%, n=370).
2. *Steadily Improving.* Students in this group started with moderately high GPAs (around 3.2/4.0) and despite a shallow dip persisted in an upward trajectory. This is the second-largest group in the analysis (37%, n=331).
3. *Sharply Improving.* Students in this group started at a similar level as those in the 'Steadily Improving' group but experienced a sharper decrease in their first few semesters. Ultimately, however, they end the three-year period with GPAs similar to those in the Steadily Improving and Consistently High Performers groups. This is the third-largest group in the analysis (8%, n=69).
4. *Starting to Struggle.* This group has experienced some ups-and-downs, always hovering

around the 3.0/4.0 mark, but the current endpoint of their trajectory suggests they are on a decline. This is the fourth-largest group in the analysis (5%, n=45).

5. *Consistently Struggling.* This group started out at a similar level as the Sharply Improving and Starting to Struggle groups, but their trajectory has been consistently downward. Although it is turning gently upwards at the end of their third year, their GPAs are still comparatively low (around 2.0/4.0). This is the fifth-largest group in the analysis (5%, n=43).
6. *Consistently At-Risk.* This group started with low GPAs (around 2.5/4.0) and their trajectory trended downwards throughout their academic careers. The current endpoint places the average GPA for this group at around 1.0, a value that would put them in academic probation at both institutions sampled in this study. This is the smallest group in the analysis (3%, n=25).

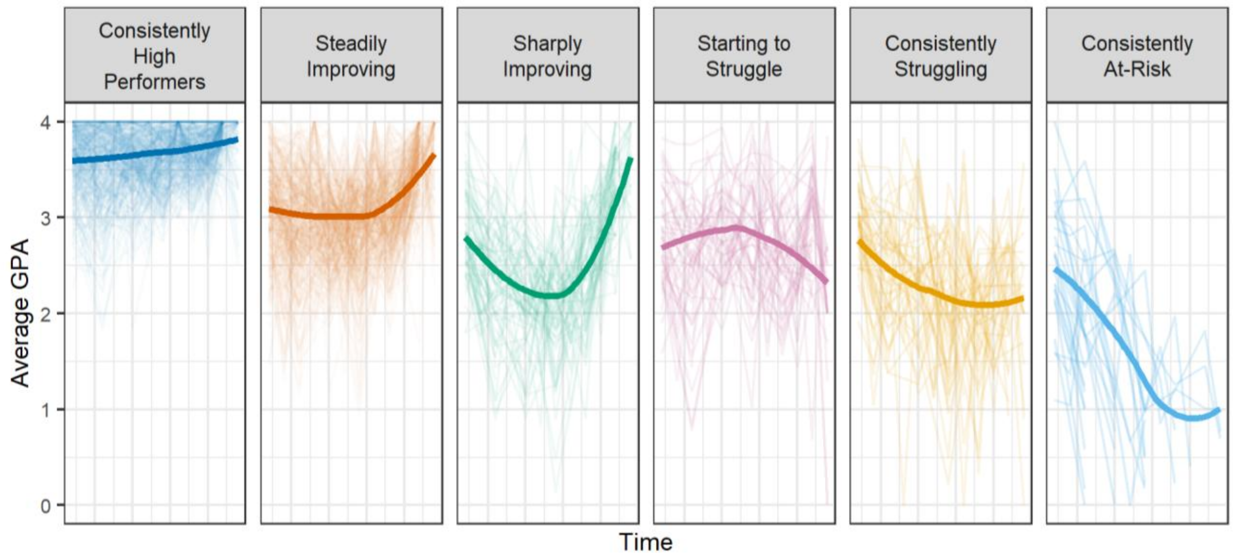


*Figure 1. GPA trajectories across academic terms by latent class. Thin lines represent individual student GPA trajectories; thicker smoothed lines show the class-level average trajectory over time. Facets correspond to latent classes described above.*

*Multinomial Logistic Regression Analysis.* Participants in the Steadily Improving profile were selected as the reference group because it represents a common experience within the sample and enables comparison with both higher-performing and struggling trajectories to identify potential risk and protective factors. Additionally, the Consistently Struggling and Consistently At-Risk groups were combined for regression analyses to maximize statistical power and ensure adequate cell sizes. The predictors were clustered into four blocks, which were tested consecutively in four models. The first block, Demographic and Academic Predictors, had a pseudo-$R^2$ of .13; adding the second block, Personality and Trait Predictors, improved the model significantly ($p$<.001) and increased the pseudo-$R^2$ to .24. Adding the third block, General Academic Experience Predictors, continued to improve the model (pseudo-$R^2$=.31, $p$<.001). The fourth block, Engineering Experience Predictors, did not significantly improve the model ($p$=.503). The full results of the final model are reported in Table 2.

Among the demographic and academic predictors, race was associated with differences in trajectory group assignment. Asian and Middle Eastern students were more likely to be assigned to the Steadily Improving reference group when compared to the Consistently High Performers and Starting to Struggle groups. In contrast, Biracial students and students identifying as Black, Indigenous, or Hispanic/Latine were more likely to be assigned to the Consistently Struggling and At-Risk group. Standardized math performance was also associated assignment to the Consistently High Performers group and, surprisingly, the Consistently Struggling & At-Risk groups.

Table 2. Multinomial logistic regression results.

| | Steadily Improving vs. Consistently High Performers | Steadily Improving vs. Sharply Improving | Steadily Improving vs. Starting to Struggle | Steadily Improving vs. Consistently Struggling & At-Risk |
|---|---|---|---|---|
| Demographic & Academic Predictors | | | | |
| Race (0 = White) | | | | |
| Asian & Middle Eastern | 0.51*** | 1.62 | 0.38** | 0.66 |
| Biracial | 0.72 | 0.48 | 0.44 | 1.88* |
| Black, Indigenous, & Hispanic/Latino | 0.61 | 1.91 | 0.89 | 4.19*** |
| Gender (0 = Men) | | | | |
| Women & Gender Minorities | 0.98 | 1.04 | 0.74 | 0.77 |
| Standardized Test - Math | 1.16*** | 0.88*** | 0.97 | 1.10*** |
| Standardized Test - Reading | 1.00 | 1.05 | 1.02 | 1.04 |
| Personality & Trait Predictors | | | | |
| Big 5 Personality Traits | | | | |
| Neuroticism | 1.34*** | 0.66*** | 0.95 | 1.17 |
| Extraversion | 0.85** | 1.25 | 0.77 | 1.00 |
| Agreeableness | 0.98 | 1.31* | 1.10 | 1.03 |
| Conscientiousness | 0.86* | 1.17 | 1.14 | 0.94 |
| Openness to New Experiences | 0.91 | 1.28* | 1.80*** | 1.21 |
| Grit | 0.88 | 1.05 | 0.76 | 0.99 |
| Mindset | 1.05 | 0.80 | 0.76* | 0.74*** |
| Mindfulness | 1.01 | 0.63*** | 0.77 | 0.98 |
| Meaning & Purpose | 1.10 | 0.77* | 1.10 | 0.99 |
| Gratitude | 1.11 | 0.97 | 1.17 | 0.81 |
| Impulsivity | 0.79*** | 1.16 | 1.03 | 1.34* |
| General Academic Experience | | | | |
| Test Anxiety | 0.78*** | 1.16 | 0.97 | 1.40** |
| Time & Study Environment | 1.24*** | 0.79 | 1.07 | 0.92 |
| Perceptions of Faculty Caring | | | | |
| Empathetic Faculty Understanding | 0.96 | 1.25 | 0.88 | 0.86 |
| Comfort with Faculty | 1.14 | 0.85 | 1.27 | 1.05 |
| Student Life Stress | | | | |
| Changes | 0.72*** | 1.18 | 0.85 | 1.06 |
| Conflict | 1.18** | 1.30* | 0.84 | 0.97 |
| Frustrations | 0.84** | 0.65*** | 0.99 | 0.82 |
| Reactivity | 1.04 | 1.06 | 1.01 | 0.69*** |
| Social Support | 1.20*** | 1.29* | 1.15 | 0.85 |
| Engineering Experience | | | | |

| | | | | |
|---|---|---|---|---|
| Engineering Identity | | | | |
| Interest | 0.97 | 1.05 | 1.00 | 0.91 |
| Performance/Competence | 1.00 | 1.09 | 0.79 | 1.15 |
| Recognition | 0.87 | 0.75* | 0.88 | 0.99 |
| Belonging in Engineering | 0.96 | 1.13 | 0.65* | 0.67* |
| Future Time Perspective | | | | |
| Connectedness | 0.94 | 1.17 | 0.79 | 0.82 |
| Expectancy | 1.16 | 0.84 | 1.16 | 1.07 |
| Instrumentality | 1.12 | 0.56*** | 0.94 | 1.13 |
| Perceptions of the Future | 0.91 | 1.15 | 1.12 | 1.16 |
| Value | 0.89 | 0.95 | 0.90 | 0.82 |

*Note.* **p* < .05; ****p** < .01; ******p*** < .001. Asterisks indicate statistical significance based on two-tailed Wald tests.
*Note:* Odds ratios (ORs) represent the multiplicative change in odds of membership in the listed category relative to the reference group. ORs greater than 1 indicate higher odds of assignment to non-reference group (Steadily Improving), and ORs less than 1 indicate lower odds, holding other variables constant.

Among the personality and trait-level predictors examined, personality characteristics, fixed mindset, and impulsivity emerged as the most consistent predictors of group assignment. Neuroticism was associated with assignment to the Consistently High Performers and Sharply Improving groups, whereas higher extraversion and conscientiousness were associated with assignment to the Steadily Improving reference group instead. Fixed mindset was also associated with assignment to the Steadily Improving reference group when compared to both the Starting to Struggle and Consistently Struggling and At-Risk groups. Impulsivity was also associated with decreased assignment to the Consistently High Performers group, and increased assignment to the Consistently Struggling and At-Risk group.

The general academic factors most strongly associated with group assignment included test anxiety, stress related to conflicts, stress related to frustrations, and social support utilization. Test anxiety predicted decreased/increased assignment to the Consistently High Performers and Consistently Struggling and At-Risk groups respectively. Stress and social support utilization were also associated with assignment to the Consistently High Performers and Sharply Improving groups. Finally, among the engineering experience factors, sense of belonging emerged as the strongest predictor of group assignment, with higher belonging associated with assignment to the Steadily Improving reference group rather than the Starting to Struggle or Consistently Struggling and At-Risk groups.

## Discussion

*Latent Class Trajectories.* Overall, these results suggest that most engineering students maintain high performance across their undergraduate trajectory, with most students (n=701, 79%) belonging to the Consistently High Performers and Steadily Improving groups. There is also a small but notable group who, despite some early academic struggles, show significant GPA improvement by the trajectory endpoint (Sharply Improving, *n*=69). The remaining three groups of students (*n*=113, 13%) show less encouraging academic trajectories. Although the Starting to Struggle group initially mirrored the Steadily Improving group, their trajectories diverged by the third year, when their GPA fell below 3.0 and continued downward. The Consistently Struggling group showed a similar endpoint, though their decline was steady across time, with a slight uptick at the final data point. In contrast, the Consistently At-Risk group began around 2.5/4.0

and declined sharply to approximately 1.0/4.0 by the third year.

Observing these trajectories provides some valuable information about undergraduate engineering students and their grades. First, 41% of the students in our sample consistently earned very high grades. These trajectories alone do not allow us to conclude they were holistically successful, as they provide no information about the potential costs of maintaining such high performance (though the regression analyses below offer some insight). Another 45% of students exhibit trajectories impacted by the ‘sophomore slump’. Educational researchers have long identified decreases in student satisfaction and success among sophomores or second-years in a variety of fields [20], [21], [31], and these findings have been borne out in engineering populations as well [32]. However, both sophomore-slump trajectories—the Steadily Improving and Sharply Improving groups—end the third year on par with the Consistently High Performers, suggesting that second-year struggles can be overcome.

The 13% of students who struggle to maintain their GPAs warrant close attention. Although the Starting to Struggle and Consistently Struggling groups begin and end at similar GPAs (about 2.75 to 2.25), their trajectories differ: the Consistently Struggling group declines from the first semester and bottoms out by the start of year three, whereas the Starting to Struggle group declines at that point. These patterns suggest distinct underlying causes. The steadily decreasing GPA trajectory of the Consistently Struggling group suggests that early intervention and consistent support efforts would be most fruitful for these students, while the stable-then-decreasing GPA trajectory of the Starting to Struggle group suggests a precipitating event and the need for additional screening and monitoring efforts.

The final group, Consistently At-Risk, is also the smallest, with about 3% of the overall population assigned to this class. Small groups are a concern for data-driven approaches like latent trajectory modeling, as there is a risk of overfitting (in which a model is over-tuned to fit a specific sample and thus is no longer generalizable [28]). However, small groups are not automatically invalid; previous work with latent trajectories have identified groups as small as 2% or even 1% [33], [34]. In both cited studies, it is the most vulnerable members of the sample – veterans with consistently high PTSD symptoms and youth in group homes with high amounts of externalizing behaviors – that make up the smallest groups, further demonstrating the need to include small groups despite the risk of overfitting. The Consistently At-Risk group is highly vulnerable to academic sanctions, as both institutions place students below a 2.0 GPA on probation, risking loss of financial aid and dismissal. On average, this group falls below 2.0 within the first year and continues declining, suggesting prolonged probation and ongoing risk of dismissal.

Although there is some evidence suggesting that students placed on academic probation report better wellness than non-probationary students [35], most of the research in this area suggests students do not benefit from academic probation. Being placed on academic probation can function as a ‘wake up call’, but that these benefits do not persist [36], and academic probation decreases retention and does not improve graduation rates [37]. This is particularly problematic as students on academic probation are more likely to belong to minoritized racial/ethnic groups [38], [39], a finding borne out by our own study (more discussion of this finding in the section below). While the effects of spending one’s entire academic career under constant threat of expulsion are beyond the current study, which only collected non-GPA measures at a single early time point, the evidence suggests that this very vulnerable group needs further study and support instead of stigmatization and censure.

*Demographics and Academic Predictors.* Overall, the demographic patterns observed in this study are consistent with longstanding evidence that structural inequities shape academic outcomes in engineering. Students identifying as Biracial or as Black, Indigenous, or Hispanic/Latino were disproportionately represented in the most vulnerable GPA trajectories even when controlling for standardized test scores, reinforcing the conclusion that disparities in academic performance are not attributable to student ability but to unequal treatment and institutional contexts [9], [40]. Standardized math performance was not a clear indicator of later academic success; its association with both the highest- and lowest-performing trajectories highlights the limited value of test scores for explaining long-term GPA patterns. Notably, these scores were obtained from institutional records to rule out any issues caused by self-report.

*Personality and Trait Predictors.* Belonging has long been linked to academic success, particularly for women, first-generation, and racially marginalized students [41], [42], and engineering is no exception to the rule [43], [44], [45]. The personality traits most relevant to GPA trajectories in this study appear to reflect alignment or misalignment with dominant norms within engineering culture. Neuroticism was associated with more successful trajectories, suggesting that heightened concern, vigilance, or fear of failure may function as a motivator in highly competitive academic environments. While neuroticism is often linked to negative outcomes [46], [47], its association with higher performance here may reflect the pressures and reward structures embedded in engineering education [7], [48]. At the same time, performance that is driven by anxiety or fear of failure may carry psychological costs, including elevated stress and risk for burnout. Openness to experience, by contrast, was more strongly associated with trajectories involving academic instability. This pattern may reflect a tension between traits linked to exploration, creativity, and risk-taking [49], [50] and the rigid expectations often imposed in engineering education. Mindset and impulsivity further highlight that different traits matter at different points along students' academic paths. For instance, fixed mindset was most relevant for distinguishing students who begin to struggle from those who recover or stabilize, suggesting that beliefs about intelligence may become consequential primarily when students encounter difficulty. If so, this can help explain some of the mixed findings regarding mindset interventions [51].

*General Academic & Engineering Experience Predictors.* The findings related to stress suggest that not all stress operates in the same way. Conflict-related stress was more common among higher-performing trajectories, while frustration-related stress was associated with less favorable patterns. This distinction complicates simple narratives linking stress to poor performance [52], [53] and suggests that stress tied to meaningful choices or high engagement may differ qualitatively from stress rooted in barriers, resource constraints, or repeated setbacks. Consistent with past work [54], [55] social support utilization emerged as a factor associated with more adaptive trajectories, particularly among students who experienced early academic challenges but ultimately improved. However, support utilization did not distinguish the most vulnerable groups, suggesting that access to or use of support may be necessary but not sufficient for preventing academic decline. Test anxiety, in contrast, was closely tied to the most at-risk trajectories, reinforcing its role as both a marker and potential driver of academic difficulty [56], [57].

Belonging has long been linked to academic success, particularly for women, first-generation, and racially marginalized students [41], [42], and engineering is no exception to the rule [43], [45], [58]. Early feelings of belonging in engineering consistently differentiated students on more stable trajectories from those on declining paths. That belonging did not predict assignment to the sharply improving group suggests that recovery from early academic difficulty may occur even in the absence of strong early belonging, but low belonging appears to be a reliable indicator of risk for persistent struggle. It is important to note, however, that these engineering experience variables were assessed very early in students' enrollment. At this stage, belonging appears to reduce the likelihood of sustained struggle, but it does not guarantee placement on the highest-performing trajectories. Other engineering-specific perceptions (e.g., identity, future time perspective) may be more malleable and shaped by ongoing academic experiences, and so more predictive of short-term success. Repeated measurement across the undergraduate years would help clarify how these engineering-focused experiences evolve and interact with academic performance trajectories.

*Limitations.* Several limitations should be considered when interpreting these findings. The latent class trajectory model is data-driven and sample-dependent, meaning some trajectories may reflect sample-specific patterns rather than stable, generalizable trends, despite efforts to avoid overfitting. The analysis was also limited to GPA trajectories across the first three years of enrollment, which may obscure later convergence or divergence. GPA was also measured as overall institutional GPA rather than engineering- or STEM-specific performance, potentially reflecting influences of course selection and grading practices. Additionally, the regression framework compared each trajectory to a single reference group rather than allowing direct comparisons across all groups. Finally, non-cognitive and affective predictors were measured only during students' first semester, limiting insight into how these factors evolve over time and potentially understating the role of engineering-specific constructs that may become more salient with increased exposure.

*Conclusion.* Overall, this study suggests that while most engineering students maintain strong academic performance, a meaningful minority follow trajectories marked by decline or persistent risk, with distinct patterns that likely require different forms of support. GPA pathways were shaped not only by prior preparation and demographic inequities, but also by personality traits and early academic and engineering experiences. Belonging emerged as an early protective factor that reduced the likelihood of sustained struggle, though it did not guarantee top performance, while anxiety-related traits appeared to support achievement at potential psychological cost. Early engineering identity, in contrast, was not strongly predictive of long-term GPA trajectory, but may prove more consequential over shorter time frames or at key transition points as students' experiences in the major accumulate. For engineering education, these results underscore the importance of moving beyond one-size-fits-all approaches: early screening, attention to sophomore-year transitions, investment in belonging-focused interventions, and recognition that different student profiles may require different supports at different time points may be critical for promoting both performance and well-being.

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