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Predictors of Student Academic Success in an Upper-Level Microelectronic Circuits Course

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Predictors of Student Academic Success in an Upper-Level Microelectronic Circuits Course

This research paper describes the development and analysis of students' academic records for the purpose of better understanding influential factors that affect student performance in an upper-level electrical engineering course. This study is contextualized within the School of Electrical and Computer Engineering (ECE) at a large, public, research-intensive institution in the Southeast United States. Undergraduate students in this School have a diverse range of backgrounds, experiences, and needs. As such, program leaders must work to (1) provide effective, accurate, and personalized support; and (2) provide information and recommendations for curricular developments and resource management. Both efforts rely on a strong foundation of data to inform decision-making. As such, this paper describes the quantitative portion of a larger mixed-methods project, from which the authors identified initial baseline conditions of students' academic performance in the focal course and revealed potential influential factors as revealed in a logistic regression model predicting the likelihood of a student to receive a passing grade. Future plans for educational data mining beyond the focal course are discussed. This work suggests some opportunities for programmatic improvements with the highest potential for success.

Introduction and Background

As undergraduate programs in the United States face changes in enrollment patterns [1], it is more important than ever to develop data-driven insights about programs' students and the factors that predict their academic success. For engineering undergraduate programs, this need is particularly relevant because of cultural norms that often label students as "smart" and place high value on academic achievement [2], yet often subject students to challenging "gateway" or "weed out" courses that can cause students to reexamine their beliefs about themselves and their abilities [3], [4]. Although academic performance (i.e., grades) is only one facet of engineering students' educational careers [5], it behooves programs to take advantage of the data available to them in order to better understand the unique backgrounds and needs of students as they navigate through the curricula.

Accordingly, engineering education researchers have identified many factors that predict engineering students' academic success [6]–[8]. To build power and generalizability, some analyses have aggregated data across multiple engineering programs and institutions, such as research using the MIDFIELD database [9]. While these generalized insights have valuable contributions for the engineering community and its subdisciplines, there is also value in contextualizing analyses within specific programs, since departmental culture, student composition, and many other factors can shape the ways that academic success looks and operates.

In the departmental context of this submission, we examine success in terms of performance in a required junior-level microelectronics course in which academic success carries significant weight. In the past, some instructors of the course have described seeing a bimodal grade distribution at the end of the semester, as opposed to a normal distribution. In other words, this course features a significant portion of students who seem to possess the knowledge, skills, and abilities to be able to achieve strong grades, and another significant portion of students who seem to struggle with the course, despite already passing several foundational courses. In this context, it is important to use data-driven approaches to understand the nature of student performance more deeply than anecdotal observations, and to identify key predictive factors that can be addressed to help unlock students' ability to succeed in the course (and, hopefully, in the rest of their time in the program).

This paper is a first part of a broader project working to develop a culture of data-driven decision-making in a School of Electrical and Computer Engineering (ECE) at a large, public, research-intensive institution in the Southeast United States. This program is one of the largest producers of electrical and computer engineers in the country, and the combination of high selectivity and high enrollment offers opportunities to develop unique insights into students' academic success predictors. First, the authors describe the cultivation progress to develop a longitudinal dataset of students' academic performance and personal characteristics from disparate institutional datasets. We then take a deep dive into a focal course, referred to as ECE 301 (a pseudonym). ECE 301 is a 4-credit hour, junior-level course on microelectronic materials, devices, and circuits that is part of the required curriculum for electrical engineering (EE) students. The course is notorious within the department for its difficulty and has been subject to many internal improvement initiatives, with varying degrees of success. The analysis described in this paper is an effort to develop a deep understanding of student performance in the course by investigating trends in the characteristics of the students and their performance in prior coursework. We focus the paper on descriptive statistics and logistic regression modeling, and we also address how this work can serve as a foundation for future educational data mining efforts.

ECE 301 delves into the fundamental principles of semiconductor physics and their practical application in the design and analysis of microelectronic circuits. The course aims to equip students with a comprehensive understanding of the physical, electrical, and optical properties of semiconductor materials and their applications in microelectronic circuits. The course has been described as "drinking from a firehose," but many instructors feel that the ability for students to conceptually move from the micro scale to the macro scale is immensely valuable to prepare students for future coursework and the engineering workforce beyond. Moreover, the course is relatively decentralized in its instruction, with each instructor bringing their own emphases and teaching philosophies. Instructors in ECE 301 are passionate about supporting students in the course and often examine student performance data in the context of their own section, but there remain opportunities to look at student performance more broadly to generate potential insights. Although the specific context of this course may constrain the transferability of findings, the authors intend this work to be valuable to any educational leaders who are seeking to use data to inform decision-making for challenging courses in their curriculum.

Engineering undergraduate degree programs have long been known to include "weed out" or "gateway" courses in their curriculum. Often, gateway courses are found in the first or second years of a degree curriculum and can exhibit challenging material and relatively low passing rates [3]. One interpretation of these courses is that their purpose is to filter out the students who do not possess the ability to succeed in later, more advanced coursework in the major. Another possible interpretation, potentially more charitable, is that the courses represent important foundational skills and material that should be mastered before students are sufficiently prepared for subsequent, more advanced topics (similar to scaffolded learning [10]). Courses may also develop vernacular reputations as "weed out" or "gateway" courses by virtue of student perceptions of difficulty, regardless of the intentions of educators and curriculum developers.

Among these three interpretations, ECE 301 carries elements of the second and third ways of thinking about challenging courses. Neither the instructors nor program leadership intentionally use the course to filter students. ECE 301 has been part of the EE curriculum for many decades as a junior-level course. Its placement means that students are firmly embedded in the EE curriculum and that a student who does not pass ECE 301 is more likely to have their degree progress delayed rather than to reconsider their intended degree program altogether. However, ECE 301 has pre-requisite relationships to several later courses in the EE curriculum because the material in this course prepares students for more advanced topics. The breadth of the course and the need to integrate many knowledge bases—including physics, geometry, calculus, and circuits—can contribute to an inherently challenging experience. ECE 301 instructors share a commitment to wanting to support students through this course. Nonetheless, the course has developed a reputation among students as a "weed-out." Engineering education researchers have documented how gateway courses can have negative effects on students' perceptions of their belongingness and their ability to succeed within the program [11]. ECE 301 is an instance in which the department's goal to promote students' academic success has not fully materialized, and there is shared interest in investigating strategies to help students perform confidently.

Literature Review

Reforms in pedagogy, course design, and curricula all sit at the heart of the engineering education research community. Within the context of reforms in ECE, educators have described efforts to improve challenging courses, often through the integration of active learning practices [12]–[14]. For instance, Kim et al. [15] describe the experiences of "flipping" a circuits course (i.e., students are expected to use out-of-class time to learn the material and use in-class time to practice and explore applications of the content). The traditional version of the course exhibited only a 54% pass rate, a rate which was significantly improved upon flipping [15]. These works are often carried out by the instructors of the course, and many of them target second-year courses.

Godfrey and Parker have discussed how "traditional" engineering disciplines (e.g., electrical engineering, mechanical engineering, etc.) have deeply rooted cultural norms about teaching and learning that can constrain initiatives for change [16]. Accordingly, there have been many NSF RED Grants (Revolutionizing Engineering Departments [17]) awarded to ECE departments, which seek to promote large-scale and enduring changes to the undergraduate student experience [18]—[22]. Outside of the RED program, other ECE units have sought to revitalize their curricula to meet the needs and interests of their students [23], [24]. In the context of this paper, the School has recently revamped their curriculum to develop concentrations among upper-level elective courses [25]. The focus of this project targets a meso-scale that spans between individual instructor pedagogy and overarching curricular design. The project seeks to use a data-driven approach to identify current gaps or opportunities to better support students, which includes understanding the quantitative factors that predict their academic success.

An immense amount of scholarship has been devoted to understanding factors that predict students' journeys and academic success in engineering undergraduate programs. One of the most prominent projects is the Multiple-Institution Database for Investigating Longitudinal Development (MIDFIELD; [9]). MIDFIELD compiles academic record data for undergraduate students across institutions; the breadth and depth of the dataset can support powerful quantitative analyses. Other scholars have also taken advantage of institutional academic records to understand predictors of academic success, although the outcome variable is often focused on overall- or STEM-specific GPAs, rather than academic performance in a particular course. Altogether, prior work has indicated the importance of prior course performance [26] and student characteristics like gender, race, transfer status, first-generation in college, students who change majors, and students who are veterans (e.g., [7], [27]). Other work has indicated the importance of factors such as motivation and belongingness [5], [28]. While those factors are not connected to a students' academic record, they are an important reminder of what academic records can and cannot reflect about students. MIDFIELD leaders point to the value of qualitative research to further explore the quantitative findings [9]. Similarly, this paper represents the early quantitative strand of a larger mixed-method project seeking to identify opportunities to support ECE students.

The past few years have seen the engineering education research community grapple with the potential contributions of educational data mining students' academic records [29]—[31] and learning trajectories [32]. At the same time, these techniques can also pose risks in perpetuating biases without thoughtful and intentional interpretation [33]. Beyond the specific techniques discussed in this paper, this project also explores the potential value of leveraging advanced techniques as an opportunity to spark interest in engineering students and faculty to engage with educational research. Ongoing work, subject to future publication, includes qualitative analysis of faculty and student perspectives and quantitative efforts beyond ECE 301.

Purpose and Research Questions

The purpose of this work is to understand the baseline conditions of students in ECE 301 and factors (accessible through institutional records) that predict their success in the course.

1) What are the baseline conditions of student composition and academic performance in ECE 301?
2) What are the relative influences of student characteristics, course characteristics, and student prior academic performance on students' final grades in ECE 301?

Methods

Data Creation

The institution maintains academic records and collaborates with faculty researchers looking to analyze those records as research data. However, many of the reports are kept in decentralized databases. The project team created a dataset that combined information from four locations: (1) ECE students' transcript data (final grades in their coursework at the institution), (2) ECE students' demographic information (gender and race/ethnicity), (3) ECE students' matriculation history (transfer or direct matriculation), and (4) course description records (instructors and modality). The project was approved by the institution's Institutional Review Board, and the data sent was deidentified with unique identifiers to protect students' information.

The initial shape of the dataset was that each row was an individual student's grade in a specific course in a particular term. Because of the breadth of the transcript records, this dataset offers the ability to support analyses beyond the scope of ECE 301, as discussed in future work in the conclusion section. This format is useful to understand the landscape of the course (e.g., average final grades across instructors, accurate enrollment counts, etc.). A secondary dataset was created to enable student-centered analyses, in which a student occupied a single row in the dataset and their relevant information (student characteristics, most recent ECE 301 grade, prior ECE 301 grades, pre-requisite grades, and course load) contained in associated columns.

Student characteristics were measured in terms of Gender (man/woman), Race/Ethnicity (underrepresented/overrepresented) and Transfer History (direct matriculation from high school or transfer/dual degree). The institution collects race/ethnicity information as six categories: Asian, Black or African American, Hispanic/Latino, Two or More, Other/Unknown, and White. For analysis purposes, the race/ethnicity analysis is reported as overrepresented (White + Asian) and underrepresented (all other categories). This approach has several limitations. For instance, students with Unknown or Two or More race/ethnicity information may in fact belong to over-represented groups (e.g., a student who is Asian and White biracial). Although the sizes of these two student groups are small relative to the rest of the dataset, interpretations from the data are nonetheless limited. Finally, we use the term "transfer" to identify all students who attended another institution after high school before matriculating to the university in this study. Students were labeled as transfer students even if they had been enrolled at the focal university for several semesters.

Student academic record data included their Final Grade in ECE 301, their Final Grades in Prior ECE Coursework, and their Course Load during the semester that they were enrolled in ECE 301. The institution reports final grades as whole letter grades (e.g., A, B, C, D, F, and W). A "W" at the institution refers to a student who withdrew from the course between the second and tenth week of the 15-week semester. All final grades are recorded in the data, even if a student had multiple attempts before passing. Course load is included to account for students' academic load; since many students are juniors when they take ECE 301, they may be enrolled in other upper-level courses that place demands on their time and energy. A common narrative in the School is that students should limit the number of ECE courses they take concurrent to ECE 301, although this narrative is culturally emergent as opposed to a programmatic recommendation. There is an important limitation to the current dataset: because the dataset can only pull final grade data from within the institute, pre-requisite performance is not captured for the students who transferred pre-requisite credits from other universities or who had AP credits. As a result, analyses using pre-requisite course performance are only applicable for a subset of students. Further limitations are discussed at the end of the paper.

Additionally, course description data was pulled, which contained information about the Instructor and modality. Although all sections of ECE 301 have a common syllabus, instructors have different emphases and a range of pedagogical approaches that may shape the data. There is no expected grade distribution for the course.

Data Analysis

The analyses reported in this paper include descriptive statistics, visualizations of the variables of interest, a correlation matrix, and a logistic regression analysis. The statistics and visualizations indicate the current baseline conditions in ECE 301, while the correlation matrix and regression model can identify the relative effect of the measured factors on final grades in ECE 301. Further, the regression model serves as a precursor to future work with other forms of machine learning.

The correlation matrix was generated to understand the relationship between prior academic performance and ECE 301, since a common narrative is that students who struggle in ECE 301 may do so because of gaps in pre-requisite knowledge (or, perhaps, limited comfortability in transferring that knowledge to a new course context). Between 2016 and 2023, there were 8 courses pre-requisite relationships to ECE 301, either as a direct pre-requisite, as part of a pre-requisite chain, or as a pre-requisite with concurrency (i.e., could be taken at the same time). Because students may need to take a course more than once if they did not pass the first time, they may have multiple grades in the dataset for a single course. This correlation matrix examines their latest pre-requisite grades to their first grade in ECE 301.

A regression model was used to gain insight into important features that would warrant further quantitative and qualitative investigation in the future. The outcome variable was selected to be whether the student ultimately passed (0) or failed (1) ECE 301 that semester. Failure was deemed the outcome of interest to target features which might currently be related to a student earning a D, F, or W. We followed a stepwise process to understand feature significance and the contributions of different types of variables. The first set of variables were student characteristics, the second set added course characteristics, the third set added concurrent course load, and the final set added prior student performance in a Circuits (the most relevant ECE pre-requisite) and Differential Equations (the most relevant math pre-requisite). Additional contributions of the variables to the model are reported as pseudo-R-squared.

Results
Between Fall 2016 and Spring 2023, 1,225 students received final grades ECE 301. Below, we first present count data breaking down the composition of students enrolled in ECE 301. We then investigate how students' final grades varied by student characteristic, course characteristic, and prior academic performance.

Count Information

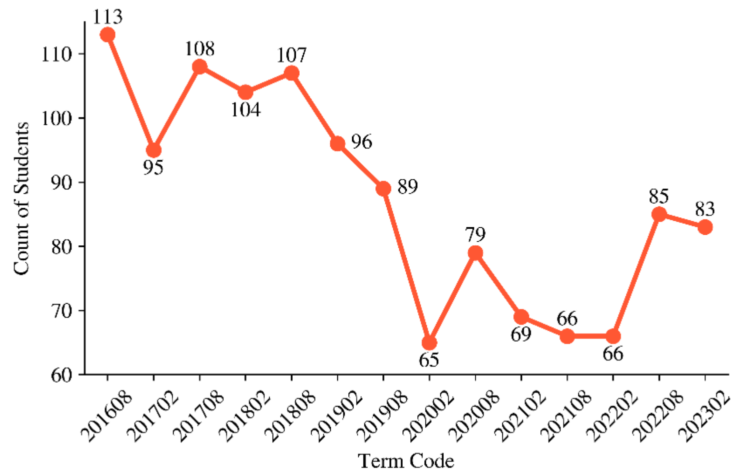


Figure 1. Count of students enrolled in ECE 301 each term

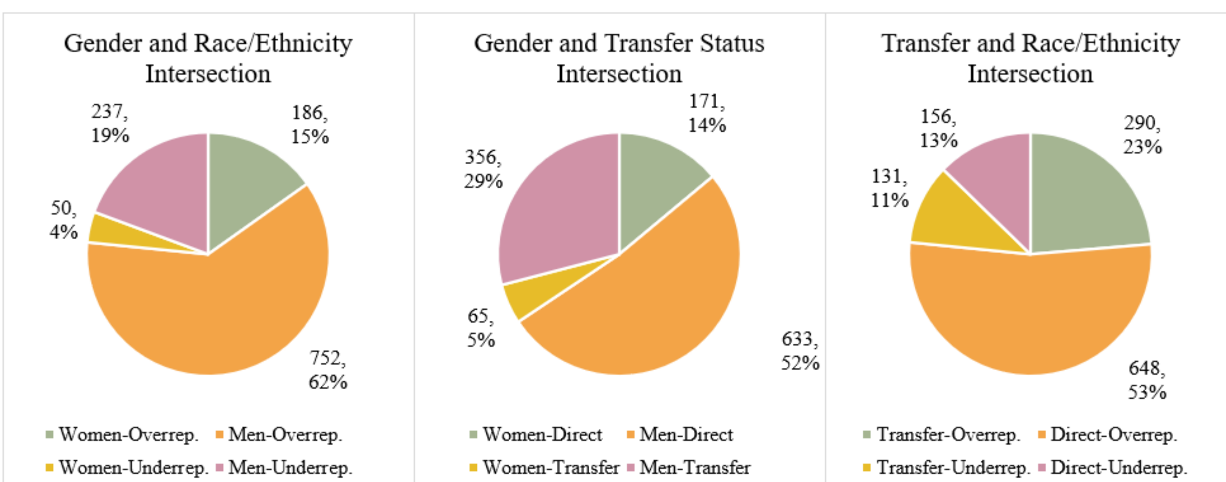
Figure 1 shows longitudinal student enrollment in ECE 301. Over the window of investigation, the enrollment has trended downwards. The naming convention for semesters is that the first four digits represent the year (e.g., 2016), and the last two digits refer to either a Spring (02) or a Fall (08) semester.

Table 1 disaggregates the enrollment numbers over time in terms of gender, race/ethnicity, and transfer status. Overall, women made up 19.2% of the course population, students from minoritized racial or ethnic backgrounds made up 23.4% of the course population, and students who had transferred into the institution made up 34.4% of the course population on average, although that number has changed over time. In recent semesters, almost 40% of the students in ECE 301 were transfer students. Because of challenges in presenting the three-dimensional intersections of the categories, intersectional information about the three measured categories of student characteristics is presented in Figure 2. Each pie wedge of a circle represents the count data of students who have both identities (i.e., a woman student who is from an overrepresented racial/ethnic background would be counted as "Woman-Overrepresented"). This information is intended to convey the relative representation of different categories and acknowledge multiple layers of experiences that students might bring to ECE 301.

Figure 3 shows the average registration load of students enrolled in ECE 301, in terms of other courses housed within the ECE subject code. In the time frame covered by this analysis, ECE 301 had paired registration with another course, "ECE 302", a hands-on laboratory course. The two courses were required to be taken in the same semester, although exceptions were made if students passed one course but not the other. Starting in Spring 2024, the two courses are now decoupled, which may affect future registration loads.

Table 1. Longitudinal Enrollment and Student Characteristics

Term	Overall enrollment	% Women	% Under-represented	% Transfer
2016 Fall	113	14.16	26.55	30.97
2017 Spring	95	16.84	24.21	34.74
2017 Fall	108	25.93	31.48	32.41
2018 Spring	104	16.35	21.15	33.65
2018 Fall	107	23.36	25.23	34.58
2019 Spring	96	13.54	26.04	38.54
2019 Fall	89	15.73	20.22	37.08
2020 Spring	65	24.62	26.15	33.85
2020 Fall	79	22.78	22.78	30.38
2021 Spring	69	18.84	17.39	28.99
2021 Fall	66	27.27	18.18	27.27
2022 Spring	66	18.18	16.67	39.39
2022 Fall	85	17.65	24.71	34.12
2023 Spring	83	18.07	20.48	44.58
Total	1225	19.27	23.43	34.37



(a) Counts of students at the intersections of gender and race/ethnicity categories

(b) Counts of students at the intersections of gender and transfer status categories

(c) Counts of students at the intersections of transfer status and race/ethnicity categories

Figure 2. Counts of students' characteristics in intersectional categories (total N = 1,225)

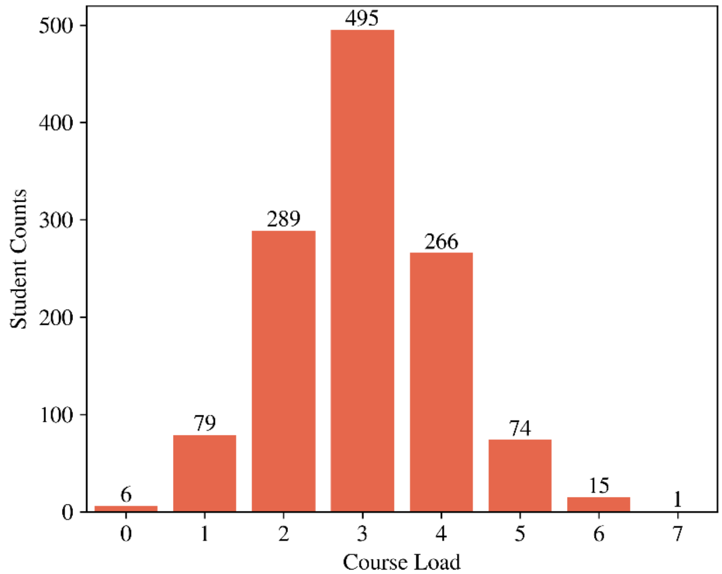


Figure 3. Visualization of the number of additional ECE courses that the students are enrolled in when they take ECE 301

Between Fall 2016 and Spring 2023, there were eleven instructors teaching ECE 301 (in this paper, we focus on the seven instructors who taught more than two sections since 2016). Starting Fall 2021 (except Fall 2022), the course scheduling shifted from three sections a semester to two, with a corresponding increase in each section enrollment. Instructor assignments are highly variable; very few instructors teach ECE 301 more than one semester in a row. The course moved to a virtual environment in Spring 2020 because of the COVID-19 pandemic, and between Fall 2020 and Spring 2021 there was a mix of virtual, hybrid, and in-person sections at the discretion of the instructor.

ECE 301 Performance

Among the 1,225 students who took ECE 301 between Fall 2016 and Spring 2023, 252 (20.58%) earned a final grade of a D, F, or W, which would prevent students from progressing along the intended EE curriculum. As shown in Figures 4 and 5, the DFW rate has decreased over time, although it can still be a major curricular roadblock for students.

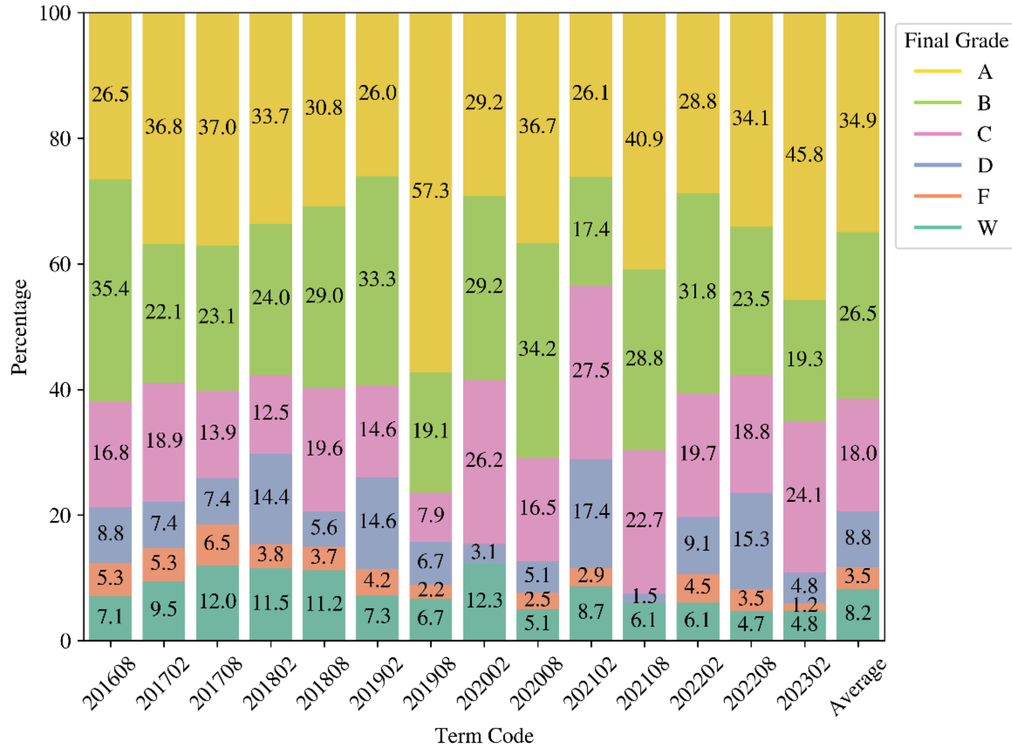


Figure 4. Percentage of students with each grade by term code

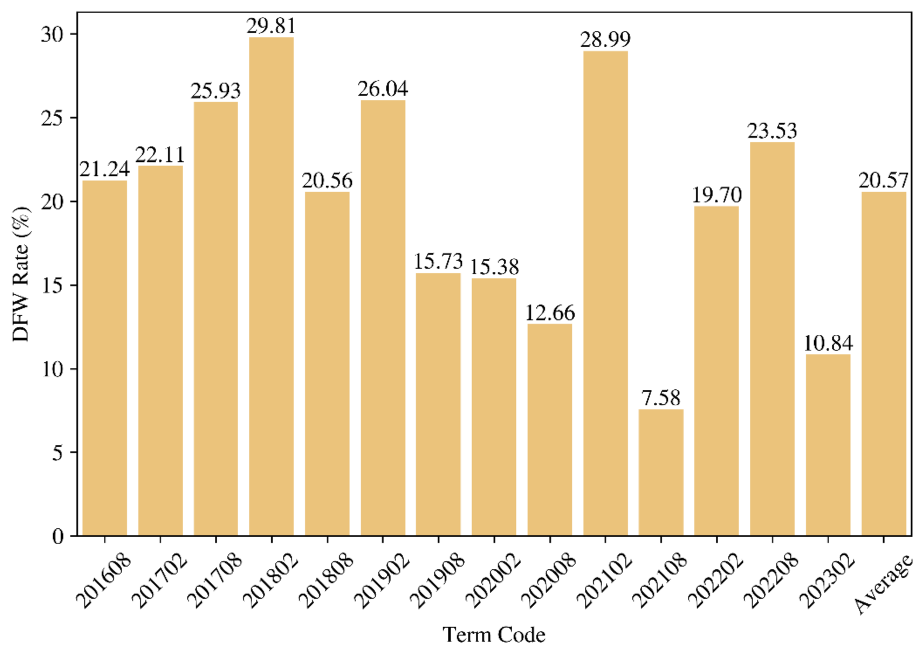


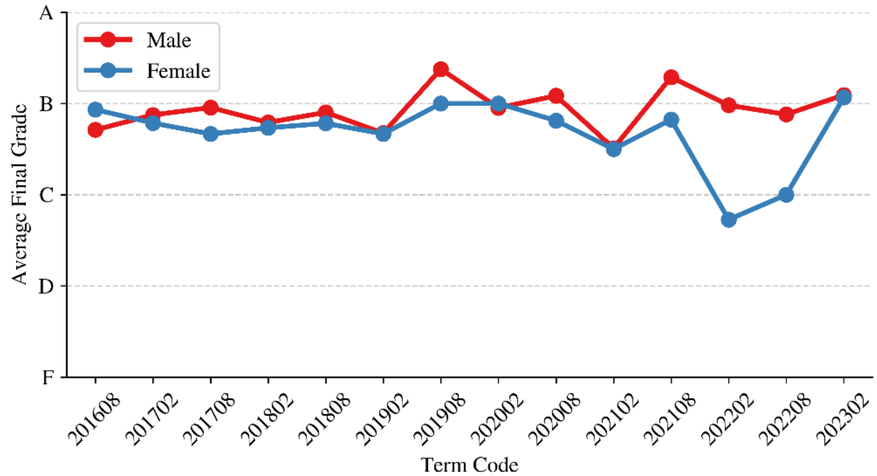
Figure 5. DFW rate of students over different term codes

Figure 6 shows three diagrams that plot final grade performance by student characteristics of gender, race/ethnicity, and transfer status. Women performed at the same level as their male peers, with the exception of the Spring and Fall 2022 semesters (after which their average performance recovered to parity). The data also reveals that, from 2019-2021, students from minoritized backgrounds had lower performance in Spring semesters compared to Fall semesters. Neither of these trends is easily explainable by course characteristics (modality or instructor), which warrants further investigation. Finally, although transfer students performed on par with direct matriculation students prior to Spring 2020, a performance disparity emerged that semester that only closed in Spring 2023. We investigated trends in academic performance through the intersections of race/ethnicity-gender, race/ethnicity-transfer, and gender-transfer, but did not identify any major patterns. Those graphs are not included to accommodate space constraints, but they are available upon request.

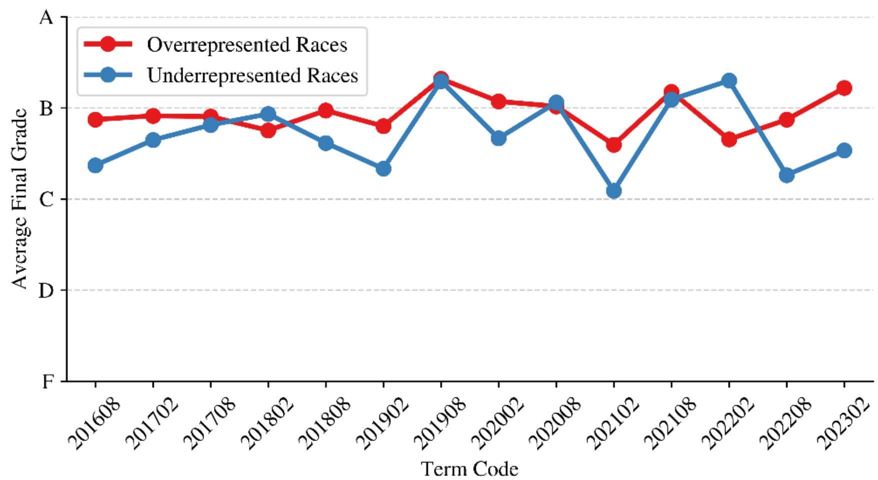
Figure 7 shows the distribution of final grades across different instructors who had taught at least 100 students across semesters. The data reveals differences in the distributions between instructors. The data also reveal that, despite its reputation, most ECE 301 instructors do award considerable numbers of A and B grades to students.

Pre-requisite Performance Correlation
Figure 8 presents the correlation of students' performance in prerequisite courses to their performance in ECE 301. The results of the correlation matrix indicate that many courses have positive relationships (i.e., doing well in those courses is associated with strong performance in ECE 301). Micro. Lab. ("ECE 302") stands out as the most strongly correlated pre-requisite course. This is unsurprising considering that there is overlap in material and students are often taking the courses in the same semester.

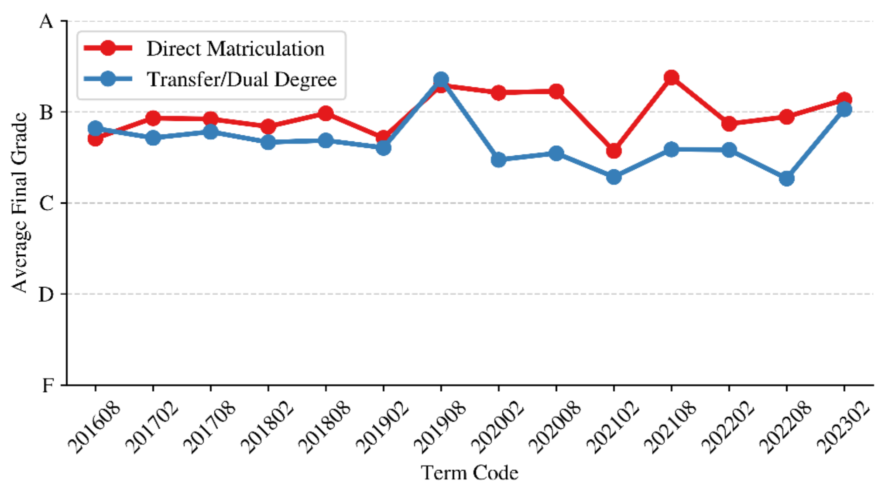
Regression Analysis
Table 2 summarizes the results of a series of logistic regression models predicting a students' odds of not passing ECE 301 on their first attempt. A positive coefficient indicates that that variable is associated with higher odds of not passing, while a negative coefficient indicates that the variable is associated with lower odds of not passing. Note that for the pre-requisite courses grade variables, those courses were measured by the more granular letter grades converted to numerical values. Increases in a student's final grade in Circuits, for instance, are associated with lower odds of not passing ECE 301. Overall, relatively few variables are statistically significant predictors, although those predictors that are significant indicate potential avenues for further investigation, as discussed in the next section.



(a) Trends of average final grade over term codes by genders



(b) Trends of average final grade over term codes by combined races



(c) Trends of average final grade over term codes by transfer statuses

Figure 6. Trends of average final grade over term codes in ECE 301

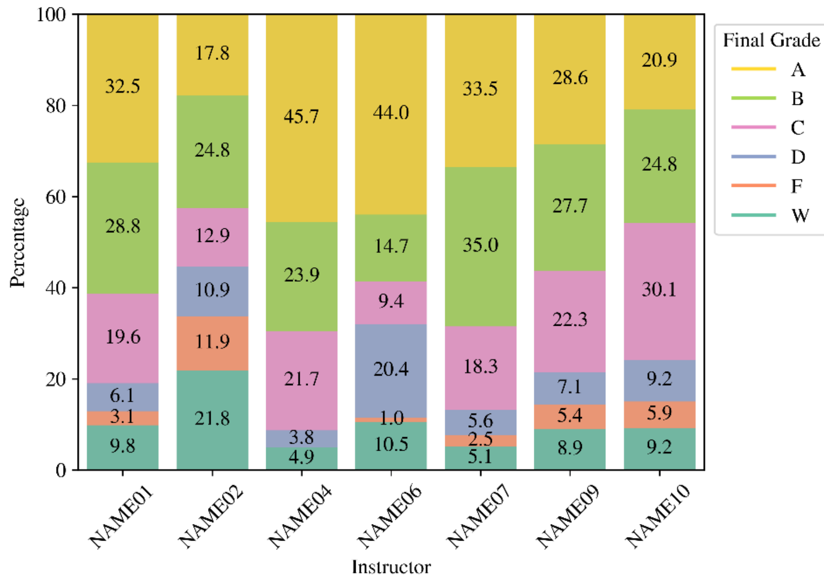


Figure 7. Percentage of students with each grade by instructor

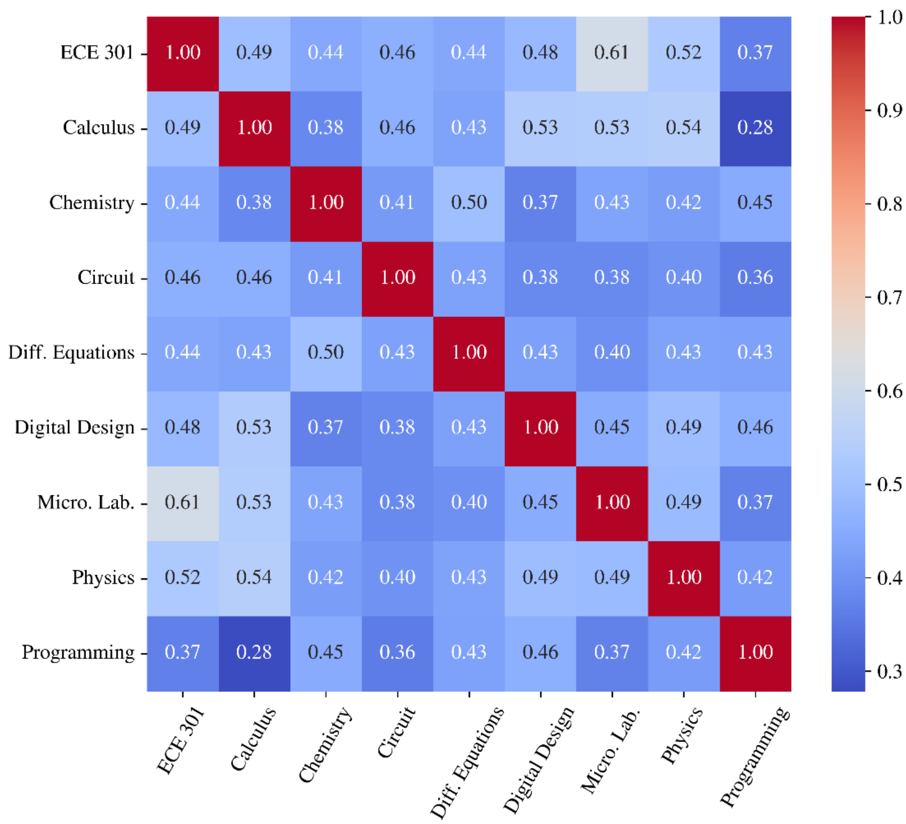


Figure 8. Correlation matrix heatmap of the grades between ECE 301 and the pre-requisites (Diff.: Differential; Micro.: Microelectronics; Lab.: Laboratory)

Table 2. Predictors of Earning a D, F, or W in First Attempt at ECE 301

Term	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Student Characteristics				
Women	0.428 (0.223)	0.428 (0.240)	0.443 (0.240)	0.381 (0.387)
Transfer	0.479* (0.188)	0.588** (0.200)	0.631** (0.202)	0.878* (0.439)
Underrepresented	0.238 (0.203)	0.237 (0.219)	0.161 (0.223)	-0.074 (0.404)
Instructor				
NAME 01		0.595 (0.392)	0.598 (0.393)	1.192 (0.732)
NAME 02		2.434*** (0.354)	2.390*** (0.365)	2.165** (0.713)
NAME 04		-0.0631 (0.436)	-0.086 (0.437)	1.039 (0.668)
NAME 06		1.265*** (0.350)	1.277*** (0.381)	2.181*** (0.656)
NAME 07		0.430 (0.380)	0.421 (0.381)	1.412* (0.650)
NAME 10		0.905* (0.387)	0.929* (0.388)	1.208 (0.701)
Course load				
Other ECE courses			-0.233* (0.110)	-0.225 (0.261)
Pre-requisite course performance				
Circuits				-1.147*** (0.261)
Diff. Eq.				-0.567* (0.233)
Pseudo R-square	0.0139	0.108	0.113	0.203

*p ≤ .05. **p ≤ .01. ***p ≤ .001

Discussion

When considering the landscape of student performance in ECE 301, the data indicate that there are many students who are not able to achieve the desired outcome of passing ECE 301. At the same time, more than half of students were able to perform an “A” or “B” level in the class. Although a true bimodal distribution was not observed across the dataset, it does seem like there may be key factors at play that can hamper some students’ academic performance, motivating the need to identify and ameliorate these factors. Further, although this is a class where students have the potential to be successful, the academic record cannot capture the effort expended by students to achieve these grades. In addition to understanding the significant factors that predict success or lack thereof, we must also collect data from additional perspectives to better understand the student experience.

We see some potential effects of the COVID-19 pandemic in the data, although we do not have the ability to draw conclusive insights. Course enrollment dropped in 2020, and the performance disparity for transfer students became apparent around the same time. Both of these trends were returning to pre-2020 values in Spring 2023, and continued longitudinal investigation will reveal whether this finding continues.

When examining the regression model, many of the predictors were not statistically significant, although the ones that were significant raise interesting suggestions about areas to target. The only student characteristic that was significant in the model was a students' transfer status. There are several plausible explanations, including different emphases in pre-requisite courses at other institutions, acclimatization to the typical workload of a student at the studied institution, and overall experiences of transitions to a new environment. In a landscape where 40% of the students in ECE 301 have started their college career elsewhere, the program must work to support these students and empower them to succeed.

Although the correlation was a useful first test to understand potential relationships between courses, the finding that all correlations were weak-to-moderate indicates that we may simply be observing a pattern of general academic acuity. Whitcomb et al. [34] describe the utility of STEM GPA as a control when predicting student performance, which the authors will investigate in future work on this project. The decision to include Circuits and Differential Equations was made because of conceptual reasons, rather than any indications from the correlation table. Nonetheless, the regression model indicated that stronger grades in those two courses were associated with passing ECE 301. Circuits and Differential Equations might be viable avenues for the development of interventions or additional support resources for students.

The addition of instructor information improved the pseudo-R-squared of the model, and several of the instructors were significant predictors. This finding is perhaps unsurprising given the distribution of grades displayed in Figure 7. A range of possible strategies exist to work towards greater consistency across instructors, which should be filtered by contextual constraints (e.g., a history of relatively decentralized course management, a disinclination towards grade curving across sections, etc.). Interviews with ECE 301 instructors will inform the most viable possible directions.

There are recent developments to improve student success in ECE 301. Some instructors have developed virtual reality (VR) environments to help students navigate the conceptual space between atoms and devices [35]. The program has also created a learning mentor program for students, in which upper-level students provide times to work on homework and study for exams. As both of these efforts on ongoing, it remains to be seen how they might affect the data in Fall 2023 and beyond.

Alongside the quantitative efforts, the research team has also conducted interviews with ECE 301 instructors and focus groups with former ECE 301 students. These strands can help flesh out possible viable interventions that are suggested by the quantitative data. Ongoing efforts are working to expand the types of variables in the dataset (e.g., AP scores, transfer credits, international status). The refinement in the data can aid in creating a prediction model with stronger metrics and greater programmatic value.

Conclusions and Implications

This paper describes efforts to understand student performance in a junior-level microelectronics course. The descriptive data reveal a landscape of considerable heterogeneity in student performance, especially by transfer status, instructor, and letter grade distribution. The data suggest that these areas might be valuable targets for further investigation and resource development. Other variables (gender, race, concurrent courseload) were not significant predictors in a logistic regression model. Future work includes qualitative strands and further quantitative modeling.

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