Validation of Temporal Curricular Analytics Graph Metrics on Historical Mechanical Engineering Degree Progress

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Abstract

Student success and timely degree completion are two of the major goals of higher education institutions because they minimize the total cost of attendance and help the institution's reputation. Institutions can examine curricular structure with the aid of graph-based metrics and visualization tools provided by the Heileman CurricularAnalytics software package in R. Blocking, delay, and structural complexity all point to a possible curricular bottleneck. This study aims to validate temporal curricular graph metrics with historical enrollment data, using ten years of anonymized mechanical engineering transcripts from a private R2 STEM-focused university. The study creates comparable observational complexity validation metrics to determine how failing or delaying a course affects completion trajectory, including whether students graduate on time, need additional semesters, or recover through adaptive strategies such as summer enrollment or out-of-sequence scheduling. By quantifying delays and recovery patterns associated with structural bottlenecks, courses whose position and connectivity pose the greatest risk are identified and evaluated. This curricular-structural validation approach provides insights for students, curriculum committees, and advisors, supporting data-driven insights of critical sequences, co-requisite policies, and scheduling flexibility to promote quicker and more equitable degree attainment.

1. Introduction

Higher education institutions are under increasing pressure to enhance student success outcomes, especially graduation rates, which are now essential indicators for funding allocation, accreditation, and institutional accountability [1]. Despite decades of investment in student support services, academic advising, and pedagogical innovations, many students still face delays or do not graduate at all. According to national statistics, approximately one-third of engineering students graduate within four years, and roughly sixty-two percent graduate within six years [2-3]. Previous studies imply that factors other than instructional quality and student services contribute to completion challenges [4-5]. Data analytics in higher education is generally intended to guide decision-making that boosts student performance. Most efforts are based on the student's past performance and demographic data. There is an emerging perspective that identifies curricular progression as the primary determinant of student achievement [6-7].

Disruptions to a student's intended academic pathway are the main causes for delayed graduation and increased attrition. Therefore, maintaining the integrity of the curricular flow is essential for institutional success [8].

According to recent studies, one important but frequently disregarded factor influencing student success is the curriculum's structural complexity. The field of curricular analytics has emerged to provide quantitative frameworks for analyzing these structural properties, demonstrating that curricula can be mathematically represented as directed graphs where courses serve as vertices and prerequisite relationships form edges [8]. This representation enables the application of graph-theoretic metrics to measure curricular complexity, revealing that programs with ostensibly similar learning outcomes and accreditation standards can differ dramatically in their structural characteristics. Moreover, empirical studies have established strong correlations between measures of curricular complexity and student outcomes, with research showing that even modest reductions in structural complexity correspond to measurable improvements in graduation rates [8-9].

The temporal dimension of student progression through curricula represents a critical but incompletely explored aspect of curricular analytics. While existing research has established that the structural arrangement of courses matters for student success, most analytical approaches have treated curricula as static structures, examining prerequisite relationships and course sequences without explicitly modeling how students progress through these structures over time. Students do not experience curricula as complete graphs but rather navigate them term by term [10], making sequential decisions about course enrollment, experiencing successes and failures that alter their trajectories, and accumulating progress toward degree requirements that may or may not translate efficiently into degree completion. The temporal patterns of this navigation, when students complete particular courses, how delays in one term propagate through subsequent terms, and whether students maintain pace with expected progression milestones, carry important information about the likelihood of ultimate success that static structural metrics may not fully capture.

Mechanical engineering programs provide a particularly compelling case for investigating temporal dimensions of curricular progression. These programs typically feature complex prerequisite structures, with foundational mathematics and science courses forming long chains that must be completed before students can access upper-division engineering coursework [11]. The sequential nature of these requirements means that students who experience difficulty early in their programs face compounding challenges as delays accumulate [12]. Moreover, mechanical engineering curricula exhibit substantial structural complexity, ranking among the most complex undergraduate programs when measured by standard complexity metrics [11]. This combination of structural complexity and strict sequencing creates an environment where temporal patterns of progression may prove especially informative for understanding and predicting student outcomes.

The validation of analytical methods against real-world student data remains a critical need in the curricular analytics literature. While simulation studies and cross-sectional analyses have established theoretical relationships between curricular structure and student outcomes, fewer studies have systematically examined historical student cohorts to validate whether proposed metrics capture meaningful variation in actual student progression patterns. Historical degree progress data, complete records of courses attempted, grades earned, and temporal patterns of enrollment for students who have completed or discontinued their programs provide a rich empirical foundation for testing whether temporal extensions of curricular analytics metrics offer predictive and explanatory power beyond static structural measures. Such validation is essential for establishing confidence that these analytical tools can guide practical decision-making about curricular design and student support interventions.

2. Problem Statement

Prior studies have established that curricular structure matters for student success, the field lacks validated methods for analyzing temporal progression patterns and their relationships to curricular characteristics. Developing and validating such methods would enable more precise identification of critical junctures where students deviate from expected progression pathways, more accurate prediction of students at risk of delayed completion or non-completion, and more targeted design of interventions to keep students on track.

Academic advisors currently lack systematic tools for monitoring whether individual students are progressing through curricula at rates consistent with timely degree completion. Traditional metrics such as cumulative credit hours or grade point average provide limited insight into whether students are satisfying degree requirements in appropriate sequences or falling behind in ways that will prevent on-time graduation. Progress analytics tools that incorporate temporal patterns could enable earlier identification of students experiencing difficulties, allowing interventions before problems become too large to solve.

The focus on mechanical engineering provides an ideal test case for several reasons. First, mechanical engineering programs exhibit high structural complexity, making it a context where temporal effects are likely to be pronounced and therefore detectable in empirical data. In addition, mechanical engineering curricula follow relatively standardized structures across institutions, facilitating potential generalization of findings.

The validation approach employed in this study addresses a key gap in the curricular analytics literature. While theoretical models and simulations have suggested that temporal factors matter, empirical validation using real student progression data remains limited. By examining whether temporal graph metrics calculated from curricular structure correlate with actual patterns observed in historical student data, this research provides an essential test of whether temporal extensions to curricular analytics capture genuine phenomena rather than theoretical artifacts.

Positive validation would support broader adoption of temporal analytics tools across institutions and disciplines.

3. Related Studies

The relationship between curriculum design and student success has emerged as a critical area of inquiry in higher education research. Heileman et al. [8] established a comprehensive framework for curricular analytics, demonstrating that the structural organization of academic programs directly impacts student progression and graduation rates. Their work introduced the concept that curricula can be quantitatively analyzed through graph-theoretic approaches, where courses serve as vertices and prerequisite relationships form directed edges. Heileman et al. [13] reported substantial differences in structural complexity among engineering programs at similarly rated institutions, despite identical accreditation standards. Their findings suggested an inverse correlation between curricular complexity and graduation rates, challenging the conventional assumption that more complex curricula necessarily indicate higher quality programs.

The measurement of curricular complexity has evolved through multiple refinements. Wigdahl et al. [14] introduced the concept of "curricular efficiency" by examining how prerequisite structures create bottlenecks that impede student progress. Slim et al. [15-16] introduced the fundamental concepts of delay factor and blocking factor as measures of course importance, demonstrating that course "cruciality" follows a power-law distribution with mathematics courses consistently ranking highest across institutions.

The temporal aspects of curriculum navigation have received increasing attention as researchers recognize that student progression is inherently time-dependent. Slim [12] developed probabilistic models incorporating geometric distributions to predict graduation rates, explicitly acknowledging that delays in completing critical courses create cascading effects throughout a student's academic trajectory. Recent work has focused on identifying and supporting students who have completed substantial portions of degree requirements but face barriers to final completion. Manasil et al. [17] developed progress analytics tools that track student advancement toward requirement satisfaction rather than credit accumulation. Their analysis revealed that institutional metrics based solely on credit hours often obscure actual proximity to degree completion, as students may accumulate credits that do not satisfy remaining requirements.

The development of predictive models for student success has increasingly incorporated curricular structure as a key variable. Slim et al. [18] employed Bayesian Belief Networks to predict student performance based on prior grades and prerequisite structures, demonstrating that network structure carries predictive information beyond individual course grades. Ojha et al. [19] compared multiple machine learning approaches, finding that curricular complexity contributes significantly to prediction accuracy, particularly for STEM students, with models achieving 76% accuracy in predicting graduation delays.

The application of curricular analytics has informed multiple intervention strategies. Klingbeil and Bourne [20] documented comprehensive curricular reform at Wright State University that restructured the mathematics sequence for engineering students not calculus-ready upon entry. By creating a first-year engineering course integrating precalculus content with application-specific mathematics, they reduced structural complexity while maintaining learning outcomes. Longitudinal studies demonstrated that students following the restructured pathway achieved graduation rates equivalent to those of their calculus peers.

Slim et al. [21] applied machine learning approaches for automated curricular restructuring, employing latent tree graphical models and collaborative filtering to identify optimal course arrangements. Applied to engineering programs at the University of New Mexico, their algorithms identified restructuring opportunities, reducing complexity by 97 points while maintaining learning outcomes, with predicted 5.42% improvements in eight-term graduation rates. Validation of curricular complexity metrics has proceeded through multiple methodological approaches.

4. Methodology

Eleven years of anonymized student enrollment data from the mechanical engineering program at an R2 university from 2010 to 2021 were collected to evaluate the impact of the structural complexity (SC) of the curriculum. Figure 1 below shows an example of the raw data file before it was transformed and analyzed. The data include all the information for each student per course as they progress through the program, roughly 64,000 rows representing 2253 students in the program from 2010 to 2021.

Supl Cohort	Primary Cohort	Student	Acad Plan	Graduated-MechE	Graduated-Not MechE	Term	Start Date	End Date	Catalog Nbr	Descr	Grade
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4132	1/10/2013	4/26/2013	CM132	General Chemistry II	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4132	1/10/2013	4/26/2013	EE268	Machine Intellig or Stupidity	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4132	1/10/2013	4/26/2013	ES100	Int to Eng Use of Computer	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4132	1/10/2013	4/26/2013	MA132	Calculus II	C+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4132	1/10/2013	4/26/2013	PH132	Physics II	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4139	8/26/2013	12/6/2013	ES220	Statics	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4139	8/26/2013	12/6/2013	ES250	Electrical Science	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4139	8/26/2013	12/6/2013	ES260	Materials Science & Eng I	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4139	8/26/2013	12/6/2013	MA232	Elementary Differential Eq	C+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4139	8/26/2013	12/6/2013	POL301	Political Theory	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4142	1/9/2014	4/25/2014	COMM310	Mass Media and Society	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4142	1/9/2014	4/25/2014	ES222	Strength of Materials	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4142	1/9/2014	4/25/2014	ES223	Rigid Body Dynamics	C+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4142	1/9/2014	4/25/2014	MA231	Calculus III	C
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4142	1/9/2014	4/25/2014	ME201	Exp Methods in MAE	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4142	1/9/2014	4/25/2014	ME212	Intro to Engineering Design	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4149	8/25/2014	12/5/2014	ES330	Fluid Mechanics	B
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4149	8/25/2014	12/5/2014	ES340	Thermodynamics	C-
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4149	8/25/2014	12/5/2014	MA330	Adv Engineering Mathematics	A-
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4149	8/25/2014	12/5/2014	ME301	Exp Methods in MAE	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4149	8/25/2014	12/5/2014	ME324	Dynamical Systems	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4149	8/25/2014	12/5/2014	PY151	Introduction to Psychology	B+
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4152	1/8/2015	4/24/2015	EC350	Economic Prin & Eng Econ	B-
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4152	1/8/2015	4/24/2015	ME326	Intermediate Fluid Mechanics	W
4129FT	2012FLFT	7736565033	MECHE-BS	Y		4152	1/8/2015	4/24/2015	ME341	Mechanics of Machine Elements	B+

Fig 1: Sample curriculum database Mechanical Engineering in a R2 university

Data Dictionary

Students Inclusion: The dataset includes any student who first entered the university between Fall 2010 and Fall 2021 as MECHE-BS, or any student whose first major was something other than MECHE-BS and later enrolled as MECHE-BS. This latter group would include anyone who was a dual degree, double major or who transferred into MECHE-BS.

The original data file includes:

1. Students' primary cohort code, based on the first semester of study
2. Anonymized student ID number, a randomized unique identifier
3. Major the student started in (or first declared if dual or double major).
4. Binary indicator (Y/N) of receiving a MECH-BS degree (non-complete data included)
5. Binary indicator (Y/N) of receiving a bachelor's degree NOT in MECH-BS
6. Course term
7. Course catalog number (including EVERY course taken, not just ME courses)
8. Course letter grade (A, A-, A+, B, B-, B+, C, C-, C+, D, D+, F, I, LW, NC, P, S, W)

The primary cohort identifies when a student first enrolled at the university and the type of entry. The primary cohort is formatted as [calendar year + term + type of entry]. For example, for the primary cohort of '2019FLFT', the first four digits represent the calendar year the student entered (2019). The 5th and 6th digits represent the term the student entered, 'FL' Fall Semester or 'SP' Spring Semester. The last two digits represent the type of entry, for example 'FT' is First-time undergraduate.

Enrollment terms are a numerical representation of the year and month in which classes began. The first digit represents the century, and the 2nd and 3rd digits represent the year in that century, for example, '399' = 1999; '418' = 2018. The fourth digit represents the month the term began.

For example, 2018-2019 includes:

4186 = June 2018, or Summer 2018 semester
4189 = September 2018, or Fall 2018 semester
4192 = February 2019, or Spring semester

Preprocessing analysis includes new data columns with aggregate statistics such as the number of courses taken, courses failed and passed, sum of credit-bearing courses, total credits (units), cumulative GPA, duration, number of semesters. Courses are statistically categorized into structural complexity (SC) ordinal bins: Low SC, Medium SC, and High SC. The CurricularAnalytics.org package was used to compute structural complexity as a graph-based metric. The normal distribution of the structural complexity was used to determine the category of the complexity.

Structural complexity of 0-5 is Low SC, 6-12 is Medium SC, and 13+ is High SC. Low SC (low structure complexity) is expected to have less impact on the student progression through the curriculum if not passed or taken as required compared to High SC (High Structure complexity). The High SC as expected could have a strong adverse impact on student outcomes like graduation if not passed when taken or if its enrollment was delayed. Courses with grades No Credit (NC) or Pass/Fail (P/NP) were excluded. To simplify data analysis and remove transfer students, the analysis was focused on students who first enrolled in the program as Fall semester. All the students whose primary cohort is the spring semester were excluded. Enrollment in FY100 and UNIV190 in the first semester in the fall was used to identify and remove transfer students from the dataset. These exclusion filters represented a small percentage (0.01%) of the population. The description of the data structure used in the analysis is shown in Figure 2

Data Field	Description
Student	Unique student identifier.
Acad Plan	Student's declared academic program or major.
Primary Cohort	Student's entry cohort year, from 2010 to 2021.
Courses_Taken	Total courses attempted.
Courses_Passed	Total courses successfully completed.
Course_Failed	Total courses failed.
Sum_of_Units_thatCounts	Total degree-applicable units earned or counted.
Total_Creditweight	Total credit-weighted course load.
CGPA	Cumulative grade point average.
Start Date	Student's first observed enrollment date.
End Date	Student's last observed enrollment, graduation, or program-status date.
Duration (year)	Time in the program, measured in years.
Semesters	Number of semesters observed in the program.
Graduated-MechE	Graduation status from Mechanical Engineering.
Graduated-Not MechE	Graduation status from another program.
Graduate-Mech(0,1)	Binary indicator for Mechanical Engineering graduation.
Grad-Mech Double Major	Indicator for Mechanical Engineering double-major graduation.
Graduate-NotMech(0,1)	Binary indicator for non-Mechanical Engineering graduation.
Non-completers	No of non-completions observed record.
Low SC	Count of low-SC courses or records.
Medium SC	Count of medium-SC courses or records.
High SC	Count of high-SC courses or records.

Figure 2: Data Structure descriptions

In this analysis, course outcomes were dichotomized into 'passing' and 'failed' states. 'Failure' was explicitly defined as a student receiving a grade of F, LW (late withdrawal), or I (incomplete), while 'passing' was defined to include standard letter grades (A–D). A general exploratory analysis was completed on the dataset, which includes the student that graduated and those who didn’t complete the program. A decision was reached to split the data into graduates and non-completers (those who pause, quit, or transfer to another program in another institution). Both the non-completers and graduates were analyzed together to determine the average failure rate for low SC, medium SC, and high SC, the mean and median CGPA, and the semester. Later, non-completers were split into non-completers without failing a course and non-completers who failed at least a course. The percentage of non-completers from the program without failing a course and those who failed some courses was determined, including the mean and median of the CGPA, semester spent in the program, and failure rate of low-, medium-, and high-structure courses. The techniques were done for the graduating student dataset as well.

5. Results and Data Analysis

Figure 3 below shows what happened to students in each primary cohort from 2010 to 2021 as a share of the original cohort enrollment. The results show that over 60% of students that enrolled in mechanical engineering graduated from the program, while around 15% changed their program to another major, reflecting normal academic realignment rather than failure. The red column bar in the graph shows that about 20-30% of the students didn’t complete their program with the institution, which is the most sensitive indicator of curricular or institutional stress. When conditions become less favorable, students are more likely to leave the program rather than switch to another major.

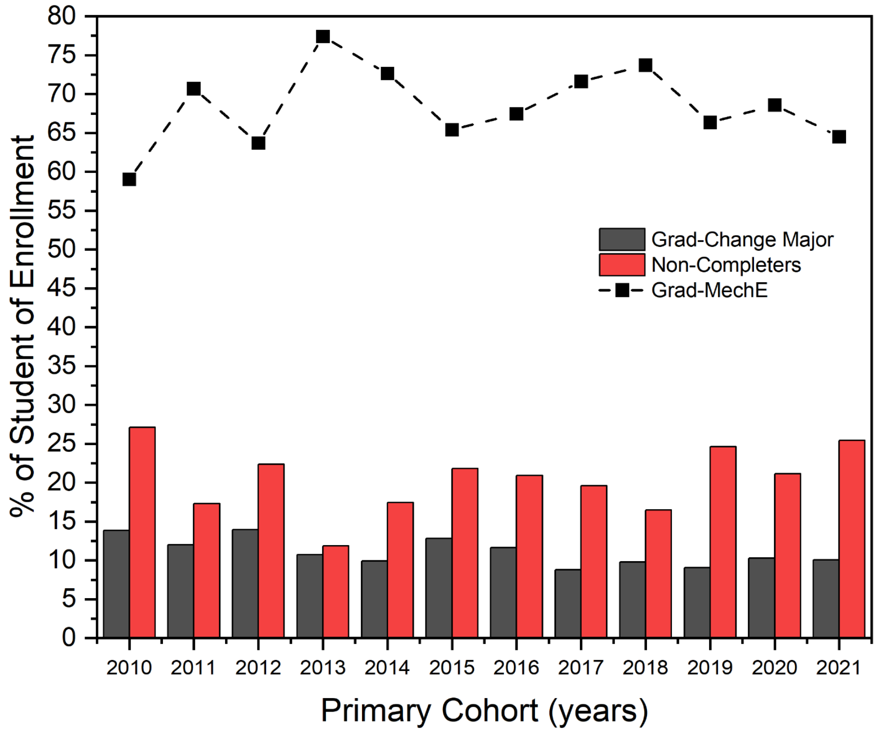

Figure 3: Percentage distribution of student enrollment

In Figure 4, between 20% to 50% of non-completers—depending on the primary cohort—did not fail any course before program non-completion, while about 70% failed at least one course before becoming non-completers. The figure 3 below shows that some students who never failed a course still became non-completers, indicating that academic failure alone does not fully explain program non-completion. Other factors, such as personal circumstances, motivation, or misalignment with program expectations, may also contribute. However, students who failed at least one course remain the dominant group among non-completers.

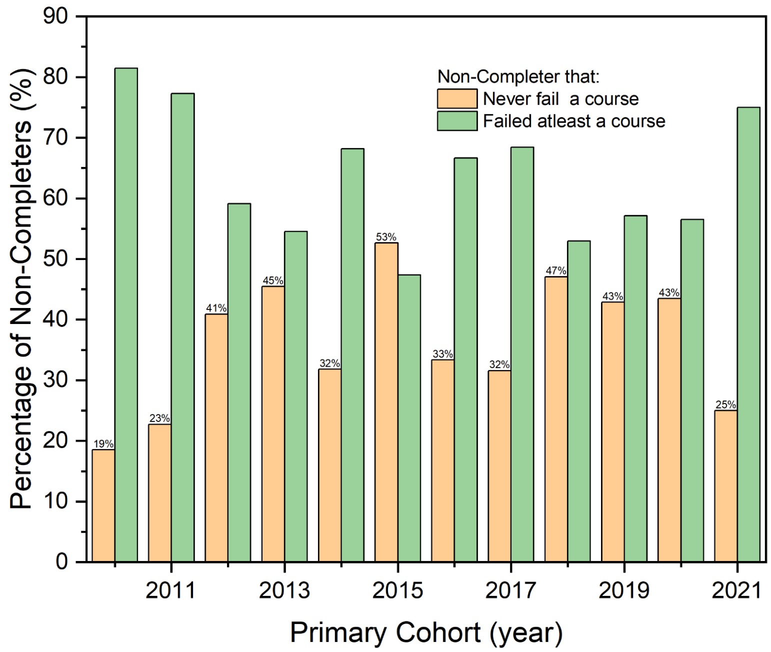

Figure 4: Percentage of non-completers that failed and never failed a course.

CGPA

Figure 5 shows the Cumulative Grade Point Average (CGPA) distribution across cohorts, showing how academic performance changes over time. Across all cohorts, the central tendency (mean and median) remains fairly stable within the same range, indicating that the academic ability of incoming and progressing students is broadly consistent from year to year. The interquartile range shows a moderate spread in performance within each cohort, suggesting normal variation among students. In this study, CGPA is a contextual baseline rather than a sole predictor of graduation, major change, or non-completion.

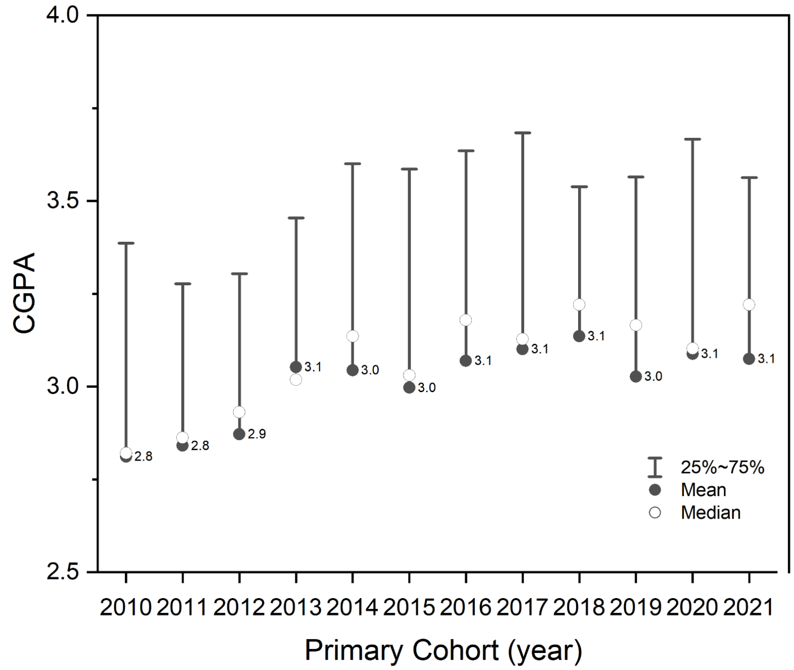

Figure 5: Mean, Median and Interquartile CGPA of Students by Primary cohort

In a deeper look into CGPA and splitting into groups by graduates (undergraduate students who graduate) and non-completers, Figure 6 shows that graduates consistently achieved higher CGPAs than non-completers across all primary cohorts. The mean CGPA of graduates generally ranged from about 3.0 to 3.3, while that of non-completers remained mostly between 2.1 and 2.5. The close alignment between the mean and median values within each group suggests limited skewness in the CGPA distributions. The persistent CGPA gap indicates that academic performance is associated with program completion, although CGPA alone may not fully explain non-completion because some students with relatively higher CGPAs were still classified as non-completers.

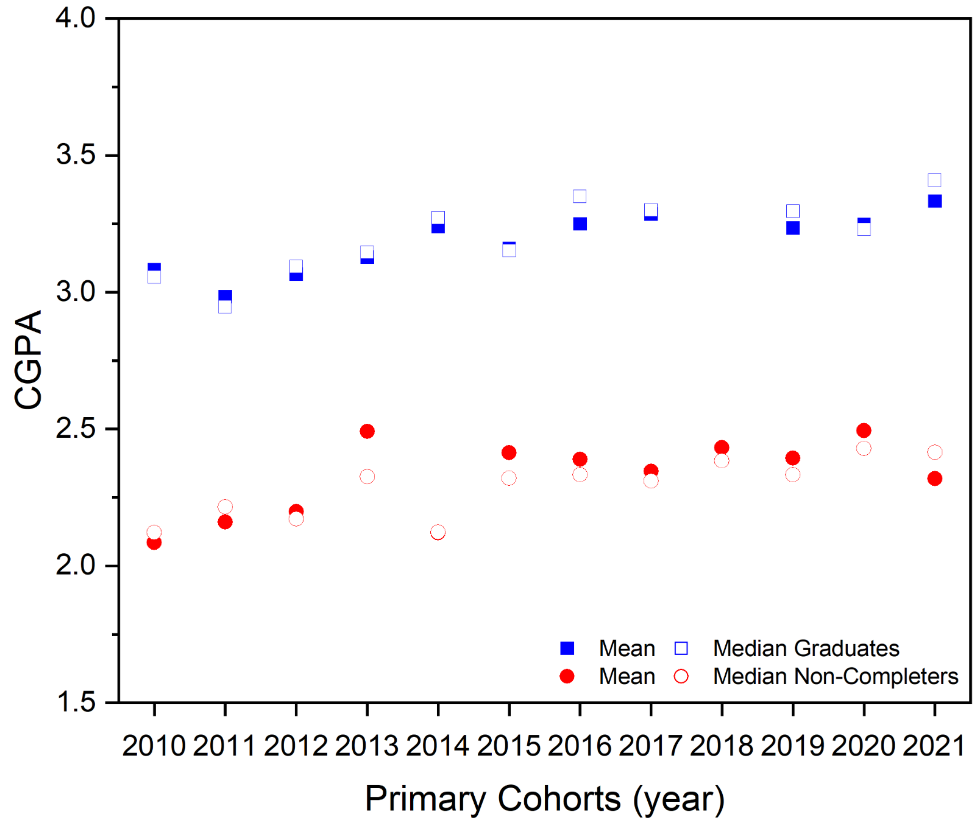

Figure 6: CGPA distribution of graduates and non-completers across different primary cohorts

Figure 7 compares the CGPA of non-completers who never failed a course with those who failed at least one course across the primary cohorts. Non-completers who never failed a course consistently recorded higher mean and median CGPAs, generally ranging from about 2.7 to 3.4. In contrast, non-completers who failed at least one course had much lower CGPAs, mostly between about 1.9 and 2.1. This trend in CGPA shows obviously that course failure (by definition) is one of the primary factors of weaker academic performance among non-completers. However, the relatively high CGPAs among some non-completers who never failed a course suggest that non-completion may also reflect factors beyond academic failure alone.

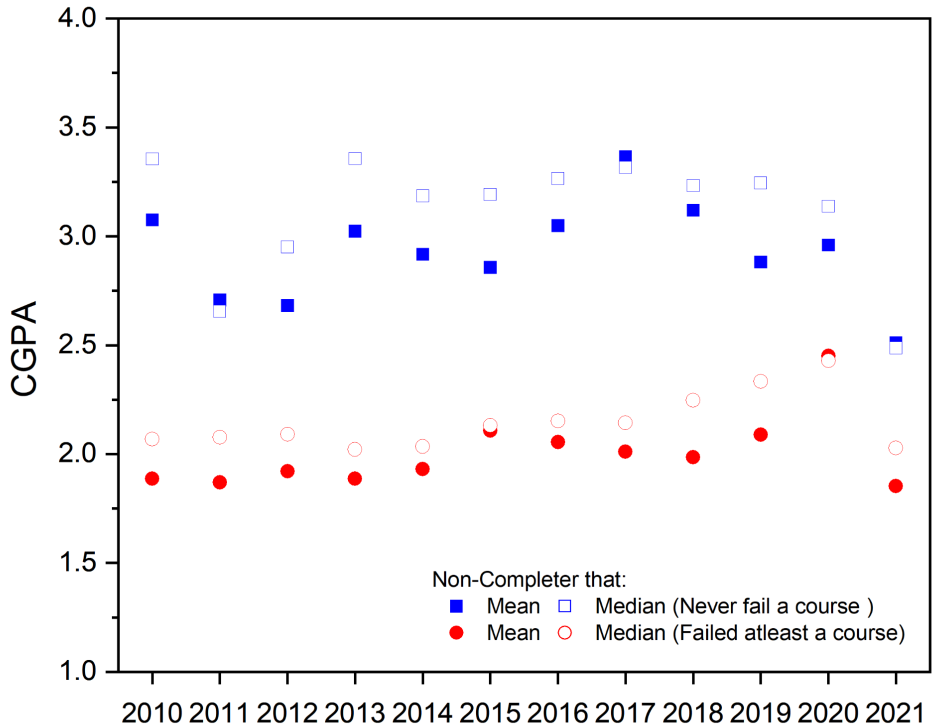

Figure 7: CGPA of Non-Completers that Failed or Never Failed a Course

Course Failure Analysis

Across the primary cohorts in Figure 8, the mean number of failed courses generally remains below one across the low, medium, and high structural complexity (SC) courses. The failure rate of low SC courses is slightly higher than high SC courses, and it always shows its lowest mean. It shows that high SC courses are less likely to fail compared to other low SC courses, as the course has the highest failure count.

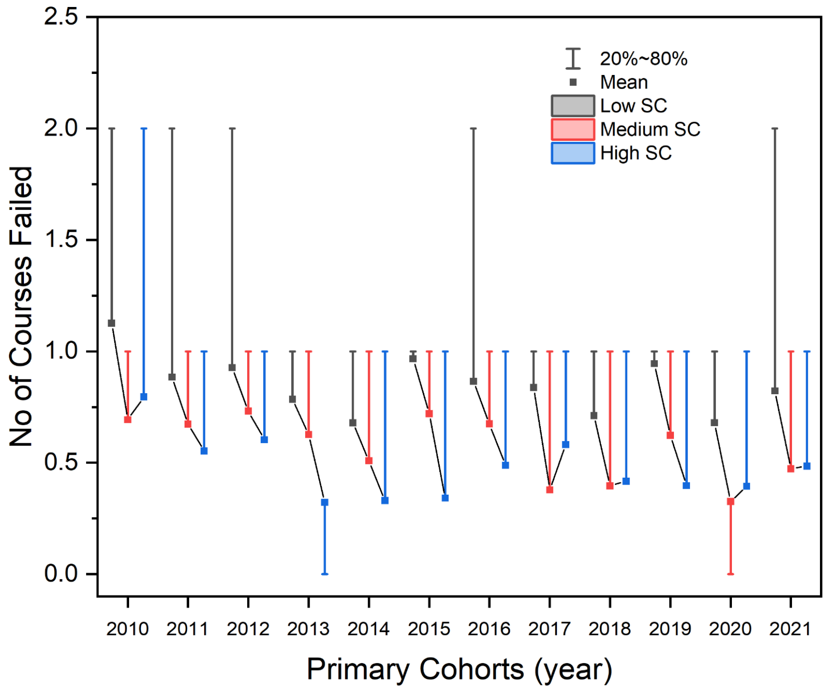

Figure 8: Failure rate of low, medium, and high structural complex courses

Non-completers generally had higher numbers of failed courses than graduates across low, medium, and high SC courses, as shown in Figure 9. The mean failed-course values for non-completers were consistently higher, often ranging from one to nearly three courses, while graduates mostly remained below one failed course. The 50th percentile (the median in Figure 9b) further reinforces this pattern, as the 50th percentile of the graduates had zero failed courses, indicating that most completed the program without course failure. In contrast, the 50th percentile of non-completers often failed a course, and in some cohorts reached two failed courses. The result shows that course failure is higher among the non-completers than among graduate students.

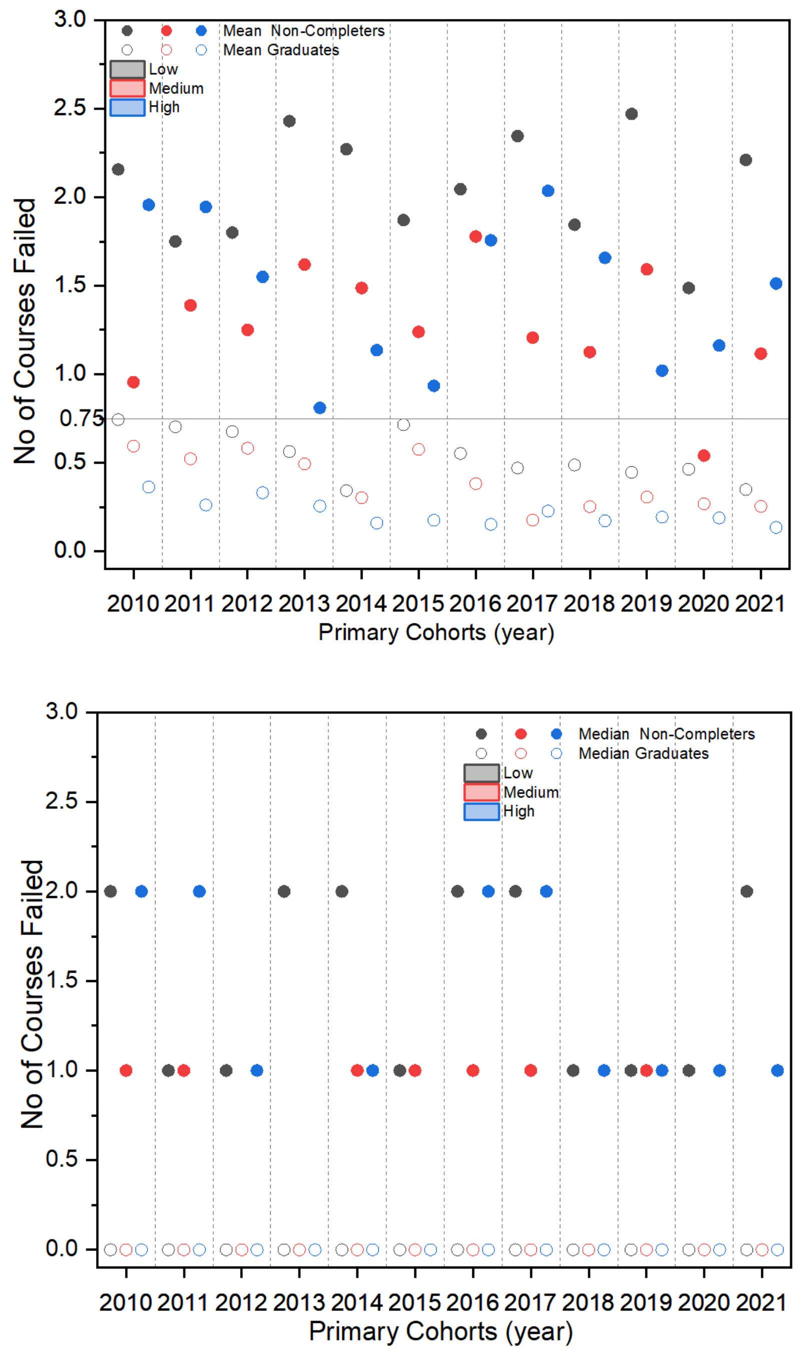

Figure 9: (a) Mean and (b) median number of failed courses among graduates and non-completers by structural complexity level

Time-to-degree Completion Analysis

The central tendency of duration in the program and semester-to-degree completion is shown in Figures 10(a) and 10(b), which show consistent time-to-degree trends across the cohorts. Average program durations varied from 3.2 to 3.7 years (about 8 semesters), confirming that most graduates finished within the expected timeline. Establishing this baseline highlights a small subset of graduates who took substantially longer (up to 6 to 7 years) and occasionally extending beyond 11 years (14 to 16 semesters). These extended cases likely resulted from progression delays such as course repeats, semester breaks, or interruptions.

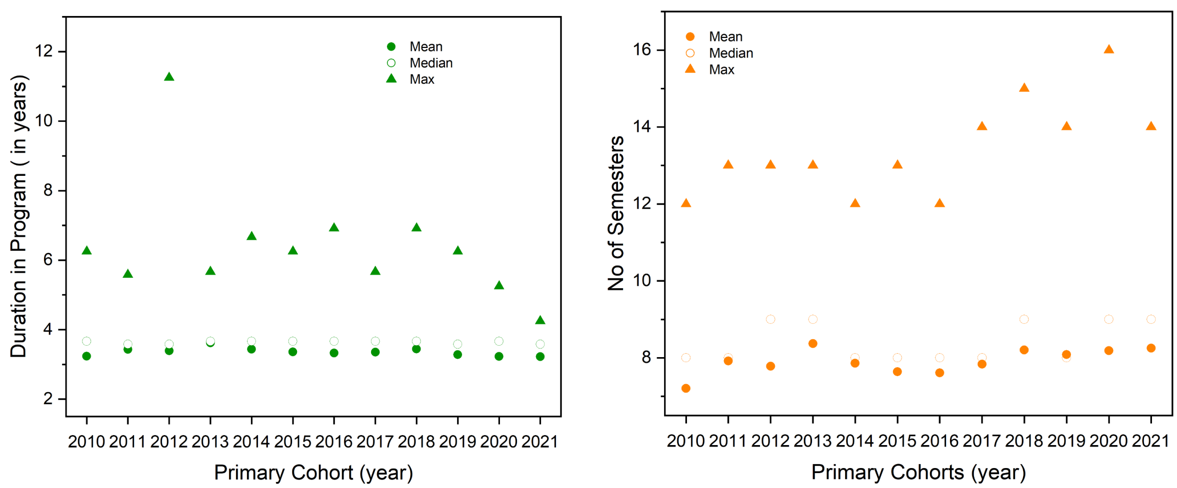

Figure 10: (a) The Duration and (b) the Semester to completion among the graduates

Also, course-failure status is related to when students either discontinue or complete the program. In Figure 11, non-completers who failed at least one course generally reach opt out earlier, mostly around 2 to 4 semesters, while non-completers who never failed a course tended to remain longer, often around 4 to 6 semesters. This suggests that students with course failures may become academically vulnerable earlier in the curriculum, whereas students without failures may discontinue for reasons beyond academic performance. In Figure 12, graduates who never failed a course typically completed the program close to the expected timeline, around 8 to 9 semesters. In contrast, graduates who failed at least one course took longer to complete, often around 9 to 12 semesters. Those who failed some courses but were able to graduate on time are more likely to adopt adaptive strategies like out-of-sequence enrollment, taking summer courses, or changing majors.

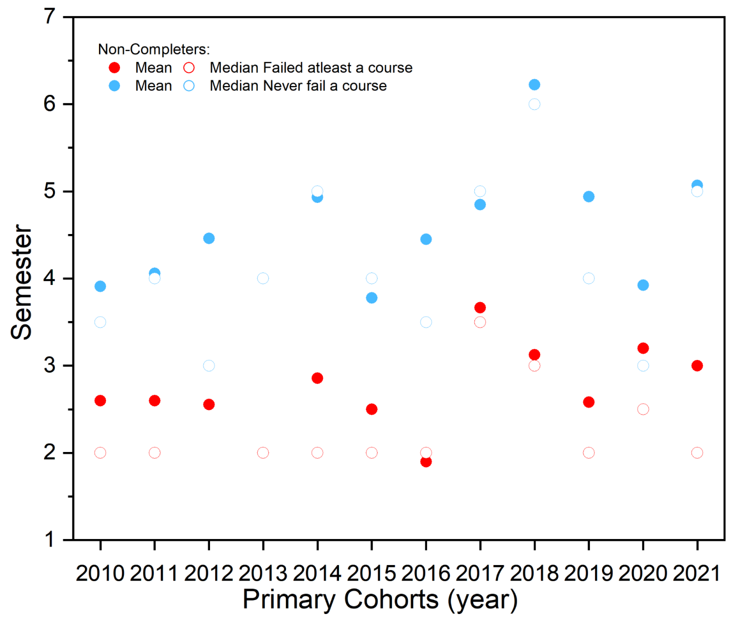

Figure 11: Semester of non-completion by course-failure status among non-completers.

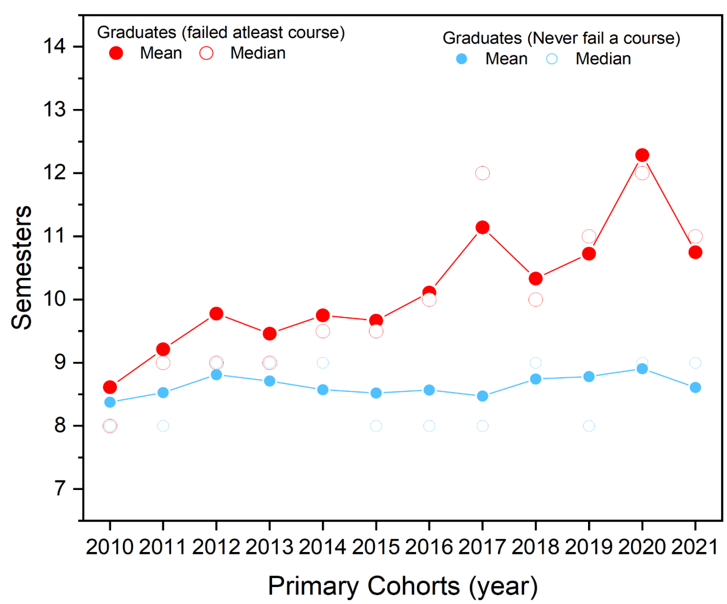

Figure 12: Semester-to-degree completion by course-failure status among graduates.

6. Conclusion

This is a work-in-progress paper. Current progress includes familiarization with CurricularAnalytics.org web-based and R-based tools, development of a university-specific mechanical engineering curricular graph, identification of crucial courses with elevated complexity metrics, acquisition of anonymized historical data, and exploratory statistical data analysis with structural complexity bins and degree completion. Next steps involve more explicit observational metric development and comparison to existing graph metrics.

While the current work is preliminary in nature, long-term, this study seeks to validate temporal extensions to curricular analytics graph metrics using historical mechanical engineering degree progress data, with the goals of: (1) establishing whether temporal progression patterns in real student data correlate with graph-theoretic measures of curricular structure; (2) determining whether temporal metrics provide predictive or explanatory power beyond static structural measures; (3) identifying which temporal metrics prove most useful for characterizing student progression; and (4) demonstrating practical applications of validated temporal metrics for student success initiatives. Through these objectives, the research aims to advance both the theoretical foundations of curricular analytics and its practical utility for improving student outcomes in engineering education. At this preliminary phase, this work cannot conclusively validate temporal curricular analytics graph-based structural complexity metrics with historical mechanical engineering degree progress. However, obvious connections between course failure and degree competition delays are evident and there appears to be an inverse relationship between 3-tiered structural complexity and course failure. This preliminary progress suggests further investigation is warranted.

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