Peer Networks and Instructor Resources as Complementary Support Systems in Six CS Classrooms

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Abstract

Collaboration with peers is associated with benefits in the form of advice, information, and positive expectations of oneself. This paper explores the peer collaboration networks that formed in six undergraduate computing classrooms along with students' usage of instructor office hours and the online class forum. We used survey responses from 166 students to construct collaboration networks and analyzed them using hypothesis testing and methods from social network analysis. We found that men were more likely than women to be isolated, and that isolation had a significant negative relationship with academic performance. Finally, we observed that students who were isolated *and* made no use of instructor help sources performed dramatically worse on a final assessment than students who either had collaborators or made use of instructor resources, suggesting that peers and the instructor acted as complementary academic support systems. Interventions to emphasize social learning and to identify at-risk isolated students may help improve outcomes for students at the margins.

CCS Concepts

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

Keywords

Peer collaboration, help-seeking, social network analysis

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1 Introduction

Learning is a sociocultural process of human development. Students in post-secondary computing courses have a number of social learning resources available to them, e.g., their peers [4, 6] and their instructors (either through a class Q&A forum [32, 34] or office hours). They may also consult non-social sources like large language models [12, 31, 36] or course materials [17]. In this paper, we studied the interplay between students' use of social resources and academic performance in six computing classrooms.

Participation in a network of peers can positively impact a student's academic persistence and performance [1, 3, 7] and expectations of themselves [25]. However, not all students participate in peer collaboration networks, e.g., because they feel underprepared (or over-qualified) for the course materials, they are wary of violating academic integrity policies [6], are working within a competitive environment [4], or they are new to the institution and do not yet have a strong social network [25]. Other social learning resources are also available, like the instructor's office hours or the online class forum [16], though not all students use them for a variety of reasons [6]. Different social resources (e.g., peers, the instructor) likely play complementary roles in supporting students academically—usage of instructor-provided social resources (like office hours) may compensate for the lack of participation in the peer network, and vice-versa.

Given the social nature of a classroom and the importance of peers as a resource, we studied students' participation in the peer networks that formed in six classrooms, their usage of instructor-provided social help resources, and their summative academic performance. We addressed the following research questions.

- **RQ1** What is the structure of the peer networks we observed? Who participates, and with whom?
- **RQ2** What is the relationship between participation in the peer network and performance on a summative assessment?
- **RQ3** What is the interaction between participation in the peer network and use of instructor help resources (office hours and an online class forum) and their relationship to summative assessment performance?

Our results shed light on computing students' use of social help resources, letting us learn who participates, who does not, and how this is associated with academic performance.

2 Background

Wenger describes classrooms or other educational settings as *communities of practice*, where learning is a "two-way relationship between people and social learning systems in which they participate" [43]. Members can benefit from sharing a joint enterprise (e.g., succeeding in a course) and differences as well as common ground (e.g., prior CS learning experiences). In this way, a classroom can be considered a social system with learners and teachers both playing a role in shaping its connectivity, boundaries, and norms.

A strong peer network is a form of *information-related social capital* [23], facilitating advice about things like which courses to take, grading policies, and study materials. The presence of high-ability individuals in a peer network can positively affect classmates' achievement [1] and students with high network centrality (students who are connected to many of their classmates) tend to also be high-achieving students [37]. Involvement in a peer network is an indication of *social integration* in an institution. This can play a role in a student's analysis of the benefits of college attendance and success [39], which in turn can affect academic performance and retention [3, 7]; these effects have also been observed in computing courses [2, 21]. Being *isolated* in the larger peer network is therefore associated with voluntary withdrawal from college [39].

Peer collaboration, when it occurs, tends to occur early during academic problem-solving [4, 6, 17, 19]. Peers are *readily available* and *adaptable* [6, 17], qualities that tend to be prioritized when students are selecting help resources [18]. Students also find peer relationships to be mutually beneficial as opposed to involving a unidirectional flow of help [4, 6], and benefits include an enhanced sense of belonging in their discipline and students' expectations of themselves [25]. Notably, students have reported preferring their peers over course staff as a source of help even if it is less likely to lead to a solution [6], a preference that appears to develop in children at an early age [8]. Instructors often play formal evaluative roles that can introduce a perceived or actual threat of judgement when seeking academic help [15], and some students, as a result, have reported avoiding seeking help from instructors [6].

That said, some factors also prevent students from collaborating with their peers. For example, students have reported worrying about accidentally violating academic honesty policies when consulting peers [4, 6]. A competitive environment—where a student's success (e.g., ability to be let into the CS major) could depend on other students' success—could also have a dampening effect on peer collaboration [4]. Finally, to benefit from peer collaboration, one must have a peer network—lacking this can lead to feelings of isolation and not knowing whom to turn to for help [6, 7, 39].

3 Methodology

3.1 Context

Our study took place at Cal Poly San Luis Obispo, a primarily-undergraduate public institution in the western United States. Our CS department has a competitive enrollment policy—students are either admitted directly into the Computer Science major or must meet GPA thresholds to transfer into the major, which can negatively impact students' sense of belonging in computing [28]. Our classes have 30–35 students. We studied peer networks in four in-person courses (six offerings).

GrC is an introductory programming course usually taken by Graphic Communication majors. 82% of students were second- or third-year students. The class was mostly made up of women (86%) and had the lowest percentage of isolated students of all the studied classes (three students, 11%).

Eng is an introductory programming course taught to various non-computing engineering majors. Women were underrepresented in this class, and all but one were either isolated or worked with other women in the class.

OOP is a first- or second-year object-oriented programming course required for computing majors and minors. Our study includes three offerings of this course taught by the same instructor in different terms. Depending on the student's entry point into the CS program, this course might be taken in the Spring of one's first year or the Fall of one's second year.

SE is a software design course taken by computing majors (89% second- or third-year students). It had the highest percentage of isolated students (37%).

While the choice of studied courses was convenient—Eng was taught by the first author, and all others were taught by the last author—they also provided good coverage in terms of how advanced they were and the population of students likely to take them.

All courses involved a lecture component and a lab component involving the same students and instructor. It is in the lab sessions that we expected course-specific collaboration networks to develop. Students are typically allowed to collaborate with each other on lab assignments, though all work they turn in must be their own. It is also worth noting that students often make use of lab time to ask the instructor questions about coursework.

3.2 Data Collection

Data collection took place during the period Spring 2024 to Fall 2025 in six classrooms (spanning four courses). We collected data primarily through a survey given to students toward the end of the ten-week academic term. Students were given around 10 minutes to take the survey during class time and were awarded a small amount of extra credit for taking the survey. This helped encourage high response rates within each classroom. This was required since we cannot accurately study a social network if it is missing many nodes. Students who did not want to consent to participate were given an alternative activity to earn the extra credit.

Consenting students were asked two broad classes of questions: background (gender,[1] race/ethnicity, and prior CS learning experiences) and peer collaborators. In the two OOP classes, our data also include consenting students' frequencies of office hour visits and the online class forum usage statistics. Finally, we collected students' scores on summative assessments. Responses to demographic questions are summarized in Table 1.

[1]The question about gender included the options *Woman*, *Man*, *Non-binary*, *Not listed*, and *Prefer not to answer*. One out of 166 students identified as non-binary. All others answered *Man* or *Woman*.

Table 1: Summary of research participant demographics.

Course	Term	*N*	Response rate	Pre-college CS	Gender		Race/ethnicity					
					W/NB	M	Asian	Black	White	Latine	2+	Other
GrC	Winter 2025	28	97%	25%	86%	14%	54%	0%	25%	7%	14%	0%
Eng	Spring 2024	25	84%	28%	32%	68%	20%	4%	44%	12%	16%	4%
OOP	Fall 2024	28	88%	39%	18%	82%	36%	0%	25%	29%	11%	0%
	Spring 2025	34	97%	94%	32%	68%	41%	0%	24%	15%	21%	0%
	Fall 2025	24	83%	50%	42%	58%	36%	0%	21%	33%	8%	0%
SE	Spring 2024	27	96%	74%	30%	70%	63%	4%	15%	11%	4%	4%

3.2.1 Peer collaboration networks. After answering demographic questions, students were asked to list any students in the class with whom they collaborated, studied, or discussed course logistics. For each listed classmate, students could classify the nature of their collaboration, choosing all that applied from the following options:

- *They helped me with coursework*
- *I helped them with coursework*
- *We collaborated on an assignment*
- *We discussed course logistics (due dates, grades, etc.)*
- *We studied together*
- *Other (free response)* — No students used this option

Students listed each collaborator in a free response question, usually by name. A member of the research team then manually standardized and encrypted each student's identifier, so that a participating student could be matched to other students' responses that listed them as a collaborator.

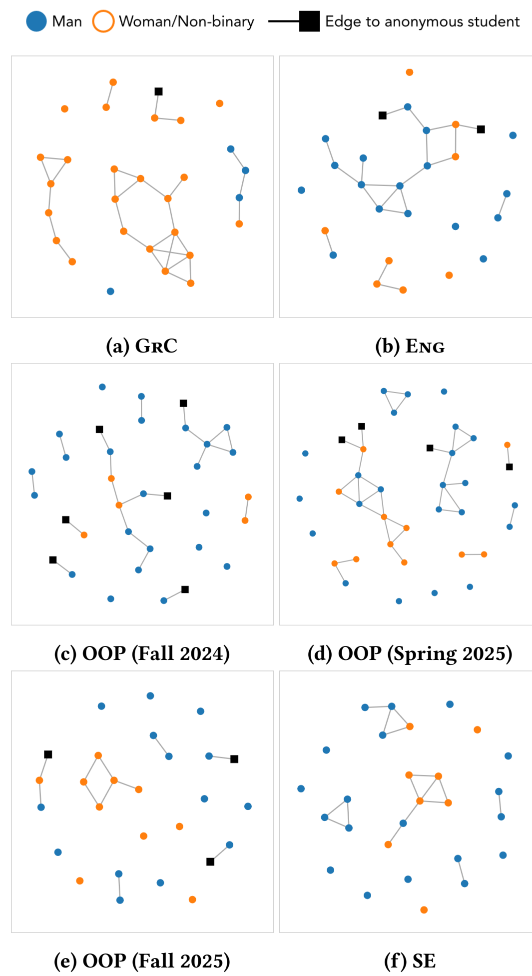
For each class, a graph was constructed in which each node is an individual student and each edge is a collaboration between two students. An edge between two nodes indicates that at least one of the pair listed the other as a collaborator. The peer networks so constructed are shown in Figure 1.

We initially intended to construct a directed graph, where edge direction denoted the direction in which helped flowed. However, echoing previous interview studies (e.g., [4, 6]) the vast majority of stated relationships were bidirectional (95%), with students selecting *I helped them* **and** *They helped me*, or selecting a bidirectional relationship like *We discussed...*, *We studied...*, or *We collaborated...*

Therefore, in the rest of this paper, we represent peer networks as *undirected* graphs: any listing of a collaboration between two students results in an edge added to the graph.

We took steps to assure students that their responses would not affect them negatively. It was emphasized that responses were assumed to be about coursework where collaboration was expressly permitted (e.g., lab exercises), and data would not be available to instructors until after the term had ended.

We took steps to omit data about students who did not consent to the research. If a student listed a non-consenting student as a collaborator, simply dropping the edge could falsely label the participating student as "isolated" if that was their only edge in the network. In these cases, the adjacent node was depicted as an *anonymous node* with no additional information. If two students listed the *same* non-consenting student as a collaborator, they would be given edges to *two separate* anonymous nodes. This ensures that no information about non-consenting students is retained in our dataset, and preserves the information that the consenting student "had a friend" in the classroom. This protocol was approved by our Institutional Review Board.



(a) GrC (b) Eng

(c) OOP (Fall 2024) (d) OOP (Spring 2025)

(e) OOP (Fall 2025) (f) SE

Figure 1: Peer collaboration networks in six classrooms.

Each network was a disconnected undirected graph made up of several *connected components*, i.e., smaller subgraphs in which each student has a path (but not necessarily a direct edge) to every other student in the subgraph. Each student is considered part of exactly one connected component, possibly by themselves (i.e., they were *structurally isolated*). Generally, each network contained a few isolates, many small components, and 1–2 bigger components. There were 166 students in our sample, of which 22% were isolated, 58% had one or two collaborators, and 20% had three or four.

3.2.2 Office hours and online forum usage. In the three sections of OOP, we collected data about students' frequency of attending instructor office hours or using the online class discussion forum.

"Instructor office hours" refers to hours during the week when the instructor is available for students to stop by to ask questions about course material. Office hour usage was collected through a lightweight online form. Only the frequency of office hour visits were tracked, not the length or purpose.

The courses used EdStem[2] as an online class forum. The forum was used for announcements from the instructor and for students to ask public or private questions asynchronously. Students were encouraged to ask questions publicly (and anonymously if preferred) if they were likely to be generally useful. We studied the number of days on which a student logged in to the forum and the number of times they posted a question on the forum.

3.2.3 Summative assessment performance. Scores ranged from 0–100%. In OOP and Eng, we used students' scores on a cumulative final exam. In SE, we used students' average performance on programming projects, since there was no final exam.

In GrC, we used students' scores on a cumulative take-home final exam. The exam was taken as a self-reflective exercise for participation credit. Students were asked to take it "realistically" and the solution was studied together in a class activity—students received full credit for participating in the activity. In this scenario, there was little incentive for students to "cheat" since they would receive full credit regardless. The exam was "graded" after the term concluded and those scores are used in this paper (mean grade 89%).

3.3 Analysis

We used the software packages NetworkX [9] and Pingouin [40] for analyses. Statistical significance for hypothesis tests was decided at $\alpha = 0.05$. We also report effect sizes to provide additional context.

For RQ1, structural properties of the peer networks (e.g., degree distribution, connectedness) can be gleaned from Figure 1 itself. In this study, we explored prior reports of reduced collaboration among men in educational contexts [10], as well as aspects of peer collaborations that were of practical relevance to instructors. We used Pearson's Chi-squared test [29] to test for a relationship between gender and isolation status, and methods from social network analysis to learn about *homophily*, i.e., the extent to which students collaborated with others who were similar to them in some way.

In social network analysis, *homophily* or *assortative mixing* is the tendency of individuals to preferentially associate with individuals that are similar to them in some way [27]. Given our later emphasis on network participation and summative assessment performance, and given prior work that highlights the importance of so-called "high-ability" individuals in the peer network [1], we studied the degree of homophily in our networks on the basis of gender and summative assessment performance (modeled in this case as an ordinal letter grade: A>=90, B>=80, C>=70, D/F<70).

[2]https://edstem.org

We sought to learn if preferential collaboration occurred to a substantially greater degree than one would expect in a randomly mixed network. For example, in a network where 50% of students received A grades, we would expect roughly 25% of edges to connect two A students under random mixing.[3] To conclude that assortative mixing between A-receiving students occurred, we would need to observe *more than* 25% of edges being between two A-receiving students. For each network, we computed Newman's assortativity coefficient (r) [27] for the ordinal grade variable. The value of r ranges from -1 to 1, with $r = 0$ indicating random mixing.

We used permutation tests [26] to decide statistical significance of the observed r value (commonly done in network science, e.g., [33]). Statistical significance can be computed as the proportion of r values from a large number of simulated networks that are more extreme than our observed r. This proportion represents the likelihood that our r occurred by chance, i.e., a p-value.

For RQ2, we used a Mann-Whitney U test [22] and Welch's unequal variances t test for differences in summative assessment scores between students who were isolated and those who were not; in addition to p-values, we report effect sizes as they are more actionable. Summative assessment scores were not normally distributed, requiring the use of non-parametric hypothesis tests.

For RQ3, we used descriptive statistics to study the performance of students who participated in the peer network, used instructor help resources, both, or neither. The small sample sizes within each group precluded the use of traditional hypothesis testing.

3.4 Threats to Validity

We describe threats to validity and mitigations where appropriate.

Construct threats are those that threaten operationalized concepts (e.g., "peer collaboration"). Students may not have remembered all the classmates with whom they collaborated, which could underestimate the connectivity of the network. An edge was considered to exist between two students if *either student* listed the other as a collaborator, which could overestimate the connectivity of the network. Requiring strict agreement between students for an edge to exist would have resulted in extremely sparse networks. Additionally, we considered it important to incorporate each student's *own perception* of their social network. Finally, isolated students were *structurally isolated* in our classroom networks, but may have had thriving peer networks outside the classroom.

Internal threats threaten cause-effect relationships. Our networks were formed in different courses with different collaboration policies. All courses involved lab exercises on which students were explicitly allowed to collaborate. GrC had a final project worked on in groups that may have inflated network connectivity.

Additionally, SE and the Fall 2025 OOP section had relatively low response rates, which may have inflated the percentage of isolated students. We note, however, that the isolated students themselves did not list any collaborators.

External threats are those that threaten the generalizability of results. We studied courses at one institution, so our results may not carry over to others. We studied six peer networks consisting of

[3]If the probability that one end of a randomly-constructed edge is an A-receiving student is 0.5, then the probability that both ends are A-receiving students is roughly $0.5 \times 0.5 = 0.25$.

students of different majors and seniority, so this threat is somewhat mitigated for results that held for all six networks. However, we are still limited to small class sizes (around 30 students)—collaboration dynamics may be quite different in large classes.

Our sample sizes concerning office hours and online forum usage are rather small, greatly reducing our statistical power.

4 Results

4.1 RQ1: Structure of the peer networks

Although the situation is improving at many institutions, computing remains a gender-imbalanced discipline. We sought to learn about network participation by men and women/non-binary students. Men made up a larger-than-expected proportion of isolated students. They made up 60% of the overall student sample, and 76% of isolated students (Figure 2). The relationship between gender and isolation was supported by a Chi-squared test of independence between two categorical variables [$\chi^2(1, N = 166) = 5.11, p = 0.024$]. Considering only the 124 non-isolated students, there was no significant difference between the number of collaborators for men and women/non-binary students [$U = 1623.5, p = 0.135$].

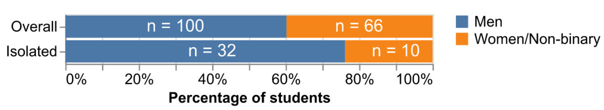


Figure 2: Men were more likely than women to be isolated.

We did not observe homophily on the basis of grades in any of the six classes (with neither the A–F split, nor a binary split between students who scored above and below the median). We return to this observation in our discussion (§5). Additionally, we applied the same procedure to measure homophily on the basis of gender. We saw strong gender homophily in five out of six networks. Coefficients and p-values for homophily on the basis of gender and grade are given in Table 2.

Table 2: Assortativity coefficients (r) and p-values on the basis of gender and ordinal summative grade.

	Gender		Grade (A–F)	
Network	r	p	r	p
GrC	**0.78**	**0.002**	-0.20	0.110
Eng	**0.56**	**0.015**	0.00	0.984
OOP (Fall 2024)	**0.44**	**0.040**	0.24	0.142
OOP (Spring 2025)	**0.50**	**0.028**	0.06	0.617
OOP (Fall 2025)	0.34	0.272	-0.12	1.00
SE	**0.49**	**0.032**	0.00	0.996

4.2 RQ2: Summative Assessment Performance

We tested for a difference in summative assessment performance between isolated ($\bar{x} = 69.14, s = 26.41, M = 73.05$) and non-isolated students ($\bar{x} = 79.49, s = 15.97, M = 83.33$).[4] Figure 3 shows the grade distributions for the two groups.

[4] $\bar{x}$: sample mean, s: sample standard deviation, M: median.

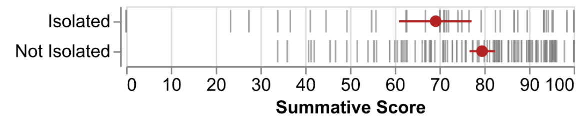


Figure 3: Summative scores for isolated ($N = 42$) and non-isolated ($N = 124$) students. The dot and line are the mean and 95% confidence interval for the group.

The Mann-Whitney U test was close to the significance threshold of 0.05, and showed a small-to-medium effect size [$U = 1901, p_{adj.} = 0.057$, CLES $= 0.40, r_{bc} = -0.20$]. We used the common language effect size measure (CLES) [41], which tells us that the probability that a randomly selected isolated student *outscored* a randomly selected non-isolated student was 40% (i.e., a 60% chance that a non-isolated student scores higher). The negative rank-biserial correlation ($r_{bc} = -0.20$) indicates that isolated students tended to score lower with a small-to-medium effect size. Welch's unequal variances t test suggested a significant difference in means [$t = -2.34, p_{adj.} = 0.047$, 95% CI [-19.25, -1.46], $d = 0.54$]. We report Cohen's d as the effect size measure, which suggested a medium effect size (about half of a standard deviation). The significant difference in means but not in the rank-based test may be because, while scores for isolated and non-isolated students had substantial overlap, there was higher incidence of outlying low scores among isolated students (Figure 3). Reported p-values include Holm-Bonferroni [11] adjustments for multiple comparisons.

Beyond the binary distinction, we explored whether the *number* of collaborators (which ranged from 0–4) was associated with performance. A Kruskal-Wallis H test [20] did not reveal differences in summative assessment performance among students with different numbers of collaborators [$H = 7.70, p = 0.10$]. We cautiously interpret these results as suggesting that (1) there is a meaningful distinction between having *some* or *no* collaborators, and (2) within this distinction, significant variability suggests other factors at play, some of which are explored in the following section.

4.3 RQ3: Office Hours and Forum Usage

Data about office hour visits and forum usage is only available for the three OOP classes. As a result, our sample size for this RQ is relatively small (86 students; 25 women, 1 non-binary, 60 men). The three networks contained 45 connected components, of which 22 contained more than one student. The summative assessment in these three courses was a closed-book final exam.

Usage of office hours and the online forum followed remarkably similar distributions. 58% of students did not visit office hours, and 55% of students did not post on the forum. 19% of students visited office hours once, and 17% of students made one post on the online forum. Only a handful of students made more than one post or visit. Pearson's Chi-squared test suggested a significant relationship [$\chi^2(1, N = 86) = 7.35, p = 0.007, v = 0.29$] between likelihood of posting on the forum and visiting office hours. A Cramér's v [5] of 0.29 suggests a medium-to-large effect size: students were likely to use *both* resources or *neither* (echoing results from Wanner et al. [42]). Unlike prior work [14, 19, 38], we found no evidence of differences in usage between demographic groups, though our lecture and lab context may influence practices in this regard (§3.1).

We explored the relationship between exam performance and use of instructor help resources. A Mann-Whitney U test suggested no significant difference in exam performance rank between students who visited office hours and those who did not [$U = 1024, p_{adj.} = 0.280$, CLES = 0.57, $r_{bc} = 0.14$]. Similarly, we did not see a difference in exam performance rank between students who posted on the forum and those who did not [$U = 1152, p_{adj.} = 0.083$, CLES = 0.63, $r_{bc} = 0.26$] (although, as in §4.2, we did see a difference in mean score between forum posters and non-posters [$t = 2.66, p_{adj.} = 0.029$, 95% CI [2.9, 20.13], $d = 0.55$]). Finally, we found that exam performance was significantly positively correlated with the number of days on which a student logged into the class forum [Spearman's rank correlation [35]; $\rho = 0.31, p_{adj.} = 0.017$, 95% CI [0.1, 0.49]]. This suggests that students appeared to benefit from the online forum even if they did not post there themselves. p-values include a Holm-Bonferroni correction for four comparisons.

We now turn to the interplay between network participation, resource usage, and exam performance. We found no relationship between isolation and resource usage: isolated students were just as likely to visit office hours [$\chi^2(1, N = 86) = 0.31, p = 0.58, v = 0.06$] and post on the online forum [$\chi^2(1, N = 86) = 0, p = 0.973, v = 0.06$] as students who had collaborators. We examined the students who had different combinations of network participation and resource usage. Given the co-incidence of visiting office hours and posting on the forum reported earlier in this section, we treat either activity as an instance of *using an instructor-provided resource*. Given our sample size, the number of students in each group is relatively small, making hypothesis testing fraught. Instead, we report summary statistics for key groups of students. The descriptive patterns below are suggestive but should be interpreted cautiously due to the small group sizes and lack of inferential testing.

11 out of 86 students were *structurally isolated from peers and did not use instructor resources*: they had no peer collaborators, did not post on the online forum, and did not visit office hours. Their average final exam score was 52% ($M = 45\%$).

12 out of 86 students were *instructor-supported*: they had no peer collaborators, but they posted on the online forum or visited office hours. Their average final exam score was 75% ($M = 73\%$).

23 out of 86 students were *peer-supported*: they had peer collaborators and did not visit office hours or post on the forum. Their average final exam score was 70% ($M = 68\%$).

40 out of 86 students were *instructor-and-peer-supported*: they had collaborators and either visited office hours or posted on the online forum. Their average final exam score was 76% ($M = 82\%$).

5 Discussion

Implications. Our results suggest that having *any* collaborators mattered more than *how many* or *which* (similar to findings from Wu et al. [44]). Students were *not* choosing collaborators on the basis of similar academic performance (§4.1) and structurally isolated students tended to score lower on summative assessments (§4.2), with a student's number of collaborators having no significant relationship with summative performance. Nevertheless, isolated students displayed high variability in grade outcomes; they were represented among both high and low scorers. This hints at the presence of additional factors that, in combination with isolation from peers, may play a role.

One such factor may be use of instructor resources. Students who did not have collaborators and did not visit office hours or post on the forum scored dramatically lower ($\bar{x} = 52\%, M = 45\%$) on the final exam than the class average ($\bar{x} = 71\%, M = 75\%$), albeit with high variability (§4.3). Exam scores improved substantially when students either used instructor resources ($\bar{x} = 75\%, M = 73\%$) or had peer collaborators ($\bar{x} = 70\%, M = 68\%$). While the small group sizes precluded hypothesis testing, these descriptive statistics are suggestive and these students ought not to be overlooked, particularly in early courses. Our observations suggest that use of instructor resources may have partially compensated for the lack of peer support within the classroom, and vice versa.

Recommendations. Although use of these social resources appears related to positive outcomes, whether or not a student will use them is a matter of their perceived availability and affordances. For example, a student may avoid office hours because they are wary of being judged for lack of knowledge or being behind [6]. Or they might struggle to engage with their peers if a course contains no collaborative components. We consider it important to encourage social learning, particularly in a time when generative AI tools threaten to erode social learning communities. That we observed positive associations between social learning and learning outcomes in the presence of generative AI tools is notable.

What and how students learn can be heavily influenced by interactions with their peers and instructor [13]. Instructors can take steps to "broker" connections between students through activities like study groups, group projects, and in-class discussions [43]. We place less emphasis on encouraging office hour visits or forum postings. The performance benefit of these resources appeared comparable to that of having peer collaborators, and relatively few students used them without also having collaborators. Moreover, visiting office hours can be challenging for students who are managing external obligations. Interventions aimed at increasing usage of instructor resources may therefore benefit only a few.

Future work. Qualitative studies may uncover reasons behind students' social learning habits, e.g., for the groups described in §4.3. For instance, we are interested in the influence of performance/mastery goal orientations [30] on network participation. Evidence of strong gender homophily and that men were more likely to be isolated (§4.1), both with support in prior work [10, 24], warrant further study. We did not study a required introductory programming course for computing majors, where disparities in access to secondary computing education may be influential. Finally, how does network participation relate to other academic outcomes like sense of belonging and intention to persist?

Acknowledgments

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