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Data-Driven Analysis of Engineering Curricula: A Cross-Disciplinary Study of Complexity in Seven Programs and Its Impact on Student Pathways and Career Outcomes

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Abstract

This study examines how curricular complexity (CC)—modeled via network analysis—shapes post-graduation outcomes for seven engineering programs at a private institution in the Northeastern United States. Post-graduation data, including employment rates, mean salaries, and graduate-school enrollment, were correlated with these CC metrics over five years. Results reveal a significant spectrum of complexity, with Mechanical and Aerospace Engineering (MAE) exhibiting the highest CC per course and Computer Science (CS) the lowest. Higher complexity did not always yield higher immediate salaries—MAE graduates initially had lower starting wages compared to CS. However, MAE graduates showed substantial long-term earnings and the highest rate of pursuing advanced degrees. A Principal Component Analysis explained over 90% of the variance in post-graduation outcomes, highlighting trade-offs between immediate job-market readiness and deeper academic engagement. These findings emphasize the importance of balancing curricular depth and flexibility to optimize student success. This research advances curriculum analytics by providing empirical metrics and actionable insights, enabling institutions to design engineering programs that better align with industry demands, support interdisciplinary learning, and promote holistic professional development.

Introduction

Background

Engineering curricula are shaped by disciplinary norms, stakeholder expectations, student career trajectories, and evolving demands on what graduates should know. However, many programs remain entrenched in curriculum design based on historical precedent rather than empirical, research-driven approaches [1]. This trend can lead to rigid prerequisite structures and outdated frameworks that do not always reflect contemporary engineering practice. As a result, curricula can become unnecessarily complex, with prior research showing that high complexity negatively correlates with graduation rates, time-to-degree, job earnings, and employment rates [2], [3], [4]. These curricula also have impacts on equity in engineering pathways as research often demonstrates equity gaps in gateway STEM course grades by race or gender [5], [6]. Complex curricula may also reduce students' opportunities to cultivate skills beyond traditional classroom environments, such as interdisciplinary thinking, interpersonal competency, research skills, and creativity, which have been shown to enhance leadership, academic experience, and analytical capabilities [7], [8].

Despite growing recognition of these issues, studies on curricular complexity in engineering have tended to focus on individual disciplines or student progression and graduation rates, with fewer investigations linking complexity to job placement or earnings. Moreover, recent studies emphasize the need for curricula that integrate industry demands, interdisciplinary approaches, and experiential learning to better prepare graduates for real-world challenges [9], [10], [11]. Transitioning to outcome-based frameworks and engaging diverse stakeholders in curriculum design could help mitigate unnecessary complexity, ultimately promoting high academic standards and flexibility. These points underscore the need for systematic ways to measure and assess curricular complexity.

Data-Driven Approaches for Quantifying Curricular Complexity

In recent years, there has been an increased interest in data-driven approaches to studying and quantifying the complexity of engineering curricula [12]. Over the past decade, several studies have introduced diverse methods for measuring this complexity. For instance, Roland et al. [13] analyzed curriculum prerequisite networks using a probabilistic student flow model. They identified how individual courses affect graduation timelines and developed software to facilitate similar analyses. Meanwhile, Heileman et al. [14] proposed a network-analysis-based framework that maps course interdependencies to capture curricular design patterns effectively. This framework is becoming increasingly popular for describing patterns in curricular design, which reflects a paradigm shift toward a data-driven approach to analyzing curricula and degree requirements [15].

Although these data-driven metrics represent a significant step forward from subjective curriculum design, they have not yet been applied comprehensively across multiple engineering programs to examine broader post-graduation outcomes, such as job placement and earnings—an area this study addresses in subsequent sections.

Gaps in the Existing Literature

Despite the growing research of data-driven approaches to curriculum design, most studies limit their scope to examining a single engineering program or a single discipline at a time. For example, a study conducted by Heileman et al. [16] focused on comparing Electrical Engineering curricula across different universities, finding that programs with simpler curricula often have higher quality. Another study conducted by the same researcher showed an inverse relationship between CC and quality of computer science programs [17].

This approach may offer valuable insights into the curriculum design in those programs; however, it does not allow for broader, cross-disciplinary comparisons. This is a critical omission given that all engineering programs, while varied in technical focus, share foundational structures and competencies. By studying them in isolation, researchers risk missing systemic patterns or discipline-specific nuances that may illuminate the root causes of curricular challenges. Direct comparisons between programs have proven challenging as CC as a metric highly depends on the number of required courses, which can vary widely between programs. Another notable gap is the insufficient exploration of the relationship between curricular complexity and key educational outcomes beyond graduation rates and time-to-degree [18]. Understanding program outcomes in relation to CC can help balance increasing demands for new graduate competencies (e.g., AI and Data Science) while supporting student workload and stress. By concurrently analyzing multiple engineering programs, the present research aims to identify common challenges and effective practices that transcend individual disciplines. A comparative approach is crucial because it distinguishes universal patterns of complexity from discipline-specific nuances. It also allows for benchmarking across programs and provides research-based assessments, which enables institutions to make informed decisions or adapt strategies in designing and evaluating curriculums.

Objectives and Research Questions

This study compares curricular complexity (CC) across seven engineering programs at a private Northeastern institution, examining relationships with post-graduation outcomes. We seek to determine which curricular features are problematic or beneficial to inform evidence-based redesign. Specifically:

1. How does CC vary across these seven programs?
2. What is the relationship between CC and placement rates within five years?
3. How does CC influence further education and median earnings in five years?
4. How can comparative CC analysis reduce unnecessary complexities?

Curricular Complexity Framework

In this study, we use the curricular complexity framework developed by Heileman et al. [13], [14], which draws on graph theory and network analysis. This framework models a curriculum's complicated arrangement of pre- and co-requisite relationships, transforming it into a network for in-depth quantitative analysis. The fundamental premise of this framework posits that as CC increases, completion rates tend to decrease, a relationship supported by both simulation studies and empirical evidence [14], [15].

Heileman's framework is operationalized using two main components: 1) structural complexity and 2) instructional complexity. Structural complexity captures how course offerings, along with pre- and co-requisite structures, create bottlenecks or delays, whereas instructional complexity focuses on more latent factors, such as the quality of instruction. Given our focus on quantifiable design elements, this research centers on structural complexity.

Structurally, CC refers to the interconnectedness of courses within a program based on prerequisite and co-requisite relationships [14], [19]. The core idea is that each course's importance (or "cruciality") is determined by its position in the curriculum—specifically, how it extends the path to graduation and how it constrains enrollment in subsequent.

To formalize this framing, each course n has a course complexity, v_n, defined as in (1):

$$v_n = d_n + b_n \tag{1}$$

Where:

- d_n is the delay factor, indicating the length of the longest prerequisite chain that includes course n.
- b_n is the blocking factor, measuring how many other courses require n as a prerequisite (directly or indirectly).

The structural complexity of an entire program, denoted α_c, is then computed by summing the complexity values of each course in the curriculum (2):

$$\alpha_c = \sum_n v_n \tag{2}$$

Here, α_c, reflects the cumulative impact of all course interdependencies on students' abilities to progress and complete the program. Figure 1 illustrates an example calculation of a course's cruciality using these two factors.

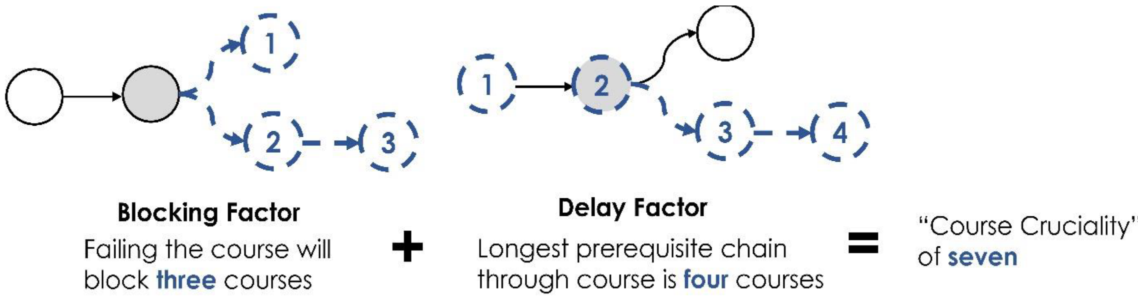

Figure 1. Example calculation of a course cruciality using the delay and blocking factors from [12]

Methods

Data Sources

We collected the degree plans data from publicly available engineering handbooks for seven engineering programs at a private Northeastern institution for the class of 2015-2019. These programs are Mechanical and Aerospace Engineering (MAE), Computer Science (CS), Materials Science Engineering (MSE), Civil and Environmental Engineering (CEE), Chemical and Biomolecular Engineering (CBE), Operations Research and Industrial Engineering (ORIE), and Electrical and Computer Engineering (ECE). These years were chosen because they capture students who have completed degrees before the impacts of the COVID-19 pandemic. While the data are from one institution, the curricular structures mirror many other engineering institutions. We supplemented this dataset with post-graduation data—namely employment rates, mean and median earnings, and graduate-school enrollment rates—provided by the same institution and appropriately approved for use in this study by the IRB. This post-graduation data then metrics were averaged over five years to provide stable estimates of graduate performance (Table 1).

Data Mapping and Network Analysis

We used network analysis techniques (via the igraph library in R[20]) to map the core courses in each of the seven programs, capturing all prerequisite and co-requisite relationships. We then applied the Heileman framework to quantify curricular complexity (CC) using blocking factors and delay factors, which reflect the position of each course within these prerequisite structures.

Adjusting Complexity Metric for Comparison

To enable direct comparisons across the seven programs, we normalized the CC scores by dividing each program's total complexity value by the number of core courses (CC/Course). This procedure placed all programs on a common scale, especially when we know that the major CC and number of courses have a strong correlation (> 0.7, $p < 0.001$). Consequently, this mitigates potential biases that arise from varying course counts between disciplines.

Statistical Analyses

First, we performed a correlation analysis using Pearson's correlation to investigate the relationship between CC/Course and key outcomes, such as earnings and employment rates. The choice of Pearson's correlation assumes of normal distribution, confirmed by the Shapiro-Wilk and Skewness results. Then, we conducted Principal Component Analysis (PCA) to determine the most salient factors influencing student outcomes. Prior to the PCA, we standardized the data to ensure equal weighting and mitigate potential bias introduced by differing units or scales. Standardizing variables is a widely recognized and essential practice in PCA to enhance reliability of results [21].

By using PCA, we aim to reduce these variables into a smaller set of underlying components. This simplifies the analysis while preserving the key insights and allows for a more efficient and interpretable analysis. Moreover, it allows for discovering multivariate patterns that might not be captured by traditional correlation analysis, which provides a comprehensive understanding of how curriculum design influences outcomes. It is also worth mentioning that while PCA does not establish causality, it serves as a powerful tool for uncovering the data structure.

Table 1. Distribution of Survey Participants by Major and Gender

Major	(n_female)	(n_male)	Total Participants (n)
CBE	177	157	334
CEE	81	72	153
CS	224	457	681
ECE	83	190	273
MSE	59	36	95
MAE	148	321	469
ORIE	160	185	345
Total	**932**	**1418**	**2350**

Results

Complexity Across the Seven Engineering Programs

The analysis revealed significant differences in curricular complexity per course (CC/Course) among the seven engineering programs. The highest CC/Course value was found in MAE (8.57), while the lowest occurred in CS (3.88). Meanwhile, CBE and MSE exhibited similar CC/Course values. Notably, ECE ranked lower than anticipated despite its strong reputation. Figure 2 demonstrates the CC/Course values for each of the engineering programs. Descriptive statistics showed a mean CC/Course of 5.63 and a standard deviation of 1.52. This variability, quantified by a coefficient of variation of approximately 28%, indicates a moderate level of variation across the programs.

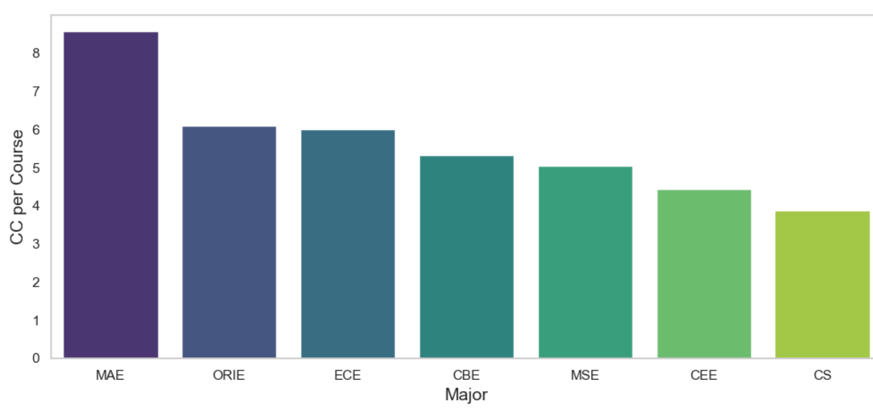

Figure 2. CC/Course Values by Engineering Program

PCA Findings

Figure 3 illustrates the distribution of the first two principal components (PC1 and PC2), which collectively account for 90.9 % of the total variance (with PC1 explaining 55.5 % and PC2 explaining 35.4 %). An examination of the loading matrix reveals that PC1 is strongly influenced by mean salary (0.62) and employment rates (0.59), suggesting that higher PC1 scores correspond to programs with robust immediate job prospects and competitive salaries. For instance, CS scored higher on PC1, which reflects these favorable outcomes. In contrast, PC2 is dominated mostly by CC/Course (0.82) and a moderate loading on graduate-school enrollment (0.51). As a result, programs that score higher on PC2—such as MAE—tend to emphasize academic depth and see relatively higher rates of graduate-school enrollment. Other programs such as MSE and CEE share similar outcomes such as lower employment and earnings compared to the other programs

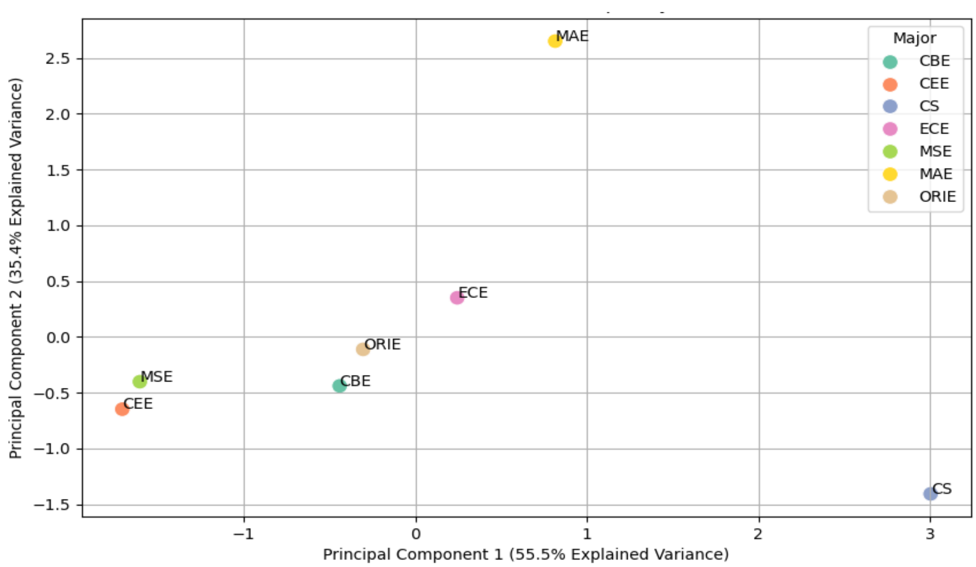

Figure 3. PCA Biplot of the First Two Principal Components (PC1 and PC2).

Correlations with Post-Graduation Outcomes

The correlation analysis revealed weak to moderate correlations between the CC/Course and the various post-graduation outcomes. Although there is a variety in complexity across programs, the employment rate for the 2015–2019 cohorts ranged from 98% to 99% across all programs. Conversely, there was a weak negative correlation (-0.27) between CC/Course and mean earnings and a moderate positive correlation (0.52) between pursuing further studies and CC/Course. Figure 4 displays the correlations between CC/Course and these outcomes. We can see from the figure that the confidence interval tends to be widest for MAE and also notably wide for CS. This result explains the high uncertainty with these two majors as they appear to be outliers compared to the other five engineering majors. This is likely due to the small size of the sample where confidence interval tends to have narrower width in larger sample, indicating greater precision in the estimate.

Taken together, the PCA findings (PC1 and PC2) and the correlation results offer a nuanced view of how different programs vary in both curricular demands and post-graduation trajectories. Programs with higher curricular complexity may see a greater inclination toward graduate study, sometimes accompanied by slightly lower immediate earnings. In contrast, programs with lower complexity appear more strongly aligned with immediate job-market advantages.

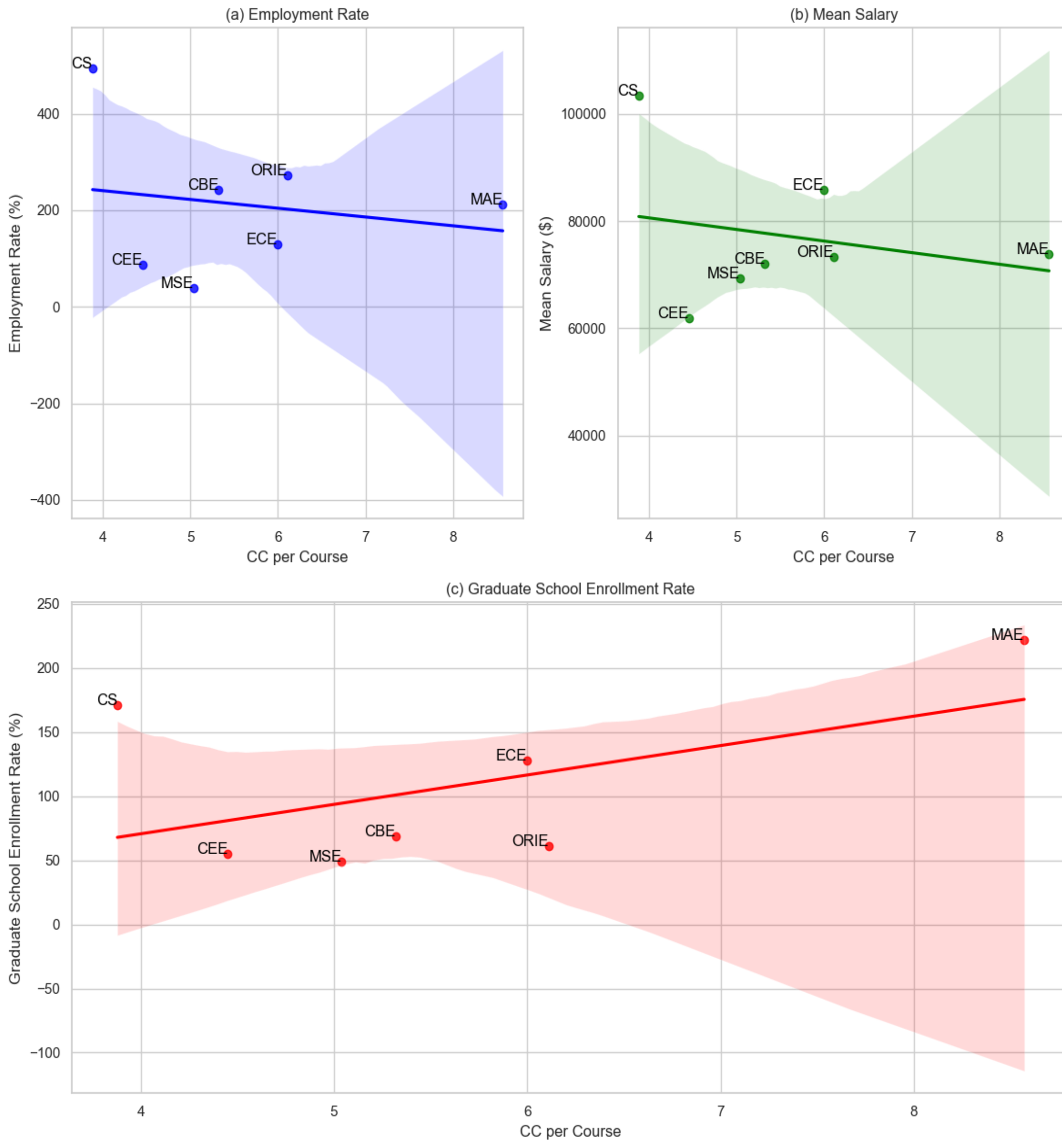

Figure 4 (a-c). Correlation Between CC/Course and Outcome Measures.

Discussion and Implications

The variability, quantified by a coefficient of variation of approximately 28%, suggests a significant divergence in how curricula are structured across disciplines. In this section, we explore four principal factors that may contribute to this variability: 1) the tension between curricular rigidity and flexibility, 2) the impact of structural complexity on labor-market and graduate outcomes, 3) accreditation standards and institutional adaptability, and 4) emerging strategies for designing modern engineering programs. Together, these perspectives shed light on how engineering curricula can be optimized for high academic standards and relevance to industry demands.

Navigating Rigidity and Flexibility

Engineering disciplines vary significantly in how flexible or rigid their curricula are—a tension shaped by historical evolution, the nature of each major, professional accreditation, and pedagogical norms. MAE, for instance, exemplifies rigidity as shown by CC/Course score, attributed to multiple factors.

First, MAE programs are renowned for their breadth and depth, frequently covering a diverse range of subdisciplines than many other engineering fields. This results in an extensive list of required courses with limited flexibility for interdisciplinary exploration [22]. Tracing their origins back to the Industrial Revolution [23], MAE programs incorporate multiple subfields—thermodynamics, mechanics, manufacturing, and production principles—built up over decades with layered core classes and labs [23]. For example, the high interconnectivity of the foundational courses—such as Calculus I, Calculus II, and Dynamics—reveals a dense network of prerequisites.

In part, such rigidity also arises from accreditation standards. Engineering Professional bodies like Accreditation Board for Engineering and Technology (ABET) enforce minimum competencies in math, science, and specialized domains. Notably, MAE has the widest ABET accreditation criteria among all engineering majors [22]. As a result, MAE programs adopt standards conservatively, mandating multiple levels of basic science, engineering sciences, technical mechanical courses, lab experiences, plus humanities, social sciences, and professional and ethical responsibility requirements. The outcome is often a double-layered curriculum that can be difficult to streamline.

By contrast, CS tends to be more flexible, as the CC/Course value indicates. Accreditation frameworks for computing, while existent, are generally less prescriptive and less universally adopted as it is often considered optional [24]. These differences may explain why many of the top-tier CS programs in the United States are not accredited [24]. Accreditation can add structural complexity; for instance, one study found that students in accredited CS programs must take an average of four additional courses [25]. Consequently, CS programs typically adjust their course offerings more rapidly, introduce new programming languages, and allow for a wider array of electives [26]. This lighter regulatory load reduces mandatory sequences, translating into lower structural complexity—even if the intellectual demands remain high.

Other engineering programs sit in between these extremes. ECE, for example, is known to be highly demanding yet showed a relatively low CC/Course score. ECE also has low “stickiness” and low graduation rates [27], a striking contrast to its relatively lower CC/Course value. Similarly, some programs such as CBE or MSE occupy moderate levels of rigidity but still require students to take 25 and 24 core courses, respectively— the highest among the seven engineering programs. This extensive core requirement can hinder the student’s ability to discover and explore other areas within the majors. Despite this rigidity in the number of courses required and moderate CC/Course scores, their mean salaries and employment rates are still moderate. This suggests that increasing the number of core courses does not necessarily translate into better post-graduate outcomes, which underscores the need to thoroughly reevaluate the curriculum scope and requirements.

It is critical to assess whether "rigid" programs like MAE overly constrain paths and hinder interdisciplinary ventures. Companies often report that graduates struggle with collaborative design of complex systems, a concern reflected in studies like Passow et al. [28]. Given the industry's growing demand for multifaceted skill sets, students in highly rigid programs may have limited opportunities to pursue cross-domain electives.

Complexity, Labor Markets, and Graduate Outcomes
Structural differences in curricula are also reflected in job market trends. Among the seven engineering programs analyzed, CS graduates have notably higher starting salaries—approximately 20% more than ECE, the next highest. This result is particularly noteworthy given that the CC/Course in CS is significantly lower than in other programs. The tech sector's exponential growth drives high placement rates and earnings in CS, given the booming demand for software development, cybersecurity, and data analytics, as the U.S. Bureau of Labor Statistics reported in 2022 [29]. This trend appears largely independent of the curricular structure. Moreover, the flexibility of many CS programs allows for quick adaptations to emerging specialties like machine learning, thereby enhancing employability prospects according to [26]. Despite the lower CC/Course, many CS graduates still pursue advanced degrees, often capitalizing on expanding research and specialized fields like data science and AI (Figure 3(c)).

By contrast, although the immediate mean salaries for MAE graduates may not match those in CS, MAE programs report the highest percentage of students continuing to graduate school—about 52%. This trend is explained in the PCA, where MAE prominently clusters high on PC2. Notably, while MAE graduates do not necessarily receive top-tier salaries upon graduation, their lifetime earnings reach $2.09 million—exceeded only by ECE at $2.18 million [30]. This indicates that while MAE's demanding curriculum might not yield immediate financial returns, it lays the groundwork for substantial long-term growth. Over time, cumulative expertise and advanced skills can lead to exponential earning potential. The sequential and thorough training MAE students undergo—covering basic sciences, diverse engineering principles, and design projects—forms a strong foundation for advanced research and specialized technical roles. Students' adept at this level often continues into master's or doctoral programs, aiming to become subject-matter experts or research scientists in aerospace or defense. In the long run, such advanced qualifications can elevate salaries and unlock leadership opportunities [31].

Conversely, CEE ranks second lowest in CC/Course and shows lower starting salaries and graduate school enrollment compared to the other programs. These outcomes could stem from multiple interrelated factors such as professional licensing pathways, mature job markets, traditional focus on technical knowledge [32], [33]. Because many roles value hands-on experience over advanced degrees, the immediate incentive to pursue graduate education is reduced, which could explain lower graduate enrollment. However, these tendencies do not indicate lower demand. Instead, they reflect how CEE's educational and professional ecosystem differs from more rapidly evolving or tech-driven fields.

Studies reinforce this perspective, showing that CEE curricula are heavily specialized in technical subjects, yet lack sufficient focus on interdisciplinary skills, systems thinking, and emerging technologies [34]. Another study further emphasizes the limited integration of digital tools like Industry 4.0 and sustainability topics, which are increasingly essential in modern engineering sectors [35]. This contrast with engineering programs that have rapidly integrated emerging technologies suggests that while CEE retains its traditional strengths, it requires transformative updates to remain competitive.

Given these varied outcomes, many institutions face the challenge of designing engineering curricula that balance foundational depth with market-aligned flexibility. Programs might revisit their structures to allow more interdisciplinary pathways while preserving core competencies, thus reducing double layering that can inflate unnecessary complexity. Ultimately, ECE's "paradox" offers a useful case although conceptually demanding, ECE's relatively lean prerequisite tree demonstrates that depth can be achieved without overwhelming students with rigid sequences. This example hints at design templates where high standards and flexibility coexist, enhancing student experience and aligning well with fast-evolving labor markets.

Limitations

While this study offers valuable insights into how CC may relate to post-graduation outcomes, several limitations should be noted. First, this investigation is intended as a starting point, centered at a single private institution in the Northeastern United States partly due to limited data-sharing across universities, which constrains broader comparisons. Second, although multiple engineering programs are examined, key confounders—such as students' socioeconomic backgrounds, prior academic preparation, and local labor market conditions—were not explicitly controlled. Third, relying on five years of post-graduation data may not reflect more recent or long-term trends, especially those influenced by global events (e.g., COVID-19). Additionally, while PCA effectively identifies underlying data structures, it does not establish causality, leaving the possibility that unmeasured factors contribute to the observed relationships. Future work could address these gaps by fostering multi-institutional studies and incorporating a wider range of variables to offer a more comprehensive picture of how CC varies in engineering programs and influences student outcomes.

Conclusion

Our curricula complexity (CC) analysis results and subsequent comparisons to graduates' outcomes—namely employment rates, mean starting salaries, and graduate school enrollment rates—show how undergraduate degree structures influence career trajectories. Overall, MAE registers the highest CC/Course score, suggesting a highly interwoven set of prerequisites and limited curricular flexibility, while CS consistently shows the lowest complexity. The remaining engineering programs—ECE, ORIE, CBE, MSE, and CEE—cluster between these extremes. PCA confirms this spread, with MAE and CS representing poles of the complexity spectrum.

While the variations in these findings could be attributed to the inherent differences among those engineering curricula, they indicate the need for a more balanced curriculum design that preserves high academic standards while promoting an interdisciplinary mindset. It is important to note that the goal of this work is not to claim that higher or lower complexity is better. Rather, this work aims to employ assessment-based analytics to help identify and mitigate unnecessary curricular complexity and help the academic community rationally design and optimize engineering curricula.

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