Factors Influencing Student Performance and Persistence in CS2

Sara Hooshangi
Virginia Tech
Blacksburg, VA, USA
shoosh@vt.edu

Margaret Ellis
Virginia Tech
Blacksburg, VA, USA
maellis1@vt.edu

Stephen H. Edwards
Virginia Tech
Blacksburg, VA, USA
edwards@cs.vt.edu

ABSTRACT

Performance in CS1 and introductory CS courses has been an area of active research in the CS education research community for more than four decades, but studies related to student performance in CS2 are not as widely available. Past studies have examined the impact of CS1 grade, prior math preparation, and other factors such as homework, test, and project grades, on the overall performance in CS2. In this work, we will build upon the existing research related to CS2 performance with an emphasis on a few factors that have not been previously considered for this course. In addition to typical factors studied by others (i.e. gender, race, CS1 performance), our work also takes into account the impact of various CS1 pathways to CS2 and the number of previous college CS courses (including transfer credits) on student performance in CS2. We also look into both persistence, by distinguishing students who stay in the course versus those who drop from the class before the mid-semester drop deadline, and performance. Gender and race were not significant factors in determining performance in CS2 but undeclared engineering majors stood out as high performers and students' CS pathway leading to CS2 was also significant. Notably, students with CS1 transfer credit had significantly lower pass rates. Students with only 1 previous CS course credit were less likely to drop or not pass the course.

CCS CONCEPTS

• **Social and professional topics → Computer science education**; **Student assessment**.

KEYWORDS

CS2, Student Performance, Data Structures, Prior CS Knowledge

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1 INTRODUCTION

The CS Education research community has interest in factors contributing to success in introductory CS courses, in particular a sequence of introductory courses that are generally referred to as CS1 and CS2. CS1 is the first programming course that most students without any programming background can take. CS2 is the follow-up course in this sequence with a focus on data structures and algorithm design, which are core concepts in any CS undergraduate curriculum. CS1 and CS2 are both important gateway courses that directly impact success and retention of students in the CS pipeline. There is a plethora of research on factors contributing to success in introductory programming courses, with the focus of most of these studies on CS1. These range from personal and behavior factors such self-regulation, self-efficacy, motivation and study habits, to academic factors such as high school preparation, prior computing experience, and overall student GPA [11]. Research work related to CS1 is so extensive that CS1 has its own ACM CCS (Computing Classification Code) Concepts code of 10003533.

As the field of Computer Science grows and CS1 is taken by a larger number of high school students, CS2 will also grow and become more important. Over the past few years, there has been a significant effort to improve the reach of computer science education across the K-12 systems with federal initiatives such as the CS10K and CSforAll projects [8], state sponsored initiatives such as Computer Science for Rhode Island Program [7], and industry sponsored projects such as the "Hour of Code" organized by Code.Org [6]. As such nationwide efforts elevate the presence of CS related material in K-12, it is not far-fetched that in the next decade CS1 topics will be offered more and more at the high school level, and CS2 will become the standard college-level course that plays an important role in retention and recruitment into the CS field.

While a large body of research work has focused on CS1, only a few studies have focused on factors that may influence student performance in CS2. Previous research in this area has examined the role of CS1, prior math preparation, and other course related analysis [4, 9, 12]. While these studies are a good starting point to look into the factors that may influence student success in CS2, there are other factors that are not widely examined, and with this paper we will introduce two new factors that have not been studied in the past. These factors are 1) various pathways to CS2, including AP credit, transfer credits, and other non-standard pathways that could allow students to transition to CS2; 2) number of CS courses that a student takes before arriving at CS2.

With our research, we plan to better understand factors that may affect students' persistence and overall performance in CS2, by examining demographics, declared major, CS1 pathway, CS1/CS2 grades, and the number of CS courses taken before CS2 enrollment of students who enroll in CS2. The focus of this study is on students who completed or dropped CS2 at our institution during the Spring 2021 semester.

Our data can be especially helpful in replicating and advancing this research area because our work can be statistically significant due to the following two reasons: 1) our large sample size where

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over 600 students enroll in CS2 each semester; and 2) breadth of student background where CS majors, minors, transfer students, and many undeclared freshman engineering students with AP credits take our CS2.

2 PREVIOUS RESEARCH

Examining factors that influence success in introductory CS courses and predicting student performance has been an active area of research in CS education since the early 1980s. It has been argued that a better understanding of factors that impact student success or developing models to predict student performance could create opportunities for interventions and resource allocation that in turn serve in-need and at-risk students earlier in the CS pipeline [11].

A 2018 ITiSCE working group [11] performed a systematic literature review of publications that attempt to predict academic performance in computer science, engineering, and informatics based on various predictors. Across these publications the metric for student success varied, the most commonly used metric was individual course grade. Other metrics for student success included assessment or assignment performance, course or program retention, and overall GPA. The most commonly studied predictors of success were performance within the course of interest, engagement in the course of interest, and performance in previous courses. Increasingly, studies consider logged interaction data and student health, gender, or psychometric factors such as self-regulation and self-efficacy. There were not many studies that considered demographics. The report divided the prediction features into 5 categories: demographic, personality, academic, behavior, and institutional. Various methodologies have been used including many machine learning approaches, but the most commonly used approach are statistical methods such as linear regression and ANOVA.

According to another literature review analysis by Quille and Bergin [13], every two decades there is a surge in the number of papers interested in modeling student success and performance in CS courses. For example, Wilson et al. have extensively studied factors that promote success in an introductory college computer science course to determine what, if any, differences appear between genders on those factors [15, 16]. Bergin et al. have also looked into this, and the results showed that both mathematics preparation in high school and self-regulation correlated positively with success in CS1[2, 3, 13]. Alavardo et al. have shown that students with AP credits have higher grades across many CS courses [1]. Catanese et al. have shown that transfer students do as well in higher level computer science courses as non-transfer students [5]. It is clear that the area of research is much richer in the CS1 landscape and there is more room to develop better indicators of success in CS2 level courses.

Several publications on CS2 performance report that CS1 course performance predicts CS2 course performance[9, 12]. Work by Bisgin et al. in 2018 verified previous studies that reported CS1 grade was the most influential factor of student performance in a data structures course. Other factors considered were prior programming experience and perception of computing [4].

Much of the research conducted in this area has aimed to decrease the rate of failure in introductory CS courses. Whilst many studies suggest interventions that could improve retention, few have focused on examining the WDF rate and improving that ratio post-intervention [14]. WDF is the percentage of students receiving a grade of "D" or "F", or withdrawing from the course before the course ends. Further research into the factors that influence WDF can shed light on effective intervention methods that could impact students who are in the danger of exiting the CS pipeline.

3 RESEARCH QUESTIONS

This project aims to examine different pathways that lead to CS2 in search of factors that influence student performance and retention in CS2. Our research questions are the following:

- RQ1: Does CS1 grade predict CS2 grade?
- RQ2: Do demographic factors such as gender, race, and student's major, influence persistence (staying or dropping) and performance (passing or failing) CS2?
- RQ3: Does CS1 pathway to CS2 (standard CS1 at our institution, APCS, transfer credit for CS1, other course sequences at the institution) influence persistence and performance in CS2?

With our proposed research questions, we aimed to better understand factors that can affect student persistence and overall performance in CS2 by examining course paths, course grades, declared major, and demographics of students who enrolled in CS2. The focus of this study was on students who completed or dropped CS2 in Spring 2021. We looked for any correlation between the above factors and student performance and persistence in CS2 based on research questions presented above.

4 INSTITUTIONAL BACKGROUND

Our institution is a large research university located in the southeast United States with more than 30,000 undergraduate students and a rapidly growing CS department. About 400 students graduated with an undergraduate degree in Computer Science in the Spring of 2021. Computer Science is one of 13 departments within the College of Engineering.

4.1 Majors

Students in the College of Engineering (COE) are considered General Engineering majors (referred to in this paper as Undeclared Engineering) in their first year at the university and until they declare a major. Students are admitted to the COE as freshmen with admission to COE being more competitive than many other colleges at our institution. They can declare a major within the college after their first year. All students in Computer Science major or minor are required to take our standard CS2 course which is taught in Java. Several other majors such as Computational Modeling and Data Analytics (CMDA), a major in the College of Science, require CS2 as part of their curriculum.

4.2 CS2 Pathways

The software and programming sequence of courses for our CS majors and minors is CS1 (Introduction to Software Design), CS2 (Introduction to Data Structures and Software Design), and CS3 (Data Structures and Algorithms) all taught in Java with no previous

experience required in CS1. However, many students enter CS2 with a CS1 prerequisite other than CS1.

Students may have earned credit for CS1 during high school by passing the APCS A exam, taking a dual enrollment Computer Science course, or a Computer Science course in an International Baccalaureate (IB) High School. Some students may earn CS1 transfer credits directly from another university or community college. A small number of our students take our Introduction to Programming in Java, which is a service course for Business Information Technology majors, and then decide to pursue more CS courses and take CS2. This course does not have an OOP emphasis, unit testing, or labs so it is less rigorous than our standard CS1 course.

A subset of our CS2 students, and especially Computational Modeling and Data Analytics majors (CMDA), satisfy the CS1 prerequisite by taking a recently developed Python two-course sequence. These students take Introduction to Python and Intermediate Python. This sequence will give these students more opportunities to continue learning to program and to bridge to CS2 by introducing unit testing, data structures use, and reinforcing object oriented programming principles in the Intermediate Python course.

Our CS2 emphasizes object oriented programming and in the first two weeks of the course, there is a concerted effort to review Java fundamentals and object oriented concepts such as polymorphism. Additional tutoring sessions are offered for students transitioning from a Python background. The IDE used in the course is new to most students and the introduction of tools is scaffolded with the recognition that students not coming from our CS1 are likely also to be unfamiliar with our auto-grading tools and online coding practices. Students from backgrounds other than our CS1 are possibly unfamiliar with JUnit testing and object-oriented concepts. We have recently begun administering a readiness assessment in hopes of increasing student awareness of expected prerequisite skills before they start the course.

Some students in CS2 are taking it to fulfill a requirement for another major and do not intend to take more CS courses. Many of the students will continue to the next programming class, Computer Organization I, which is also a prerequisite for our CS3 Data Structures and Algorithms course. Students who are moving on to graduate studies in Computer Science will take a variation of CS3, Intermediate Data Structures and Algorithm Analysis, before continuing on to graduate-level coursework.

Our university accepts transfer credit for CS1 from many sources as listed above. However, the qualifications for CS2 transfer credit are typically only met by a subset of four-year universities. The vast majority of students in upper-level CS courses earned a C or better in our CS2 course.

4.3 Dataset

This study focuses on the examination of students who took CS2 during the Spring 2021 semester. Due to the COVID-19 pandemic, all instruction at our institution was online during the Spring 2021 semester and there were no in-person classes. This course was offered asynchronously online and all course material including pre-recorded lectures, assignments, quizzes, labs, projects, and exams were posted on our institution's Learning Management System (Canvas). Heavy support was provided with 2 instructors and 16 teaching assistants who offered synchronous online lab and office hours via Zoom from approximately 11am - 7pm six days per week and an active Piazza forum with an 11-minute average response time. he two lowest grades were dropped from lab and homework assignments and late submission windows were provided for projects. The number of students enrolled in the course has been rising in recent years by 30 to 50 students per semester, so both the student population and student experience have been evolving.

Data for the Spring 2021 CS2 students was acquired from the University Registrar's office upon IRB approval. Information was requested regarding CS2 grades, CS course history, and student demographics. Below are some basic descriptive statistics about our sample population. Table 1 shows the gender distribution for students who completed the course or dropped before the mid-semester drop deadline. Any student who remained in the course after the drop deadline received a grade in the course, which may have been a Withdraw (W) grade. A W is given when a student withdraws from the course between the end of the drop deadline and last day of the classes. The number of students in our CS2 class is consistent with the overall rate of female students in our department.

Table 1: Gender distribution

Race	Pass	WDF	Dropped	Total
Male	384 (77.6%)	42 (8.5%)	69 (13.9%)	495 (100.0%)
Female	88(79.3%)	6 (5.4%)	17 (15.3%)	111 (100.0%)
Unknown	3(75%)	0 (0.0%)	1 (25.0%)	4 (100.0%)
Total	475 (77.9%)	48 (7.9%)	87 (14.3%)	610 (100.0%)

Table 2 shows the demographic distribution for students who completed the course. We have used similar categories found in other Computing Research Association (CRA) publications, but our data does not separate non-resident students from domestic students. In order to protect the anonymity of the data, we have combined a few groups together. In our dataset, URM (Under Represented Minority) included the following categories; Black and African American, Hispanic of any race, Native American and multiracial students. Students without a disclosed race are marked as NR (No Response) in our tables and figures.

Table 2: Demographics distribution in CS2

Race	Pass	WDF	Dropped	Total
White	218 (76.0%)	22 (7.7%)	47 (16.4%)	287 (100.0%)
Asian	197 (81.1%)	15 (6.2%)	31 (12.8%)	243 (100.0%)
URM	45 (71.4%)	9 (14.3%)	9 (14.3%)	63 (100.0%)
NR*	15 (88.2%)	2 (11.8%)	0 (0.0%)	17 (100.0%)
Total	475 (77.9%)	48 (7.9%)	87 (14.3%)	610 (100.0%)

* NR means No Response.

5 RESULTS

For our Spring 2021 CS2 dataset we analyzed 6 factors: gender, race, student major, CS1 pathway, number of CS courses taken before CS2, and CS1 grade. We investigated the relationship between these

factors and CS2 grades for students who persisted. We also analyzed the significance of these factors in whether students passed the course with credit, stayed in the course past the drop date but did not earn credit (WDF), or dropped the course before the mid-semester drop date. For this course students must earn a C or better to proceed to the next course, so C- students were categorized in the WDF group. Drops include students who dropped the course between the start of semester until the drop date which is roughly six weeks after the start of the semester. Between the drop date and last day of classes, students can request to be dropped from the course, but they will receive a grade of W on their transcript.

5.1 RQ1: Does CS1 grade predict CS2 grade?

For our dataset, CS1 grade reasonably predicts CS2 grade. Figure 1 shows the relationship between CS1 grade and CS2 grade.

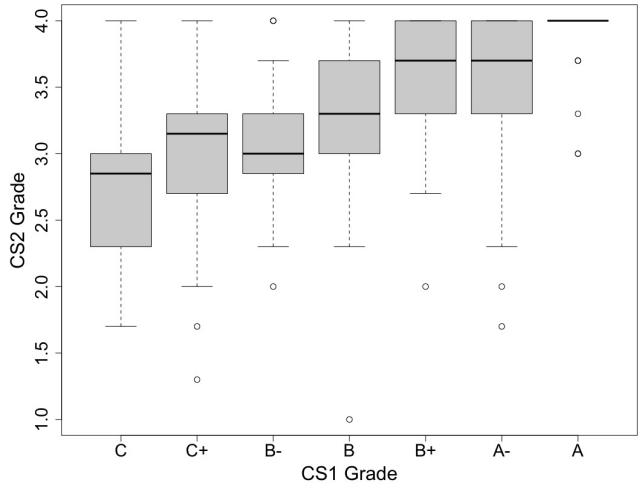

Figure 1: CS2 performance based on CS1 grades

Students need a grade of C or better in CS1 before they can complete CS2, hence the grade distribution for CS1 only includes the range of C to A grades. As shown in Figure 1, the grades of students who took CS1 at our institution are correlated with their CS2 grades. This correlation is statistically significant with a p-value < .0001 and a correlation coefficient of 0.49. The mean grades for both courses for this group is in the B range, at 3.05 for CS1 and 3.11 for CS2. As shown in the box-plot, there is variation in performance but CS1 grade is a significant factor in CS2 grade. For each category of CS1 grade students have an average grade in CS2 that is slightly higher, notably the B+ CS1 students averaged an A-(3.7) in CS2. These findings align well with many previous studies that have correlated CS1 and CS2 grade as discussed in Section 2.

5.2 RQ2: Do demographics factors such as gender, race, and student's major influence persistence (staying or dropping) and performance (passing or failing) CS2?

To examine demographic factors (gender, race, and major) that may influence student performance in CS2, we looked at each of these factors separately and examined the performance of students belonging to each group within a given factor. For race and major, several groups were aggregated to ensure the anonymity of students in the small sample size as required by our IRB guideline. Figure 2 shows the corresponding box-plot for groups within each factor where student performance in CS2 can be compared across the various groups for each factor.

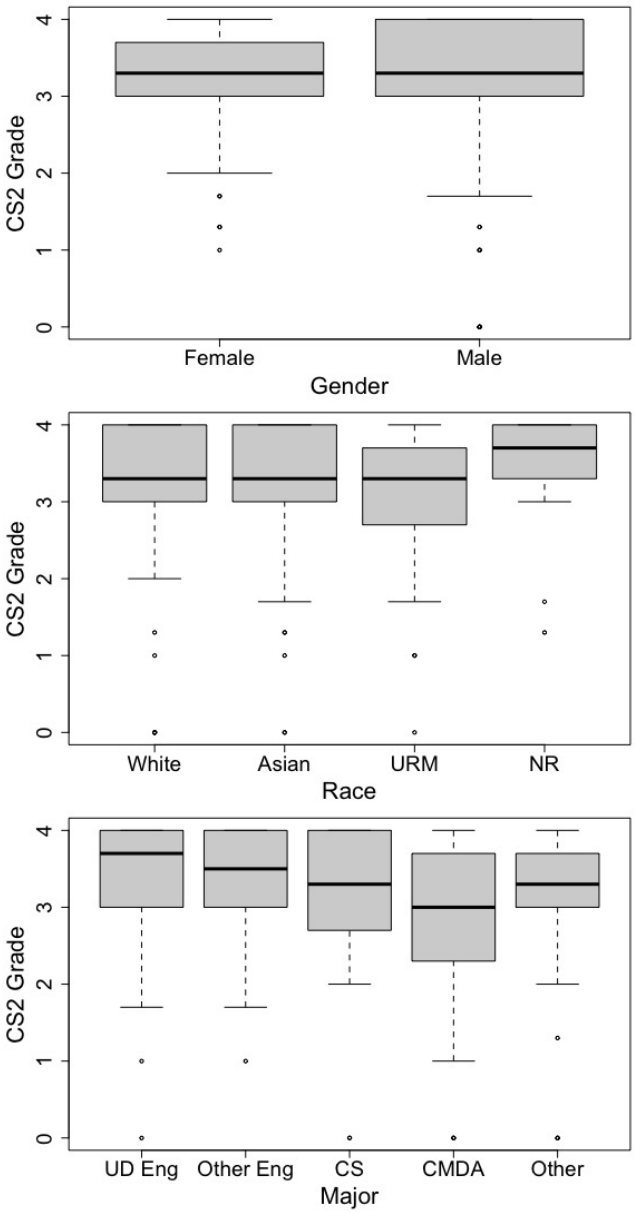

Figure 2: CS2 performance based on gender, race and major

We further analyzed the relationship between groups by running a Chi-squared analysis on each factor based on three possible CS2 outcomes (passing, not passing (WDF), or dropping the course). Our Chi-squared analysis reveals that for gender ($\chi 2 = 1.24, p = 0.53$) and race ($\chi 2 = 9.26, p = 0.16$), there is no significant difference between CS2 outcome-based on gender or race groups. On the other

hand, the Chi-squared calculation shows a significant difference is observed for student major ($\chi 2 = 30.85, p < 0.001 * **$). A post hoc test was performed on student major to further find the groups that show this significance and our analysis indicates that the significance difference is seen for Undeclared Engineering and Pass grade, and Undeclared Engineering and WDF.

Table 3: Student Major Contingency Table

Major	Pass	WDF	Drop	Total
Undeclared	**267 (84.8%)****	**14 (4.4%)****	34 (10.8%)	315
Other Eng	44 (69.8%)	3 (4.8%)	16 (25.4%)	63
CS	43 (78.2%)	7 (12.7%)	5 (9.1%)	55
CMDA	62 (69.7%)	13 (14.6%)	14 (15.7%)	89
Other	59 (67.0%)	11 (12.5%)	18 (20.5%)	88
Total	475 (77.9%)	48 (7.9%)	87 (14.3%)	610

** Significance was detected in the Chi-square post hoc test.

Table 3 shows the contingency table for student major, and highlights the cases where we see a significance based on our post hoc analysis of the Chi-squared test. Given that this dataset is from a spring semester, a large number of undeclared engineering freshman students are included in this class. These students usually have the intention of becoming CS majors, and take CS2 in the spring term of their freshman year as a follow-up to the CS1 course they take in their first semester. It is not surprising that this group has outperformed other groups, as becoming a freshman engineering student is competitive and students who are admitted to the College of Engineering tend to be strong students. While we cannot make inference about the variations in the other groups in this factor, we are not surprised that those who are declared as CS majors and taking CS2 during their second year are not performing as well as freshman engineering or other engineering students. Taking CS2 after being a declared CS major means that the student is behind schedule in their CS curriculum. The CMDA major is a less competitive major and has a higher rate of admission than COE. We expect these factors relate to the overall distribution of grades for students in each of these groups, but further analysis and qualitative measures are needed to further investigate these results.

5.3 RQ3: Does CS1 pathway to CS2 (standard CS1 at our institution, APCS, transfer credit for CS1, other course sequence at the institution) influence persistence and performance in CS2?

To get a better grasp of pathways that lead to CS2, our next analysis was to look at the CS1 sources and where students gained their programming experience before they came to CS2. As described earlier, the traditional CS1 course at our institution is a Java-based programming course required for all CS majors and minors. Students may come to CS2 from other pathways. AP Computer Science is popular among our freshmen engineers who plan to major in CS. If they score a 3 or higher on their APCS test, they receive credit for CS1 and can move directly to CS2. Other pathways include a sequence of Python courses which is popular among our CMDA majors as a substitute for CS1. Our Electrical and Computer Engineering department also offers an introductory programming course in C language which can fulfill the CS1 requirement. Transfer credit for CS1 can come in the form of transfer credits from community colleges or other universities and International Baccalaureate high school programs. Based on the data summarized in Table 4, about half of our students take our CS1 course, and the second largest source for CS1 credit is AP Computer Science. Table 5 shows the number of courses a student took prior to CS1. The table indicates that more than half of our students come to CS2 from a single college course, which in all likelihood is CS1 or APCS. Students who have taken more than 3 courses, tend to have brought those courses as electives from a community college. Our institution does not give transfer credit for CS2 from a community college, so prior CS work at a community college tends to be transferred into other courses. A handful of students have come into CS2 without any prior CS coursework. These students tend to be either university staff, master's students, or someone with special permission to take the course.

Table 4: CS1 Pathway Contingency Table

CS1 Path	Pass	WDF	Drop	Total
CS1	262 (76.8%)	26 (7.6%)	53 (15.5%)	341
AP CS	154 (83.7%)	12 (6.5%)	18 (9.8%)	184
Other Path at U	35 (79.5%)	4 (9.1%)	5 (11.4%)	44
Transfer	**24 (58.5%)****	6 (14.6%)	11 (26.8%)	41
Total	475 (77.9%)	48 (7.9%)	87 (14.3%)	610

** Significance was detected in the Chi-square post hoc test.

Figure 3 shows the corresponding box-plot for groups within each factor where student performance in CS2 can be compared across the various groups for each factor. We further analyzed the relationship between groups in each factor by running a Chi-squared analysis on each factor. Our Chi-squared analysis reveals that for both the CS1 pathway ($\chi 2 = 13.53, p < 0.05*$) and number of prior CS courses ($\chi 2 = 18.22, p < 0.01 * *$), a significant difference is observed. A post hoc test was performed to further find groups that show this significance and our analysis indicates that the significance difference is seen for Transfer and Pass grade, and 1 course and WDF, and 2 courses and WDF as seen in tables 4 and 5.

Table 5: Number of CS courses before CS2

Number	Pass	WDF	Drop	Total
0	3 (37.5%)	2 (25.0%)	3 (37.5%)	8
1	324 (81.0%)	**22 (5.5%)****	**54 (13.5%)****	400
2	105 (71.4%)	**20 (13.6%)****	22 (15.0%)	147
3 or more	43 (78.2%)	4 (7.3%)	8 (14.5%)	55
Total	475 (77.9%)	48 (7.9%)	87 (14.3%)	610

** Significance was detected in the Chi-square post hoc test.

6 DISCUSSION

Our analysis corroborates previous research on predictors of CS2 performance and also provides some new and specific insights that can be further investigated. CS1 grades are significant factors in our students' CS2 grades. Our results confirm findings in previous

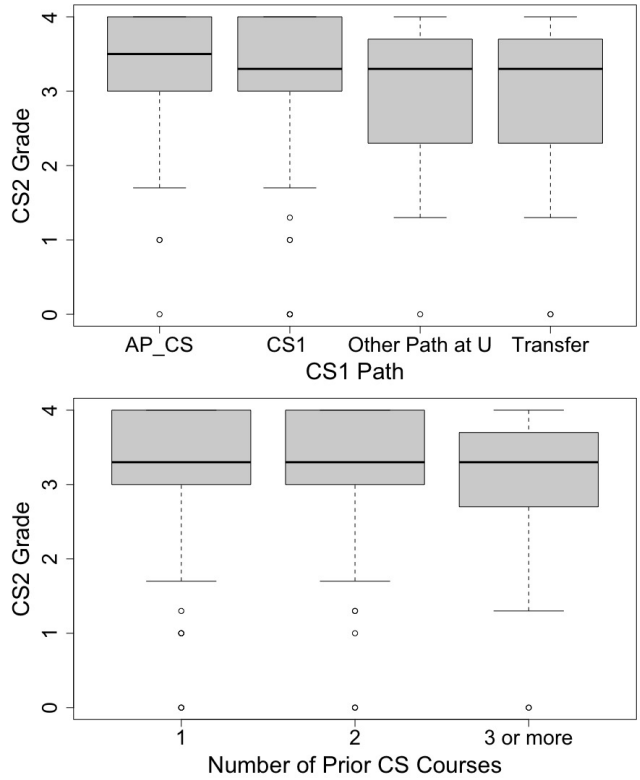

Figure 3: CS2 performance based pathways/prior courses

studies with smaller sample sizes [4, 9, 10] and also a study with a similar sample size [12]. In all of this previous work, CS1 grades were found to have a statistically significant effect on CS2 grades. Furthermore, in our study neither race nor gender were significant factors in whether a student passed, did not pass (WDF), or dropped the course. Previous studies have also shown that no significant gender differences were found when looking at factors that may contribute to student success in introductory CS courses [15, 16].

However, major was a significant factor in our study. Undeclared Engineering majors, who are College of Engineering students who have not yet declared a specific major, had a high rate of passing the course and a low rate of not passing the course. This population comprises a little more than half the students in the course and are mostly freshmen who are very interested in, or at least considering, becoming CS majors. Students who take CS2 in their freshman year may have APCS credit for CS1 or may begin their CS1 coursework in their first semester of their freshman year along with a demanding general engineering curriculum and are likely very motivated.

Other factors that were also significant in whether a student passed, did not pass (WDF), or dropped the course were the type of CS1 course that the student took and the total number of CS college courses the student took before CS2. Students who transferred CS1 credit have a significantly lower pass rate than students who earned CS1 credit via APCS or at our institution. While the CS2 course intentionally attempts to help fill in CS1 gaps, it is not enough. Efforts have begun to revamp and synchronize CS1 curriculum with feeder community college and this analysis verifies such efforts are needed. Expanded studies across semesters can provide a larger dataset to also investigate International Baccalaureate CS1 preparation.

The APCS students have a high pass rate but it was not significant. It is of interest to note that these students are likely very similar to the A and B students from CS1. Students who earn a 4 and 5 on the APCS test have a similar experience level to students who earn a B or A in our CS1 course. Because students who earn a 3 on the APCS course are encouraged to repeat CS1, the APCS population is comprised of previously higher performing students since other CS1 students may have earned a C.

Students who only took one CS course before CS2 had significantly lower rates of WDF or drop in CS2. These are most likely students from CS1 or APCS. Students who had 2 courses before CS2 had a higher rate of not passing the course. Further investigation could indicate which sequences of courses these 20 students took and the analysis of a larger dataset across several semesters may provide more information. This appears to be a group who may benefit from added academic support in CS2 or additional advising and mentoring. A qualitative study may provide additional information for how to better support this group. Not surprising is that the students with no previous CS courses had lower pass rates, but this set is too small to be significant and requires further study.

6.1 Threats to Validity

While analyzing this dataset was insightful, some categories of students were still in the single digits and we could not fully investigate those categories. A dataset across several semesters would provide more information. Our dataset indicated which CS courses students earned credit for, but did not indicate which courses were taken multiple times, which could affect a student's performance.

Internal Validity: Since we only have one data collection point for each participant, there is no potential for history, maturation, or instrumentation threats. Because there are no defined experimental and control groups in this study, a direct causality between process measurements and our outcomes cannot be inferred. Our sample size is large, and we believe the diversity in our student population is enough so that our study does not suffer from selection bias. Differential experience could be a potential threat to this study, as students come from diverse academic backgrounds.

External Validity: Our findings are based on a particular semester data for students at a larger research institution during the COVID pandemic. As such our results might not be generalizable to all undergraduate students, or for a regular semester without the effects of COVID. However, the characteristics of our students are representative of typical undergraduate students who enroll in CS2 offered at large research institutions in the United States.

7 CONCLUSION

We verified that CS1 grade predicts CS2 grade but we also performed novel analysis on factors impacting student performance in CS2 as indicated by passing, not passing, or dropping the course. Gender and race were not significant factors but undeclared engineering majors stood out as high performers and students' CS pathway leading to CS2 was also significant. Notably, students with CS1 transfer credit had significantly lower pass rates. Students with only 1 previous CS course credit were less likely to drop or not pass the course.

REFERENCES

[1] Christine Alvarado, Gustavo Umbelino, and Mia Minnes. 2018. The Persistent Effect of Pre-College Computing Experience on College CS Course Grades. In *Proceedings of the 49th ACM Technical Symposium on Computer Science Education* (Baltimore, Maryland, USA) *(SIGCSE '18)*. Association for Computing Machinery, New York, NY, USA, 876–881. https://doi.org/10.1145/3159450.3159508

[2] Susan Bergin and Ronan Reilly. 2005. Programming: Factors That Influence Success. *SIGCSE Bull.* 37, 1 (Feb. 2005), 411–415. https://doi.org/10.1145/1047124.1047480

[3] Susan Bergin, Ronan Reilly, and Desmond Traynor. 2005. Examining the Role of Self-Regulated Learning on Introductory Programming Performance. In *Proceedings of the First International Workshop on Computing Education Research* (Seattle, WA, USA) *(ICER '05)*. Association for Computing Machinery, New York, NY, USA, 81–86. https://doi.org/10.1145/1089786.1089794

[4] Halil Bisgin, Murali Mani, and Suleyman Uludag. 2018. Delineating Factors that Influence Student Performance in a Data Structures Course. In *2018 IEEE Frontiers in Education Conference (FIE)*. IEEE, 1–9. https://doi.org/10.1109/FIE.2018.8659300

[5] Helen Catanese, Carl Hauser, and Assefaw H. Gebremedhin. 2018. Evaluation of Native and Transfer Students' Success in a Computer Science Course. *ACM Inroads* 9, 2 (April 2018), 53–57. https://doi.org/10.1145/3204471

[6] Code.org. 2021. *Retrieved August 13, 2021 from https://code.org/* (2021).

[7] CS4RI. 2021. Computer Science For RI. *Retrieved August 13, 2021 from https://cs4RI.org/* (2021).

[8] CSforAll. 2021. Computer Science For All. *Retrieved August 13, 2021 from https://csforall.org//* (2021).

[9] Holger Danielsiek and Jan Vahrenhold. 2016. Stay on These Roads: Potential Factors Indicating Students' Performance in a CS2 Course. In *Proceedings of the 47th ACM Technical Symposium on Computing Science Education* (Memphis, Tennessee, USA) *(SIGCSE '16)*. Association for Computing Machinery, New York, NY, USA, 12–17. https://doi.org/10.1145/2839509.2844591

[10] Richard J. Enbody, William F. Punch, and Mark McCullen. 2009. Python CS1 as Preparation for C++ CS2. *SIGCSE Bull.* 41, 1 (mar 2009), 116–120. https://doi.org/10.1145/1539024.1508907

[11] Arto Hellas, Petri Ihantola, Andrew Petersen, Vangel V. Ajanovski, Mirela Gutica, Timo Hynninen, Antti Knutas, Juho Leinonen, Chris Messom, and Soohyun Nam Liao. 2018. Predicting Academic Performance: A Systematic Literature Review. In *Proceedings Companion of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education* (Larnaca, Cyprus) *(ITiCSE 2018 Companion)*. Association for Computing Machinery, New York, NY, USA, 175–199. https://doi.org/10.1145/3293881.3295783

[12] Lucas Layman, Yang Song, and Curry Guinn. 2020. Toward Predicting Success and Failure in CS2: A Mixed-Method Analysis. In *Proceedings of the 2020 ACM Southeast Conference* (Tampa, FL, USA) *(ACM SE '20)*. Association for Computing Machinery, New York, NY, USA, 218–225. https://doi.org/10.1145/3374135.3385277

[13] Keith Quille and Susan Bergin. 2018. Programming: Predicting Student Success Early in CS1. a Re-Validation and Replication Study. In *Proceedings of the 23rd Annual ACM Conference on Innovation and Technology in Computer Science Education* (Larnaca, Cyprus) *(ITiCSE 2018)*. Association for Computing Machinery, New York, NY, USA, 15–20. https://doi.org/10.1145/3197091.3197101

[14] Arto Vihavainen, Jonne Airaksinen, and Christopher Watson. 2014. A Systematic Review of Approaches for Teaching Introductory Programming and Their Influence on Success. In *Proceedings of the Tenth Annual Conference on International Computing Education Research* (Glasgow, Scotland, United Kingdom) *(ICER '14)*. Association for Computing Machinery, New York, NY, USA, 19–26. https://doi.org/10.1145/2632320.2632349

[15] Brenda Cantwell Wilson. 2002. A Study of Factors Promoting Success in Computer Science Including Gender Differences. *Computer Science Education* 12, 1-2 (2002), 141–164. https://doi.org/10.1076/csed.12.1.141.8211

[16] Brenda Cantwell Wilson and Sharon Shrock. 2001. Contributing to success in an introductory computer science course: a study of twelve factors. *Acm sigcse bulletin* 33, 1 (2001), 184–188. https://doi.org/10.1145/364447.364581