

Additional Evidence for the Prevalence of the Impostor Phenomenon in Computing

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ABSTRACT

Motivation Despite the widespread belief that computing practitioners frequently experience the Impostor Phenomenon (IP), little formal work has measured the prevalence of IP in the computing community despite its negative effect on achievement.

Objectives This study aims to replicate recent work that has suggested that IP experiences are widespread in computing students and to extend that work by exploring the relationship between the IP, progress in the program, and ethnic identity.

Methods A survey with several demographic questions (gender, ethnicity, international status, and year of study) and Clance’s IP scale (CIPS) was deployed to students in post-secondary computing courses. Correlations between demographic factors and CIPS scores were evaluated, and a linear model was constructed to explore the interaction between demographic factors of interest.

Results We reaffirm that a high proportion of CS students meet the IP diagnostic criteria and that women report higher CIPS scores than men. We also present evidence that Asian students with domestic and international status report different levels of IP experiences.

Discussion These findings highlight the importance – to educators at all levels – of cultivating belonging in computing communities.

CCS CONCEPTS

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

KEYWORDS

impostor phenomenon, impostor syndrome, belonging

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1 INTRODUCTION

The Impostor Phenomenon (IP), identified by Clance and Imes [11], occurs when an individual fails to recognize that they are as successful and competent as others perceive them to be. The phenomenon is common among high-achieving individuals. While the relationship between IP and performance is complex, IP has been linked to higher anxiety [3] and lower self-efficacy [21], which can impact performance outcomes such as retention [32].

In computing, the IP has received limited formal treatment, with only a single recent study providing alarming evidence that the IP is experienced at higher rates in computing than in other fields, with over half (57.4%) of the computing students surveyed exhibiting feelings associated with IP [28]. Women reported IP experiences at particularly high rates (71%). The IP may be particularly prevalent in minority groups in computing and may exacerbate the problem of retaining these individuals in the field [28].

This study aims to replicate and extend Rosenstein et al.’s investigation [28] of IP in computing in a different setting. We analyzed 754 survey responses about the IP from students attending a North American, research-focused university system to address:

- RQ1** Do the high rates of IP experiences reported by Rosenstein et al. replicate in a different post-secondary computing context?
- RQ2** Is the rate of IP experiences reported consistent across years of study in a computing program?

2 RELATED WORK

The Impostor Phenomenon (IP) was originally identified by Clance and Imes [11]. People facing the IP experience self-doubt and discount their successes, attributing them to external factors like luck,

rather than internal factors like persistence and ability. As a result, they fear that others will decide or discover that they are frauds and do not deserve the success they have enjoyed [12]. IP experiences have been linked to negative factors, such as higher anxiety [3] and underestimation of talents and accomplishments [12, 16, 21, 29], that impact important outcomes such as retention [32].

The IP is a general phenomenon that is experienced by high achieving individuals from a range of backgrounds [11, 12, 16, 26], but it has been specifically studied in STEM graduate students [7, 30, 32]. The IP has been found to be particularly prevalent in under-represented groups [13, 14, 29, 32], making it particularly relevant to computing education, given our ongoing issues with minority representation [4, 6, 24]. Despite the potential relevance to computing, only one recent study has focused on the issue of IP in computer science. Rosenstein et al. surveyed over 200 computer science students at a North American university to identify the prevalence of IP experiences [28]. They used the Clance Imposter Phenomenon Scale (CIPS) to measure the IP and found that computer science students reported, on average, a higher CIPS score (more IP experiences) than students in a range of other fields. 57.40% of the students in the CS population reported scores that exceed the diagnostic criteria, as compared to an estimated 27-48% in other fields. They also found that women in their population reported significantly higher CIPS scores than their male peers [28].

While not explicitly focusing on the IP, other work in computing education has reported findings that align with the results from Rosenstein et al. For example, Alvarado et al. reported that students perform equally well in class regardless of gender, but female students do not feel as confident about tutoring the courses in the future or even about future success in general [1]. Furthermore, male students with low marks tend to feel more confident to keep pursuing computer science than female students with higher marks [2]. Female students are also less likely to ask questions or participate in class [27]. Unfortunately, these issues do not appear to improve over time. The number of women in computer science courses tends to decrease through the course of study, and while the largest drop in participation occurs in the CS1 to CS2 transition [2, 23], upper year students report that the issues they experience persist or even increase through the years [1, 27].

Rosenstein et al. primarily measured the IP in upper year students [28], so more early year data is required to help us understand whether IP experiences contribute to the drop in participation between CS1 and CS2 and whether the prevalence of IP experiences changes through the course of study. Data from racially under-represented students is also needed. Work in other fields has found that the IP is particularly prevalent in under-represented groups [14, 32], but Rosenstein et al. did not detect a difference between racially represented and under-represented groups [28]. Few of the participants (25 of 203) identified as being in a racially under-represented group [28], so additional data is required to have sufficient statistical power to detect any difference.

3 METHOD

This study was designed to replicate and extend the previous study of impostor phenomenon (IP) experiences in computing authored by Rosenstein et al. [28]. As a result, similar data collection and

analysis methods were used where possible. The major differences in our study are (a) the target population, which is drawn from a different university and which includes undergraduates at all levels, rather than a selection of upper-division undergraduates and graduate students, (b) the inclusion of a brief explanation of IP in our consent materials, (c) differences in the timing of the survey, and (d) changes to the phrasing of questions soliciting ethnicity and program of study information. The first change affords an opportunity to replicate and extend prior work, and the latter changes were required by differences in our context. They are described in more detail in this section.

3.1 Data Collection

Data was collected using a three-part survey containing demographic questions and the Clance Impostor Phenomenon Scale (CIPS). The survey was administered to undergraduate students at two campuses of a research-intensive North American public university system. On both campuses, referred to as Site A and Site B, students were recruited by email at the end of the academic year (after all exams). Participation was strictly voluntary, with no compensation provided for participation. Unlike the Rosenstein et al. [28] study, students were briefly informed of the purpose of the study on the consent form.¹ At both Site A and Site B, all students enrolled in a CS course during the 2020-21 academic year were invited to participate. At Site A, 519 students participated from a total pool of 2430 (21.4%) and at Site B, 235 students participated from a total pool of 1750 (13.4%).

The first (demographic) section of the survey asked about the participant's program of study, international student status, year of study, gender, and ethnic or cultural origins. Four sections require further explanation. First, we asked about both *current* and *intended* program of study, since admission to computer science programs is competitive and occurs between the first and second years. Second, we asked for the number of courses (credits) completed, rather than a year of study, since the year of study may be interpreted in various ways. Third, when asking about gender, we used a short answer field to allow participants flexibility; the responses were then reviewed and coded as "man", "woman", "other gender identity", or "no response". Fourth, the question asking about ethnic or cultural background is derived from the census materials for our region, since some locally important groups were not included in the ethnic groups reported by the original study. As a result, some of the labels for specific categories differ from those reported in Rosenstein et al. [28], but we are able to map from our categories to theirs. The ethnicity question was implemented as a multi-select question to allow students to identify as having mixed ethnic origins. During analysis of ethnicity, we analyzed these students as being in a mixed-ethnicity category, rather than discarding their responses or including them in just one single-ethnicity category.

The second section of the survey administered the Clance IP Scale (CIPS) [9].² The CIPS is composed of 20 5-point Likert-style

¹The first paragraph of the form reads, "We are requesting your participation in a study investigating the extent of the impostor phenomenon (IP) in computer science students. The IP is characterized by self-doubt about skills and accomplishments and is commonly experienced even by highly successful people. These feelings can be accompanied by anxiety, which is why we are interested in identifying how common it is at our university."

²Permission is required to use or reproduce the CIPS and was obtained for this study.

questions and has been found to be internally reliable [8, 18, 20]. We chose to use this scale because it allows easy comparison to Rosenstein et al. [28] and also because it is the best evaluated and most frequently used scale for measuring IP [22, 30]. Concerns have been raised about the CIPS factor structure [18], so like Rosenstein et al. [28], we restrict ourselves to evaluating a single score from the instrument obtained by summing the responses, which generates a score between 20 and 100 [10]. Under Clance’s original interpretation, a score of 41-60 represents “moderate” impostor experiences, a score of 61-80 represents “frequent” IP experiences, and 81-100 represents “intense” impostor experiences.

The third section consists of a single, optional open text field that invites the participant to share “any feelings, events, or stories that illustrate your experience with the Impostor Phenomenon.” The responses to this question were not analyzed for this work but may have impacted responses or completion rates of the survey.

3.2 Analysis

In the next section, we describe the responses to CIPS for both the entire population (all students) and various sub-populations (e.g., by gender and year of study). Based on using D’Agostino’s K-squared test and visual inspection of QQ plots, the data did not appear normally distributed for sub-populations such as gender, year of study, and ethnicity, so we report the number of students in each population and the median and interquartile range (IQR) for the CIPS scores for that population, rather than the mean and standard deviation. We also chose to use the non-parametric Kruskal-Wallis H-test to compare the distributions of responses (a) between sites and (b) in sub-populations. Dunn’s multiple comparison test is used as a post-hoc test when the Kruskal-Wallis test indicates that there may be differences. When reporting Kruskal-Wallis results, we do not adjust for the total number of tests run across all populations; we provide the p-value for each test rather than claiming significance at an arbitrary α level. Box-and-whisker plots illustrating the distributions of the populations were produced and examined to support the analysis of the Kruskal-Wallis results. Due to space constraints, these plots are not provided in the text.

We also use linear regression to investigate the relationship between factors. Each of the predictor variables is categorical data, and the dependent variable is the CIPS score. We report R^2 for the model and standardized coefficients and p-values for each predictor.

4 RESULTS

Figure 1 shows the distribution of CIPS scores for both sites, and Table 1 provides more detail for various subgroups. The distributions at the two sites are similar, but Site B exhibits a slight left skew. The median CIPS score at both sites was 70 (with an IQR of 21-22), and over 68% of respondents at both sites exceeding the diagnostic criteria (a CIPS score ≥ 61).

The Kruskal-Wallis results reported in Table 1 provide evidence that the distributions observed at the two sites are comparable for most sub-populations. The exception is students in their second year of study, who exhibited generally higher CIPS scores at Site A (median: 73) than at Site B (median: 70). The two sites also have a different mix of respondents by ethnicity. At Site B, relatively

more respondents have East and Southeast Asian ethnic origins and fewer have European origins.

Due to program admissions policies at our university, characterization of students by program of study requires that we consider both *intention* to study computer science as well as current program of study. Table 2 presents details about these sub-populations. As before, the sub-populations appear comparable across sites, although students who are neither in the major nor have intentions to enter it have a notably higher median CIPS score at Site A and relatively fewer students at Site B are in the situation of not being in the CS major but intending to be. These differences are likely the result of program admissions policies and are discussed in Section 5.2.

Table 3 presents the results of Kruskal-Wallis H-tests comparing the distributions of CIPS scores between the sub-populations. We ran the analysis on each site as well on data from both sites where there is no evidence that the populations may be different. Low p-values were observed in two sub-populations: students in various years of study, and men and women.

The analysis of students in various years of study is inconsistent; possible evidence of a difference was observed at Site A but not Site B. (Previously presented analysis in Table 1 also suggests that the distributions between the two sites are different.) A post-hoc Dunn’s test of the Site A data identified suggestive but marginal differences between second-year students and most other groups (first years, $p=0.083$; fourth years, $p=0.078$; graduated students, $p=0.038$). These p-values were adjusted automatically using the Benjamini-Hochberg procedure to account for the multiple tests performed. This suggests a local effect at Site A affecting second-year students.

Table 3 presents strong evidence at both sites that women report higher CIPS scores than men. The effect size, ϵ^2 , across both sites is 0.037, a small effect as classified by Bosco et al. [5]. This data aligns with observations by Rosenstein et al. [28]. The data for students reporting another gender in Table 1 also suggests that they report higher CIPS scores, and we explore this in a post hoc analysis in combination with a more focused investigation of ethnic origin.

Although we saw no differences between students from represented and under-represented ethnic backgrounds as explored by Rosenstein et al. [28], we observed anomalies in the finer-grained ethnic background data. In particular, we know that the majority of the international students at our sites have South, East, or Southeast Asian ethnic backgrounds, yet in Table 1, we see that the median CIPS score for international students is lower than the median scores for students from those backgrounds. We performed a post hoc analysis to investigate this interaction as well as interactions with gender. Table 4 provides details on the linear model we identified, which was run on combined data from both sites and used domestic, male students of European descent as a baseline. The fit of the model is low ($R^2=0.086$), which is expected since we do not have a predictor that explains individual variation. However, the model reaffirms that women report higher CIPS scores than men ($\beta=6.37$, $p<0.001$) and suggests that people of other gender identities also report higher CIPS scores ($\beta=10.54$, $p=0.023$). The model also suggests that *domestic* students with East and Southeast Asian ($\beta=6.02$, $p=0.002$) and South Asian ethnic origins ($\beta=7.82$, $p<0.001$) report higher CIPS scores than domestic students of European ethnic origins. No evidence of a similar effect is seen in students with international status.

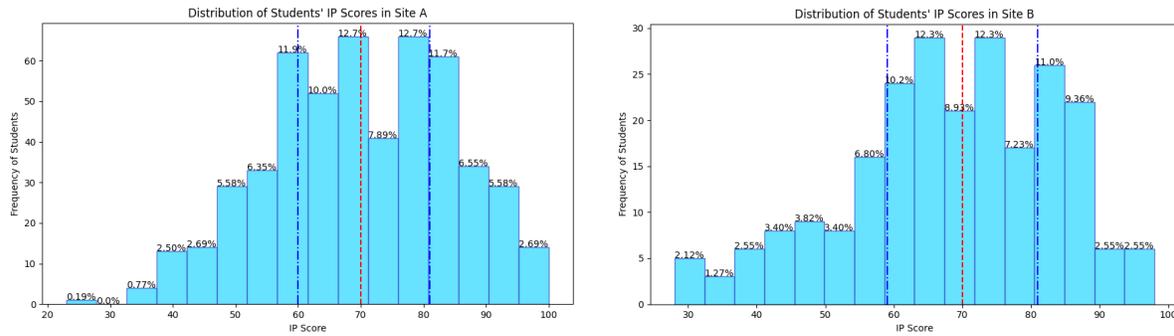


Figure 1: Distribution of CIPS scores observed at Site A (left) and Site B (right). Scores are in bins of size 5. The middle line indicates the median, and the lines to the right and left represent the IQR.

Table 1: Response counts, median CIPS scores, and the percent above the diagnostic criteria (a score ≥ 61) for various populations. Students did not answer all demographic questions, so n varies between populations. The rightmost columns report the results of a Kruskal-Wallis test between the two sites. Low p -values are in bold emphasis.

Population	Count (% Total)		CIPS Median (IQR)		Above Diag. Criteria		Cross-Site Comparison	
	Site A	Site B	Site A	Site B	Site A	Site B	Test Stat.	p-value
All Valid Responses	519 (100%)	235 (100%)	70 (21)	70 (22)	69.94%	68.94%	1.111	0.267
Domestic Students	394 (76%)	167 (71%)	71.5 (22)	70 (21)	72.84%	70.66%	1.542	0.123
International Students	113 (22%)	62 (26%)	68 (21)	67 (25.5)	62.83%	62.90%	0.314	0.754
All Undergraduate Students	504 (97%)	228 (97%)	71 (21)	71 (22.75)	70.83%	69.74%	0.993	0.321
Year 1	100 (19%)	68 (29%)	70 (22)	69.5 (21.5)	71.00%	64.71%	0.480	0.631
Year 2	125 (24%)	60 (26%)	73 (20.5)	70 (16)	78.40%	71.67%	2.148	0.032
Year 3	117 (23%)	49 (21%)	71 (22)	77 (29)	67.52%	65.31%	-0.193	0.847
Year 4	162 (31%)	51 (22%)	70 (21)	69 (20)	67.28%	78.43%	-0.525	0.600
Graduated Students	14 (2.7%)	7 (3.0%)	59 (20.75)	57 (20)	42.86%	42.86%	0.970	0.332
Male Students	338 (65%)	151 (64%)	70 (20)	67 (22)	68.64%	62.93%	1.609	0.108
Female Students	123 (24%)	53 (23%)	77 (23)	76 (19)	76.42%	84.91%	0.382	0.702
Students of Other Gender Identities	9 (1.7%)	†	85 (28)	†	77.77%	†	†	†
Racially Represented Student Groups	385 (74%)	184 (78%)	70 (21.5)	70 (20.75)	70.39%	70.11%	1.118	0.264
European Origins	76 (15%)	22 (9.4%)	67 (26.75)	60.5 (28.75)	60.53%	50.00%	1.064	0.287
South Asian Origins	142 (27%)	66 (28%)	74.5 (23)	71.5 (19.25)	73.94%	77.27%	0.455	0.649
East and Southeast Asian Origins	167 (32%)	96 (41%)	70 (21)	69.5 (19)	71.86%	69.79%	1.022	0.307
Racially Underrepresented Student Groups	117 (23%)	43 (18%)	72 (23)	66 (28)	72.65%	60.47%	1.363	0.173
African Origins	13 (2.5%)	†	77 (17.5)	†	92.31%	†	†	†
Caribbean Origins	11 (2.1%)	†	75 (19)	†	90.91%	†	†	†
Latin, Central, South American Origins	11 (2.1%)	†	69 (34)	†	63.64%	†	†	†
Middle Eastern Origins	41 (7.9%)	15 (6.4%)	68 (16.5)	66 (27)	68.29%	53.33%	0.537	0.592
Mixed Origins	40 (7.7%)	18 (7.7%)	73 (25.75)	64.5 (29.25)	70.00%	66.67%	0.765	0.444
Other Origins	†	†	†	†	†	†	†	†

†Populations with count < 5 are omitted.

5 DISCUSSION

5.1 RQ1: Replication of Rosenstein et al.

This study was primarily designed to replicate a study by Rosenstein et al. [28] that demonstrated that, at their site, upper year undergraduate and graduate students in computing reported higher CIPS scores and met the diagnostic criteria for IP at a higher rate than students in other disciplines. Our findings corroborate theirs. They found that 57.4% of their students met the diagnostic criteria for IP – higher than estimates of 27.93% to 47.69% in other disciplines. An even larger number (68%) of our respondents met the criteria.

We do not yet have evidence to explain why we observed higher CIPS scores than Rosenstein et al. or why, in general, we are seeing higher CIPS scores than in other disciplines. There are, however, small differences between the processes used in our work and in Rosenstein et al.’s which may have influenced our results. First, the original study was conducted at an unspecified time during the term, and our survey was delivered after the end of the term when students have finished final exams and are receiving grades. The recent exam experiences could have triggered impostor feelings. Second, the original study did not use the term “impostor phenomenon” in the materials. Anecdotally, we know that students who

Table 2: Response counts, median CIPS scores, and the percent above the diagnostic criteria (a score ≥ 61) for students in various programs of study. Not all students provided program of study information, so categories may not add up to 100%. The rightmost columns report the results of a Kruskal-Wallis test between the two sites.

Program of Study	Count (% Total)		CIPS Median (IQR)		Above Diag. Criteria		Cross-Site Comparison	
	Site A	Site B	Site A	Site B	Site A	Site B	Test Stat.	p-value
Pre-program admission	113 (22%)	76 (32%)	70 (22.5)	72 (20.75)	69.03%	67.11%	0.380	0.704
Has Intentions for Major	88 (17%)	64 (27%)	72 (24.5)	73 (25)	71.59%	67.19%	0.842	0.400
Has No Intentions for Major	25 (4.8%)	12 (5.1%)	63 (17)	66.5 (12.75)	60.00%	66.67%	-0.892	0.372
Post-program admission	401 (77%)	155 (66%)	71 (21)	68 (22)	70.32%	70.32%	1.205	0.228
CS Major	247 (48%)	104 (44%)	69 (21)	67.5 (24)	68.02%	68.27%	0.297	0.766
Not CS Major, has Intentions for Major	85 (16%)	10 (4.3%)	73 (23)	70 (9.5)	72.94%	90.00%	0.546	0.585
Not CS Major, has No Intentions for Major	69 (13%)	41 (17%)	76 (21)	68 (21.5)	75.36%	70.73%	1.437	0.151

Table 3: Results of Kruskal-Wallis tests between sub-populations. Low p-values are in bold for emphasis.

Sub-populations (N)	Test Stat.	p-value
International and Domestic Students		
Both Sites (561, 175)	2.767	0.096
Site A (394, 113)	2.493	0.114
Site B (167, 62)	0.244	0.621
Year of Study (1, 2, 3, 4, grad)		
Both Sites†		
Site A (100, 125, 117, 162, 14)	12.219	0.016
Site B (68, 60, 49, 51, 7)	7.393	0.117
Men and Women		
Both Sites (489, 176)	24.363	<0.001
Site A (338, 123)	14.695	<0.001
Site B (151, 53)	9.984	0.002
Represented and Underrepresented Ethnic Origins		
Both Sites (569, 160)	0.0702	0.791
Site A (385, 117)	0.171	0.680
Site B (184, 43)	0.002	0.961
Pre-Admission Program (CS, not CS)		
Both Sites (152, 37)	2.151	0.143
Site A (88, 25)	2.758	0.097
Site B (64, 12)	0.132	0.716
Post-Admission Program (CS, intending CS, not CS)		
Both Sites†		
Site A (247, 85, 69)	5.439	0.066
Site B (104, 10, 41)	0.453	0.798

†Omitted due to evidence that populations may not be comparable.

took the survey found the term – and the experiences described in the scale – identifiable, and some expressed relief in having a name for those experiences. This emotional release was intense enough that we sent a debriefing message after all responses were collected to offer students resources to help manage their feelings. This provides further evidence that the IP experiences catalogued are real and intense, but it is also possible that students reported higher scores because of their reaction to the term.

We do have access to responses to the third section of our survey, which asked students for examples of experiences that illustrated their experience with the IP, which may provide insight into factors that contribute to impostor experiences in computing. A qualitative analysis of that data is the subject of future work.

Table 4: Details of the linear regression investigating the interaction between international status and ethnic background. Low p-values are in bold for emphasis.

Model:

$$\text{CIPS} \sim \text{Gender} + \text{Ethnicity} * \text{InternationalStatus}$$

$$R^2=0.086, F(17,625)=3.439, p<0.001$$

Predictor	Coeff. (β)	p-value
Female	6.37	<0.001
Other Gender	10.54	0.023
Domestic African Origins	7.02	0.165
Domestic Caribbean Origins	6.92	0.195
Domestic East and Southeast Asian	6.02	0.002
Domestic South Asian Origins	7.82	<0.001
Domestic Middle Eastern Origins	3.87	0.183
Domestic Other North American	13.63	0.185
Domestic Latin/Central/South American	5.16	0.263
Domestic Mixed Origins	3.14	0.256
International	0.732	0.904
International African Origins	-1.87	0.859
International Caribbean Origins	6.29	0.556
International East and Southeast Asian	-3.95	0.536
International South Asian Origins	-7.55	0.256
International Middle Eastern Origins	0.37	0.962
International Mixed Origins	4.21	0.601

5.1.1 Gender. Rosenstein et al.’s study also found a statistical difference between CIPS scores reported by men and women. They used ANOVA and reported a small to moderate effect (Cohen’s $d=0.47$, $p=0.0046$). We can corroborate this finding, having also found a small effect ($\epsilon^2=0.037$, $p<0.001$). We also found suggestive evidence, in a linear model generated as a post-hoc analysis, that students who identify with a gender other than man or woman also report a higher CIPS score, although this population is small (~ 9 participants). These results reinforce the need to create more welcoming spaces in computing and to build academic programs that make development of a sense of belonging [15] and social identity [19] core goals.

5.1.2 Ethnic Origins. The original study did not observe a difference between students identifying with represented (White or Asian) versus under-represented ethnic groups. Due to regional differences, we used a different set of questions to elicit this information, asking for ethnic origin and providing a larger set of

options. We mapped European origins to their “White” category and those with South, East, and Southeast Asian origins to their “Asian” category. We also included students with Mixed origin in the underrepresented category, rather than dropping them from the analysis. Under that categorization, we, like them, did not find any evidence of a difference in reported CIPS scores between students in represented and under-represented groups.

We had asked students about international status due to the relatively large number of international students in our university system (22%-26%). When combining that predictor with ethnic origin, we find strong evidence that domestic-status Asian students have a very different experience from domestic students of European origin or international-status Asian students. In short, the experiences of students from similar ethnic origins can vary significantly, and this result suggests that we should look beyond ethnicity when considering the experience in computing programs of students with diverse backgrounds.

The lack of statistical evidence of an effect for other ethnic groups should not be taken as a signal that the IP is predominantly an Asian issue. The median reported CIPS scores for several under-represented ethnic groups is high (e.g., 77 for students claiming African origins and 75 for students claiming Caribbean origins), but the demographics of our program are such that these groups are relatively small (e.g., less than 15 students each). Additional studies will be required to obtain a large enough sample to have the power necessary to make a claim on statistical evidence.

5.2 RQ2: IP across Years of Study

This study collected data from students at all stages of an undergraduate computing program. Rosenstein et al. [28] compared undergraduate and graduate populations; they did not see a difference between those two groups and did not investigate finer-grained populations. We examined students in each year of study as well as by program status – comparing students who were still seeking entrance to a computing program to those in the program.

Overall, we did not see a general increasing or decreasing trend through the undergraduate program: CIPS scores remained relatively consistent across all four years. At both locations, graduated students (those who had just finished their degree) reported the lowest CIPS scores, as might be expected. This could be an effect of reaching a recognizable milestone, but it’s also possible that it’s merely an effect of a small sample: very few graduated students responded to the survey.

As documented in Table 1, we saw slightly different distributions across years at our two sites. In particular, there is marginal evidence that the scores for students in year 2 at Site A are higher than those at Site B ($p=0.032$). We also saw weak evidence, from a post-hoc Dunn test, that scores in the second year at Site A were higher than those of students in other years of the program.

We believe these differences are the result of local issues and are unlikely to generalize across contexts. The central issue is that program admission at our university happens after the first year and is competitive. Nguyen and Lewis have demonstrated that competitive enrollment practices have a detrimental effect on students’ sense of belonging [25]. Similarly, prior work in our context has found that the stress of program admission affects students not

only in the first year but also later in their program [17]. At Site A, these issues have been particularly acute recently, and it has led some students in the second year to be trapped in a liminal state, as they continue to seek admission to a program that many of their peers have obtained entrance to. In Table 2, we report on two categories of students not in the major. These groups are composed of a mix of students who (a) are continuing to seek entry, (b) were interested in entry but later decided they were unlikely to meet the requirements, and (c) always sought entry to the minor (not major). The first two of these groups, who have been denied entry to the program, are at high risk of feeling like an impostor, and we believe this accounts for the higher CIPS scores documented in that table.

5.3 Threats to Validity

We have discussed several threats related to differences between our study and the original we are attempting to replicate: differences in the question soliciting ethnic origins, the inclusion of the term IP on our consent form, and the timing of our survey (end of term) relative to the original (middle of term). These are a threat to direct comparisons of CIPS values across studies, but the overall trends we have observed – higher rates of students above the diagnostic criteria than those observed in other fields and higher reported CIPS scores by women – are consistent with the original study.

The COVID-19 pandemic is another threat. This study was conducted at the end of the 2020-21 academic year, which was the first year to be delivered fully online due to the pandemic. Students experienced a very different academic year than normal. Many remained at home, for example, and none were able to form the same kind of bond with instructional staff and peers that they would expect in an in-person academic year. As a result, many students have experienced additional stress and disconnection from the community [31] that may have increased the prevalence of IP experiences. This may partially explain the higher CIPS scores that we observed as compared to Rosenstein et al.

6 CONCLUSIONS

This study provides additional evidence that students in computing programs experience the IP at higher rates than in other fields and that women, in particular, report high rates of IP experiences. Beyond a direct replication of the results reported by Rosenstein et al. [28], we also found evidence that ethnicity is correlated with IP experiences. Our data suggests a complex relationship between ethnic origin and international/domestic status, which suggests that there are underlying factors, such as local community and culture, that will need further study in a computing context. These results also suggest that we must move beyond a coarse analysis of “represented” and “under-represented” groups.

While additional replication in other contexts – in particular, outside of post-secondary, research-intensive environments – will be needed, we believe these results suggest that *cultivating a sense of identity and belonging* is of utmost importance and, as suggested by DuBow et al., should be a priority in program development [15]. We also suggest that further work in this area should be expanded to qualitatively investigate the kinds of experiences that students report as contributing to their feelings of being an impostor.

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