A Quantitative Analysis of Study Habits Among Lower- and Higher-Performing Students in CS1

Soohyun Nam Liao
soohyunl@cs.princeton.edu
Princeton University
Princeton, New Jersey, United States

Kartik Shah
kdshah@princeton.edu
Princeton University
Princeton, New Jersey, United States

William G. Griswold
wgg@eng.ucsd.edu
University of California, San Diego
San Diego, California, United States

Leo Porter
leporter@eng.ucsd.edu
University of California, San Diego
San Diego, California, United States

ABSTRACT

Our prior work found differences in study habits between high- and low-performers in a small-scale qualitative study, and this work seeks to verify and extend these findings by examining the study habits of a larger population of CS1 students. To do this, we devised a survey based on the findings of our prior qualitative study. The responses of CS1 students reveals that some study habits are more frequently practiced by higher-performers then lower-performers or vice versa. One concern with these findings is that the differences in study habits might simply be explained by prior experience. As such, we compare study habits between students with and without prior experience as well. We find that although prior experience translates to better class performance, it is not associated with the same study habits as lower- and higher-performers, suggesting that prior experience and study habits are separately associated with better student performance. These findings encourage further inquiry into the role of study habits in student success and whether explicit instruction on better study habits might be the basis for successful future interventions.

CCS CONCEPTS

• **Social and professional topics** → **Computing education**.

KEYWORDS

study habits, lower-performing students, higher-performing students, CS1, self-regulation

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1 INTRODUCTION

The issue of high failure rates in CS1 is well-known [33]. To help uncover why so many students struggle in CS1, a number of previous studies have investigated factors correlated with student success [7, 17, 19, 20, 26, 28, 35, 37, 38]. However, it is still unclear what interventions instructors could use to boost success rates, and some attempts at large-scale interventions aimed at inclusion and metacognition have not had the desired outcomes [16]. As such, recent work has begun to look at differences in behaviors (e.g., study habits) between higher- and lower- performing students [7, 18] with the goal to uncover insights which might be useful for crafting future interventions.

Our recent small-scale qualitative study investigated behavioral differences between higher- and lower- performing students by conducting multiple interviews with a few students as the CS1 course progressed [18]. We found noticeable differences in the study habits of higher- and lower- performing students. As the findings resulted from interviews with a small sampling of students, it is unclear if these findings hold true at scale. Also, our prior findings did not take into account how prior experience, one of the primary factors that impact student learning outcomes in CS1 [35], might influence student study habits.

As such, this work seeks to examine our findings for a larger student population. Using quotes from our student observations, we crafted a survey and collected responses from a CS1 course at a large public institution in North America. We first split the dataset into higher-performers and lower-performers and compared their survey responses to uncover differences in student study habits. We then investigated whether some study habits are more closely related to prior experience than performance by comparing responses between students with and without prior CS experience.

We find that higher- and lower- performing students self-report mostly the same study habits. However, for some of the self-reported habits, there are indeed differences between the two groups. Those different habits include how students approach understanding new code and their willingness to ensure they fully understand the behavior of their own code.

We also found differences in study habits when dividing students based on prior CS experience. Also, the set of different study habits for those with/without prior experience and lower/higher performing students were almost entirely unique except for one habit -

helping other classmates. Prior experience seems to be more associated with students' interest levels and eagerness to learn beyond the course. This suggests that prior experience may not necessarily instill better study habits, and good study habits and prior experience provide different benefits for students. Encouragingly, although we cannot offer students prior experience at the start of a term, interventions based on improving study habits might be possible. This motivates future inquiry into the potential causal nature of the different study habits identified in this work and improved student performance.

2 BACKGROUND

Research into study habits has spanned from middle school to higher education [6, 8, 13, 15, 22, 27, 29, 36]. These studies have found correlations between student performance and study habits related to self-regulation (e.g. attendance, being proactive in getting their doubts solved, doing assignments on time) and/or resources used (e.g. taking notes, reading the textbook). Other examples include asking instructors for feedback, recalling prior examples, executing targeted review, and memorizing the course content. Although these studies were not performed in the context of CS, some of these study habits may also help student success in CS1. Research in computing education has found that study habits influence student success [7, 18, 23]. Their findings showed that study habits are related to students' dropping CS1 courses [23] and student learning [7, 18].

One highly relevant work to ours is that of Chinn et al. who designed a survey based on instructors' opinions of factors that matter to students learning outcomes (i.e. took a top-down approach to the survey design) and collected a large number of responses from CS1 students [7]. Their analysis on the relationship between the student responses and their performance indicated that prior programming experience and lecture attendance were positively correlated with performance, while using the internet and working with others were negatively correlated.

On the contrary to Chinn et al.'s top-down approach [7], our prior work employed the bottom-up approach [18]. We used interviews with a small number of CS1 students to observe their overall study behaviors and then synthesized the interview results to uncover differences in student behaviors. A few of the habits observed more from higher-performing students included reviewing course notes, seeking out extra resources, and creating new questions to solve. We also observed that higher-performing students are more likely to successfully take actions to address their confusions. Some study habits we found among lower-performing students included memorizing existing code and procrastination.

Our descriptive approach produced a set of study practices deserving of further inquiry, but because of the small scale nature of the qualitative work, more work is needed to confirm these findings at scale. Also, our study did not factor in prior experience, which might have played a role in impacting students' study practices.

The link between prior experience and performance has been extensively studied in computer science, demonstrating that prior experience is a factor associated with student success in CS1 [3, 5, 12, 14, 30, 32, 34, 35]. However, the influence of prior experience on study practices has not been explored, and it is unclear if benefits incurred from prior experience are associated with knowledge or with learning better study practices. The closest study to answering this question is by Alvarado et al. [2]. Their work studied how experience and confidence influence student "study attitudes". However, the "study attitudes" in their study refer to more high-level study approaches (e.g., deep, shallow, or strategic approach) that may or may not map to specific study practices.

Thus, this work builds on our prior work [18] by extending our work to a larger-scale quantitative study through a student survey. Moreover, we investigate whether prior experience explains the differences in study habits emerged from the survey responses.

3 METHOD

3.1 Research Questions

This study seeks to investigate the following two research questions:

- **RQ1:** Do students' survey responses on self-reported study habits confirm our prior findings [18] in terms of differences between the study habits of lower and higher performing students?
- **RQ2:** Does prior experience explain the differences in study habits found in RQ1 (i.e., does prior experience cause students to adopt study habits associated with better performance)?

3.2 Study Habits Survey

The survey questions were designed based on the findings from our own prior work that explored study habits of higher- and lower-performing students in CS1 [18]. In that work, we interviewed 19 CS1 students in an North American research-intensive institution, using a similar strategy as Fincher et al.'s [11]. The interview participants were first asked to log their study settings for a week then recall what they were doing at a specific time on the logs at the interview. Although the work only focused on the relationship between study habits and performance, the interviews still revealed a variety of study habits. These included how students address confusions, seek help, utilize resources, and plan their studying. In this present work, we extracted those habits, along with the context of when these habits were exercised, from the prior work in order to construct a survey to be given at scale. In constructing the survey, we used the same (or similar) terminology and phrasing used by interview participants to prevent question misinterpretations.

The survey consisted of 37 questions, six of which asked demographic information including gender, age, ethnicity, major, and prior experience. The demographic questions were placed at the end of the survey to avoid impact on the responses. Our two questions related to prior experience asked if it was informal (e.g., after-school clubs) and/or formal (e.g., courses). The remaining 31 questions described study habits in different situations.

Out of these 31 questions, 28 of them asked how frequently they exercise that particular study habit on a 5-point Likert scale: Never, Rarely, Sometimes, Usually, and Always. We chose the Likert scale format as it helps characterize frequencies of practicing different study habits throughout multiple weeks of a term. This was based on our observations from the student interviews that each student actually exercised a variety of study habits at least once, but they often have a small set of practices that they exercise more frequently than the rest. The remaining three questions had multiple-choice responses intended to expose why students exercise a specific habit.

Table 1: Likert-Scaled Questions on the Survey

Identifier	Question
ask-instructors-when-confused	When confused, I ask instructional staff for help.
ask-classmates-when-confused	When confused, I ask classmates or friends for help.
ask-forum-when-confused	When confused, I ask Piazza for help.
use-textbook-when-confused	When confused, I refer to textbook, slides, or podcasts.
use-notes-when-confused	When confused, I use my notes from class.
use-external-sources-when-confused	When confused, I use external sources (ex: search online, another book, course material from another course).
attend-exam-review-sessions	For exam prep, I go to midterm review sessions or watch their podcasts.
use-notes-for-exam-prep	For exam prep, I review my notes from class.
use-textbook-for-exam-prep	For exam prep, I review textbook, slides, or podcasts.
use-coding-assignments-for-exam-prep	For exam prep, I review my prior programming assignments.
use-external-sources-for-exam-prep	For exam prep, I refer to external sources.
use-sample-questions-for-exam-prep	For exam prep, I practice questions from sample exams or quizzes.
use-external-questions-for-exam-prep	For exam prep, I practice questions from external resources outside class.
memorize-facts-for-exam-prep	For exam prep, I try to memorize facts from course material.
memorize-code-for-exam-prep	For exam prep, I try to memorize code I have seen before in class.
recall-similar-questions-if-stuck-for-exam-prep	For exam prep, if I don't know how to solve a problem, I try to recall a similar question I worked on to see how I solved it
figure-out-question-types-for-exam-prep	For exam prep, I use sample exams to figure out the types of exam questions.
make-own-questions-for-exam-prep	For exam prep, I try to make up different kinds of exam questions.
write-code-on-paper-for-exam-prep	For exam prep, I practice writing code on paper to get used to it in the midterm.
write-new-code-for-exam-prep	For exam prep, I write new code to implement new features of prior assignments.
solve-new-coding-problems-for-exam-prep	For exam prep, I write code to solve problems I come up with.
predict-output-to-understand-code	To understand code, I read through the code and try to predict its output.
run-program-to-understand-code	To understand code, I simply run the code on a computer.
predict-then-run-to-understand-code	To understand code, I predict the output then run it to check my understanding.
recall-similar-code-to-understand	To understand code, I compare it to a similar piece of code I already understand.
help-classmates-understand-concepts	I help my classmates understand concepts because it helps me understand them better.
form-study-groups	I form informal study groups with classmates.
understand-all-code-before-submitting	When I solve a programming assignment, I make sure I understand all the code I turn in (including any code given to me by TAs/tutors when I asked for help).

Table 2: Non-Likert-Scaled Questions on Survey

Question	Response Choices
When unclear about course material	I prefer to ask classmates for help, I prefer to ask instructors for help, I have no preference
When seeking help from classmates instead of instructors, it is mostly because	I do not seek help from classmates, classmates are more convenient to access, I am more comfortable with classmates, instructors are unavailable when I need help
When I post a question on Piazza to seek help, it is mostly because	I don't use Piazza, I get answers quickly and conveniently, classmates are unavailable when I need help, instructors are unavailable when I need help, it's anonymous to my classmates

Table 1 and 2 provides details on the survey questions. We also provide identifiers for each category and question statement, used from here on for the sake of brevity.

3.3 Data Collection and Analysis

We surveyed CS1 students from a North-American research-intensive institution in Spring 2019 in accordance with our approved Human Subjects research protocol. The survey was administered right before the midterm exam to ensure that students were able to reflect on their study habits as they were in the process of exam preparation.

Out of 259 students who took the midterm, 242 students also submitted the survey responses (93% response rate). The respondents earned 2% of extra credit on the midterm exam. Table 3 explains how we split students. The first split was based on students' performance, represented as their midterm exam score rank. We defined Higher-Performers (HPs) as students whose midterm score were ranked in the top 50% of the class, and Lower-Performers (LPs) as students in the bottom 50%. This definition is consistent with

Table 3: Dataset Breakdown

	HP	LP	Total
SPE	46	22	68
SNPE	75	99	174
Total	121	121	242

(a) Whom to Ask for Help and Resources Used **(b) Other Study Habits**

Figure 1: Survey Responses Differentiated between HP (solids) and LP (stripes). Questions with asterisks(*) had $p \leq 0.05$

our prior study [18], and other prior work [1]. We note that we categorized the students based on the entire class, not just based on those who submitted the survey, to ensure that HPs and LPs reflect the performance of the entire class. We had 121 students in each group, for which 94% of HPs and 93% of LPs completed the survey. The second split was based on prior experience. We defined Students with Prior Experience (SPE) as students with either formal or informal prior experience, or both, whereas we defined Students with No Prior Experience (SNPE) as students with neither formal nor informal prior experience. Out of the 242 students, there were 174 SNPE and 68 SPE.

We ran statistical tests for the 28 questions of which the responses were in 5-point Likert scale to identify any difference in the responses with respect to class performance and prior experience. Mann-Whitney U tests were used as the Likert-scaled responses are ordinal variables. However, for the three multiple-choice questions whose answer choices were categorical, we ran two-sided Fisher's Exact Tests to see if student performance or prior experience is correlated with their reasons for particular study habits. We used $p \leq 0.05$ as the margin for statistical significance.

4 RESULTS

Section 4.1 describes our observations from the survey responses of HPs and LPs and then discusses whether our results are consistent with our prior work [18]. Section 4.2 examines the notable differences in study habits between SPE and SNPE and their overlap in differences with those between HPs and LPs.

4.1 Performance and Study Habits

Figure 1 describes the survey responses of LPs and HPs and shows that only 6 out of 28 Likert-scaled questions had statistically significant differences between LPs and HPs.

Preference on whom to ask for help. Although ask-classmates-when-confused on Figure 1a indicates that HPs and LPs seek help

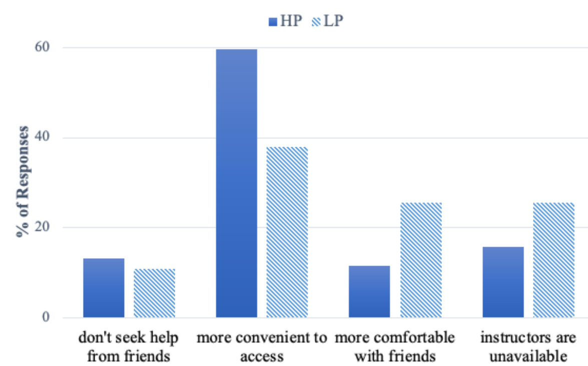
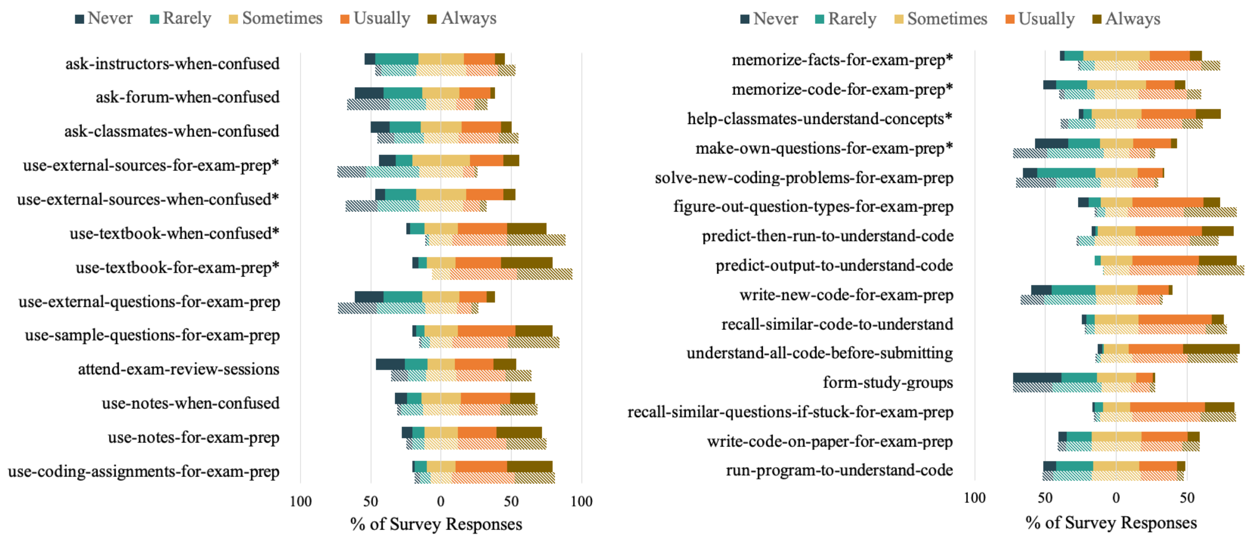


Figure 2: Student Responses on Why They Seek Help from Friends instead of Instructional Staff

from classmates and friends at a comparable frequency, more nuanced responses reveal more differences between LPs and HPs. As seen on Figure 2, HPs' preference is based on convenience while LPs' is based on availability and comfort. Two-sided Fisher's Exact test also confirmed that the difference is statistically significant ($p = 0.001$). This is consistent with our prior work in that LPs mentioned they had no choice but to ask friends for help because they could not make it to the last available office hours [18].

Also, both HPs and LPs use instructional staff and the online forum for help and we found no statistical difference. This is inconsistent with our prior work [18] where LPs were found to less frequently use instructional staff or the online forum.

Resources used. Figure 1a indicates that both HPs and LPs use almost all resources at a comparable level of frequency. The only resource that showed a statistically significance difference was midterm review sessions. From the responses to attend-exam-review-sessions, HPs attended the midterm review session or watched its podcast less frequently than LPs. This is inconsistent with one of



(a) Whom to Ask for Help and Resources Used

(b) Other Study Habits

Figure 3: Survey Responses Differentiated between SPE (solids) and SNPE (stripes). Questions with asterisks(*) had $p \leq 0.05$

the findings from our prior work which found HPs utilize notes, external sources, and midterm review sessions more than LPs.

Other Study Habits. Figure 1b points out some habits that HPs exercise more frequently: understand-all-code-before-submitting, predict-then-run-to-understand-code, recall-similar-questions-if-stuck-for-exam-prep, help-classmates-understand-concepts. The remaining habits showed no statistically significant difference.

The difference between HPs and LPs for understand-all-code-before-submitting was quite large and statistically significant. This is consistent with prior work, observing that LPs do not always address their confusions and may simply focus on having their program meet assignment requirements without understanding why. However, it may also be that HPs are in a position to report fully understanding their code because they have a better understanding of course content in general.

However, some of our findings are inconsistent with our prior work. Our prior work found that HPs tend to create new problems on their own to test their knowledge more than LPs, whereas LPs tend to memorize the course material and practice code writing on a paper more. Neither of those findings appear at scale, suggesting the differences in behaviors is less common than it appeared in the qualitative study or that student self-reporting of these behaviors on the survey may be inaccurate.

4.2 Prior Experience and Study Habits

Figure 3 highlights differences between Students With Prior Experience (SPE) and Students with No Prior Experience (SNPE). Eight questions show statistically significant differences. They are related to resources used and other study habits. Only one of these questions, help-classmates-understand-concepts showed statistically significant difference between HPs and LPs as well.

Resources used. use-external-sources-when-confused and use-external-sources-for-exam-prep revealed that SPE tend to use external sources more often than SNPE. SPE also report practicing questions from external resources more frequently, but the difference was not significant ($p = 0.056$, $r = 0.247$). On the other hand, SNPE report using core course material (textbook, slides, or podcasts) more than SPE (use-textbook-when-confused and use-textbook-for-exam-prep).

Other Study Habits. According to memorize-facts-for-exam-prep and memorize-code-for-exam-prep, SNPE report memorizing facts and code more frequently than SPE. Moreover, make-own-questions-for-exam-prep indicates that SPE are more likely to report creating their own exam questions. Lastly, SPE tend to report helping friends more often than SNPE (help-classmates-understand-concepts).

5 DISCUSSION

5.1 Performance and Study Habits

Many of the differences in study habits between HPs and LPs might be considered forms of self-regulation [21]. This would be consistent with the findings of Chinn et al. [7], who found that self-regulation-related habits, such as attending lectures, are highly correlated with student performance. We find that habits exercised more frequently by HPs (i.e. understand-all-code-before-submitting, predict-output-to-understand-code, predict-then-run-to-understand-code, and recall-similar-questions-if-stuck-for-exam-prep) all indicate that HPs tend to follow through with their learning process.

Although the questions above could be considered self-regulation, they could also be simply associated with more motivation to learn the course content. Students who are more motivated to learn might be more apt to spend more time with their code to understand it fully (understand-all-code-before-submitting) and to engage in the prediction process when learning new code as they may be more curious to see how it works (predict-output-to-understand-code and predict-then-run-to-understand-code).

Consistent with our prior work [18], we found that procrastination exhibited by LPs often resulted in them asking friends and classmates for help, rather than instructional staff. According to our prior work, LPs had a tendency to start their assignments late so they often lacked the opportunity to ask instructional staff for help. We do note, however, that the prior work reported that HPs procrastinate as well, but they were just more likely to finish the assignment quickly without needing this help. So both groups of students procrastinate, but only LPs suffered for it.

Despite the contradiction to the prior work, we suspect HPs' less frequent attendance of midterm review sessions could be because they were more confident in their understanding and felt less compelled to attend the midterm review. It could also be that our prior interviews only included SNPE and in the present work, HPs who were SPE chose not to attend. It may also be that HPs had fewer confusions in the timeframe leading up to the midterm as they were able to resolve them earlier, whereas LPs needed more assistance closer to the midterm.

It may be tempting to assume causation from these findings, that the study habits associated with HPs and LPs are what cause students to struggle or succeed. However, as noted above, there are multiple explanations for why HPs and LPs differ in their behaviors. For example, HPs may be simply more motivated to learn the content and that is what leads to the differences in study habits; or LPs may be simply unable to spend the time to fully understand all the code they submit because they are already behind. As such, future work should seek to understand the causal nature of the associations found in this study.

5.2 Predictions Matter

We were encouraged by the finding that HPs were more likely to report making predictions about new code in the process of trying to understand it. This is consistent with the literature on constructivism and the importance of students engaging with concepts deeply [4]. It is also consistent with the improved learning outcomes from Peer Instruction in CS1 as the Peer Instruction process requires students make predictions [10, 24, 25, 31, 38] and from the important role predictions play in causing students to learn from classroom demonstrations in physics [9].

5.3 Performance and Prior Experience

Section 4 indicates that not all HPs' or LPs' study habits based on our prior work [18] are closely related to performance. For example, using external resources and creating new practice questions on their own are more frequently exercised by SPE relative to SNPE than HPs relative to LPs. Moreover, memorization is exercised more often by SNPE relative to SPE, rather than LPs relative to HPs. This suggests that some of the observed behaviors in our prior study that were associated with HPs or LPs may have really been observations of SPE or SNPE, since SPE are more likely to be HPs.

Only one habit, help-classmates-understand-concepts is related to both performance and prior experience. We suspect this is because HPs are more likely to feel confident about their understanding and are hence willing to help others. Similarly, SPE are likely to have more knowledge at the start of the class and feel more comfortable helping. Again, causation is difficult here, as it is possible that the act of helping students leads to better understanding.

One surprising, but encouraging, outcome of this study is that the observed differences in study habits between HPs/LPs and SPE/SNPE appears to be mostly orthogonal. We know from Section 2 that prior experience is one of the primary factors in student success [35], and SPE in our dataset are more likely to succeed than SNPE according to the two-sided Mann-Whitney U test ($p = 9.57 \cdot 10^{-4}, r = 0.861$). Given that SPE are more likely to also be HPs, the orthogonality is all the more interesting.

We provide two possible conjectures as to the source of this orthogonality. First, higher performance of SPE could be the result of actual knowledge gained through prior experience rather than learning better study habits. This would mean that study habits of HPs are not conferred simply by having prior experience. Second, the eagerness of SPE to learn beyond the given course material could simply be a byproduct of their existing knowledge and higher performance in class. For instance, SPE could simply have more time to explore external study materials since they already understand some of the course material.

In sum, prior experience still appears to impact student outcomes. In order to better aid students in need, we may wish to disaggregate possible benefits incurred through gaining prior experience: study practices and prior knowledge.

5.4 Threats to Validity

The survey was administered in a single course at a single institution, so the results may not represent the overall student population. Moreover, although survey questions were crafted using student quotes from a prior qualitative study, students may have not interpreted the prompts properly. Lastly, our dataset comprised of students' self-reported responses which might be different from the observations uncovered during qualitative interviews.

6 CONCLUSION

In this study, we explored the differences in self-reported study habits between higher- and lower-performing students. We found that some study habits are more common among higher performing students (e.g., predicting the output of new code in the process of understanding it). As these study habits might simply be an artifact of prior experience, we also examined the differences between students with and without prior experience. Although there were different study habits for those with or without prior experience, these were not the same as those for higher- and lower-performing students. Instead, many were associated with learning from sources outside of the course. Our findings suggest that prior experience and study habits are different in how they are associated with student success. We recommend that instructors encourage students to understand all their code before they submit it, and perhaps even enforce this by adding a follow-up checkpoint after each coding assignment. Additionally, to prepare for written exams, we suggest instructors also recommend students to try and make connections to similar questions they have seen before, if they get stuck. Lastly, we believe that instructors should encourage students to predict the output of code snippets, as this was another successful study practice.

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