LESSONS LEARNED COMPARING COMPUTER SCIENCE STUDENT AND RECRUITER RESUME SCREENING EVALUATIONS

A Thesis

by

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ABSTRACT

Only about 11% of applicants receive an invitation to interview for a typical computer science position because of the highly competitive nature of the field. Therefore, there is a need for future computer science graduates to understand which factors contribute most to the quality of their resume and how these qualifications translate to their employability. To explore students' understanding of resumes, college students and professional recruiters were shown sample entry-level computer science resumes and asked to determine which resumes they would move to the next level of the hiring process. Findings support the importance of GPA, work experience, projects, and technical skills on entry-level computer science resumes. Students were more likely to move resumes to the next level and spent about 3 seconds longer than recruiters screening each resume. Students also significantly overestimated the value added by previous work experience such as internships, and the value of personal projects on resumes. Additionally, students differed from recruiters in the proportion of time spent evaluating resume sections. Taken together, these factors may account for students being more lenient in resume screening decisions and suggest that students may have misunderstandings regarding industry resume expectations.

DEDICATION

To my mother, father, and sister who support me in everything.

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All other work conducted for the thesis was completed by the student independently.

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1. INTRODUCTION*

1.1 Transitioning from College to Industry

Computer and Information Technology is a broad field of computing-related occupations comprised of roles typically sought by graduates from Computer Science and related majors such as Information Technology (IT) and Information Sciences (IS). Jobs within this field enjoy much higher wages than average and are projected to increase in demand within the next 10 years (1). A combination of these factors contribute to the attractiveness of computer science as a major, and the competitiveness that arises from such popularity. To enter this industry, prospective students must first navigate the hiring process.

1.1.1 The Computer Science Hiring Process

As described by recruiters in Stepanova's (2021) work (2), the typical hiring process for entry-level computer science positions consists of 10 steps:

1. Identifying the Hiring Need
2. Recruiting
3. Review Applications
4. Phone-Screen
5. Interviews
6. Background and Reference Check
7. Decision
8. Job Offer
9. Hiring
10. Onboarding

The pivotal step within this process is step 3, the Review Applications phase. In addition to being the most common hiring practice mentioned by recruiters, the majority of applicants are cut from the process in this stage. Quotes from recruiters involved in Stepanova's study indicate that only the top 10-20% of resumes are selected to continue with the hiring process. These recruiter comments align with data from application tracking software. Reports indicate that for a typical computer science position, only about 11% of applicants will receive an invitation to interview (3). Effectively, for computer scientist positions, 80-90% of applicants are eliminated from further consideration due to the quality of their application. It stands to reason that the candidates with superior applications are chosen to move forward in the process. While job applications generally consist of submitting a cover letter and various personal information, arguably the most universal and influential component of the application is the resume.

1.2 The Importance of Resumes

Perhaps no singular document is of greater importance or relevance to gaining employment than the resume. Whether through a traditional paper resume or a digital portfolio, the onus of the job seeker is to impress upon employers that he or she possesses the requisite skills and abilities for the position being applied.

Resume screening is the initial step of the job selection process (4; 5) and often serves as the first point of contact between job seekers and employers (6; 4). To organizations, resumes provide an economical means of identifying qualified candidates before investing in more expensive methods of selection such as interviews (7). To applicants, resumes play a key role in establishing first impressions, maintaining candidacy in the selection process, and gaining invitations to interview (8; 6; 5).

The significance of resumes extends far beyond this initial screening process. Research indicates that initial application screening also has a considerable impact on post interview evaluations (9; 10; 8). Assessments following interviews are especially important because hiring recommendations from interviewers strongly influence organizational hiring decisions (11).

Candidates are often selected to be interviewed because of the credentials on their application and the resulting impressions formed as a result of the information presented (12). A resume is a snapshot of these credentials. Accordingly, in order to optimize an application it is imperative to first establish what constitutes an attractive resume.

1.3 Proposed Work

In this work, data collected from a student study and a recruiter study are compared in order to draw conclusions regarding the overall competency of students in regards to their ability to identify the value of items on computer science resumes. The hope of this study is to aid computer science students trying to enter the computing industry by revealing any misconceptions students may have as well as providing recommendations. An additional aim of the following research is to provide recommendations for computer science educators, so that they are equipped with current information regarding how recruiters are screening computer science resumes. Another motivation of this thesis is to extend the current research in eye tracking, particularly as it relates to expertise-related differences, to resume screening.

The goal of this research is to establish answers to the following questions:

1. Which items on entry-level computer science resumes most directly influence screening decisions?

2. What gaps exist between computer science students' and their recruiters' perceptions of entry-level computer science resumes?

3. Do computer science students and recruiters exhibit similar resume screening behavior?

2. RESUME COMPONENTS AND SIGNIFICANCE*

2.1 Common Resume Sections

Within resume literature there are three sections that have been established to be effective for all types of job seekers. These sections are as follows: Academic Qualifications, Work Experience, and Extracurriculars.

2.1.1 Academic Qualifications

The academic qualifications section of resumes can further be divided into several parts. For entry-level resumes, these segments may include the candidates' education, GPA, and relevant coursework.

2.1.1.1 Education

The education section on the resume of a university graduate typically contains the college attended as well as the major and minors either attained or being pursued at that college. Having a relevant major is often a prerequisite depending on the type of position. Possessing a relevant education has also been shown to produce more positive perceptions of a candidate's competence potential and predicted salary (13). College major may also influence the interpretation of other resume components. For instance, recruiters associate accounting majors with a high GPA as indicative of mathematical prowess whereas a high GPA in sales is associated with higher language ability (14).

The reputation of the university attended also influences hiring decisions. A survey by Indeed reported that only 4% of hiring managers do not care about where a candidate's degree was obtained and that 48% believe the college attended plays a somewhat important role in the hiring process (15). Despite graduates from elite colleges performing only slightly better than their peers on average and being more likely to create work environment issues (16), candidates from premier institutions are preferred by hiring managers for entry-level and executive positions (15). Graduates from superior academic institutions also tend to have higher earnings than their peers (17; 18). Notably for computer science graduates and other majors within science, technology, engineering, and mathematics (STEM), one study found there were no differences in income regardless of institution quality (19).

2.1.1.2 GPA

Ample evidence supports the inclusion of GPA on entry-level resumes across all majors (20; 21; 22; 23; 24; 6; 25). Although listing GPA is more beneficial to candidates with high GPA, including GPA on the resume regardless of its quality was found to be more favorable than withholding the information (24; 6). In general, GPA is more important for entry-level workers than for experienced workers (26) and GPA loses its predictive value over time following graduation (27). GPA is often used by organizations as a screening tool where a minimum or cutoff GPA is set to reduce the applicant pool and simplify the process of selecting candidates to interview (28; 29; 30). Though common, this practice is not universal, suggesting that the precise usage of GPA in screening decisions may be dependent on the recruiter (31).

As a result of both actual and perceived linkages between GPA and desirable employee qualities, GPA is considered useful for predicting future job performance. College GPA may indeed be a valid metric for assessing candidates. A metastudy determined that GPA was positively correlated with job performance .16 overall and .30 after correcting for research artifacts (27). GPA may correlate with job performance because of the fact that a high GPA is a strong indicator of conscientiousness (32; 33; 34; 35; 36), general cognitive ability (34; 37; 38), and motivation (34; 37). Perhaps even more importantly for candidates, GPA has also been linked to recruiters' perceptions of conscientiousness (39; 40), cognitive ability (41; 14; 28; 29; 33; 39), and motivation (22; 41; 14; 28).

Past studies of students and recruiters in business-related occupations such as accounting, marketing, and managerial work have contradictory findings regarding GPA. Students either underestimated the significance of GPA (42; 43) or had a realistic understanding of its importance as compared to recruiters (44). In one study of accounting students and recruiters, students were less harsh when reviewing candidates with low or average GPA (20). However, a more recent study of marketing graduates reported that students overestimated the importance of GPA (45).

Academics are regarded as highly important for majors within the computing field (46). Although recruiters are cautioned against relying on GPA for screening Information Technology (IT) resumes (30), a high GPA is of moderate importance when hiring for IT positions (47). Students in majors within the computing field recognize that GPA is a factor in the hiring process; when hiring for a fictional software development position, CS undergraduates were more likely to recommend the applicants with high GPAs than low GPAs (48). While students recognize that GPA is often used in screening decisions in the computing field, the extent to which students believe GPA influences application quality may differ from recruiters. This current study tests if GPA is considered when hiring CS majors and whether CS students correctly valuate GPA.

2.1.1.3 Relevant Coursework

Support for the inclusion of relevant coursework on resumes is mixed. A survey of Fortune 500 personnel administrators reported that listing minor or major courses on the resume was fairly unimportant (24). However, a survey of business professionals taken two years later found that resumes listing relevant coursework received more invitations to interview than those without (6). Given that job-related coursework has been linked as a significant factor in recruiter perceptions of applicant fit and employability (49). Relevant coursework may indeed be worth including in the academic qualifications section.

2.1.2 Work Experience

The inclusion of previous work experience on resumes is also strongly supported by literature (21; 50; 23; 51; 24; 25). One metastudy identified work experience as the highest correlated measure in predicting future job performance (52). For students applying for entry-level positions, work experience is often in the form of internships. Prior to graduation, having at least one past internship improves a students' chances of obtaining other, future internships (53). Following graduation, internship experience increases the probability of being invited to interview (54; 55).

One study of business-related industries found that previous internship experience improved the probability of an interview invitation by 14.3% (54). A separate study across all industries reported an only marginally smaller 12.6% improvement to interview chances for applicants with past internship experience(55). Internships may improve a prospective hires' chances because of the job-related technical and non-technical skills that are developed as part of the experience (56; 57). Although relevant experience results in more positive applicant perceptions (13), even irrelevant work experience may merit inclusion in the resume (51; 25).

The only studies found in the literature review that directly compare student and recruiter perceptions of work experience involve business-related majors. In these studies, students either overestimated the importance of work experience (20; 58) or correctly assessed its value (44; 42; 59) as compared to recruiters. It is difficult to draw a conclusion from these earlier studies because they did not explicitly use internships to represent work experience. More recently, a study of marketing majors found that students significantly overestimated the importance of internships on resumes compared to either recruiters or faculty (45).

In a study of desirable qualifications for entry-level software application developers, previous internship experience was among the most desirable qualifications for prospective candidates and was only becoming more important over time (60). In support of this finding, a later study of job postings identified previous work experience as one of the most frequently requested competencies for CS graduates (61). Another identified relevant work experience, irrelevant work experience, and internships/co-ops as important for entry-level IT workers (47). Students in the computing field recognize the importance of previous work experience in hiring decisions; one study reported that 60% of participating students considered experience when hiring for a fictitious software development position (48). We test the extent internships and other work experiences are factored into the resume screening process for entry-level CS recruiters and whether students are able to identify the role that internship experience plays on entry-level resumes.

2.1.3 Extracurricular Activities

Opinions on whether or not to include extracurriculars on resumes are mixed, ranging from inconsequential (24) to being of moderate importance (23; 5). Recruiters favorably view leadership positions in extracurriculars and career-related societies (4). For business, sales, and accounting majors, applicant employability is higher when the extracurriculars are not related to fraternities or sororities (14; 62). Honor societies with Greek titles received a similar treatment to fraternities and sororities from recruiters, implying that students may need to provide a description to help recruiters distinguish between honor societies and social organizations on resumes (62). Extracurriculars may add value to resumes because they are associated with higher interpersonal skills (14; 63; 39) and higher levels of conscientiousness and extraversion (64). However, there is minimal evidence that extracurricular activities are desirable for entry-level computing positions. Of the seven given hiring criteria for hiring Information Systems (IS) employees, leadership through extracurriculars was the lowest rated hiring criteria by recruiters (65). In a more recent study, extracurricular activities were the lowest rated skill, trait, or knowledge area considered somewhat important for entry-level IT majors (47).

Studies comparing student and recruiter perceptions of extracurriculars are limited to majors outside of CS. In these studies, students either overestimated (45) or correctly assessed the importance of extracurriculars (44). Only one of these studies differentiated between Greek societies and professional organizations. However, students overestimated the importance of the extracurricular in either case (42). In a study involving non-Greek undergraduates, Greek undergraduates, Greek Alumni, and hiring personnel, the non-Greek undergraduates were the least likely group to agree with positive Greek stereotypes and most likely to agree with negative stereotypes (66). The present study divides extracurriculars into clubs and Greek societies and tests the influence that each has on the resume screening process.

2.2 Computer Science Sections

For entry-level CS students, additional sections to list skills and to describe projects may also warrant inclusion. It should be noted that no literature directly supporting the inclusion or omission of these sections was found during the literature search.

2.2.1 Skills

Although studies support the inclusion of skills and special aptitudes on the resume (50; 67), there is less support for dedicating a section on the resume to skills. Despite this, the frequency with which technical and non-technical skills are mentioned in CS literature suggests these skills need to be included in some form on the resume. The idea of creating a separate section to list skills may be limited to more technical occupations.

The majority of research for computer-related majors such as IS, IT, and CS makes references to technical and non-technical skills, alternatively referred to as hard and soft skills (68; 69; 70; 71; 60; 72; 73; 74; 61; 75; 76; 77; 78; 79; 80; 81; 47). Although technical skills were universally seen as important by recruiters, they were often ranked lower in importance as compared to non-technical skills (68; 71; 72; 74; 75; 79; 80; 47). The idea that non-technical skills are of greater importance was not universal however, with some studies finding the opposite to be true (60; 73). The previous studies all found that both technical and non-technical skills were important in the computing field.

Out of all the technical skills, programming fundamentals and programming languages were the most frequently requested (60; 73). More often, technical skills are sufficient in new graduates (82); however, a lack of project experience and the inability to properly utilize software tools are some of the more commonly mentioned insufficiencies of recent CS graduates (83; 84).

Non-technical skills that fall under categories such as communication, teamwork, problem-solving, and time management have become a point of emphasis across all industries (85). Three of these skill categories — communication, teamwork, and problem-solving — were also identified as essential by CS recruiters. Notably though, for computer science positions specifically, critical thinking skills as a category were mentioned more frequently than time management skills (69; 60; 86; 79; 80; 81; 47). Recent CS professionals are more commonly reported to have deficiencies in non-technical areas, specifically concerning verbal and written communication skills (82; 83; 84). These preparation gaps likely exist because of differences between coding assignments within academia, and those performed in a professional setting (87).

In a study where students considered applications for a fictional software developer position, CS undergraduates most frequently considered technical skills when making hiring decisions (48). Despite technical skills being the largest factor in the study, the majority of students also agreed that soft skills were still vital qualities for candidates to possess (48). Similarly, an earlier survey of IT students found that students were able to recognize technical skills as important, but not sufficient in themselves (88). One survey of IS majors compared student and recruiter perceptions of skill requirements. Interestingly, students underestimated the importance of nearly every non-technical and technical skill category, implying there is a significant perception gap between computing professionals and students (74). Despite this finding, undergraduates generally understand the importance of non-technical skills (69; 74; 86) although students significantly underestimate the importance of problem-solving ability (69). Students and recruiters differ more regarding technical skills with students underestimating their importance (69; 74). The current study tests both the influence of technical and non-technical skills on recruiters' resume screening decisions and the ability of students to assess the role these skills play in the resume screening process.

2.2.2 Projects

Compared to other established resume sections, the projects section of the CS resume may be the most niche. CS majors are encouraged to work on projects in part because they facilitate the development of soft skills (48; 89). In the eyes of recruiters, software projects provide insights on the teamwork abilities and critical thinking skills of a candidate (79). Software projects completed outside of regular coursework are considered especially valuable, because they convey motivation (80).

Open source software projects are also beneficial, as they are considered to be good indicators of ability (90). As opposed to resume credentials which are susceptible to exaggeration or faking, open source projects are highly transparent and reflective of true programming skills (91). Repositories on hosting services such as GitHub often house these projects. If made public, these repositories can be mined to estimate a programmers skillset (92). Based on GitHub profile activity, employers make inferences regarding a candidates' technical skills, motivation, and values and believe these impressions are more reliable than those gathered from resumes alone (93). Furthermore, user activity on GitHub such as the number of commits, languages used, projects owned, and post discussions provides employers with insights on a candidates' coding ability, soft skills, and personality (93; 94).

CS students also recognize the importance of projects in their education. Students often cited projects as a means of developing teamwork abilities and communication skills (95) and preferred project-based learning courses over those with only traditional lectures and exams (96). Although these findings suggest that students recognize the importance of projects to their professional development, they offer little help in predicting how students believe projects are factored into an application. This study seeks to establish whether or not projects listed on resumes contribute to the success of resume screenings and if students are accurate in their beliefs.

3. THEORETICAL BACKGROUND*

3.1 Expected Factors Differentiating Recruiters and Students

Recruiters and students are entirely separate populations and as such will likely exhibit differences in their resume screening behavior. Though there will likely be some variation within these groups, members of either population will in all likelihood be more similar to one another than to members belonging to the other group. The difference in performance would likely be due in part to the gap in expertise and differences in their understanding of real-world computer science positions.

3.1.1 Expertise

Differences in resume screening experience between students and recruiters likely account for discrepancies in resume screening decisions. In personnel selection, recruiters are relative experts compared to students. Here, an expert is defined as a member of the more knowledgeable group and a novice as a member of the less knowledgeable group (97). Experts possess more domain-specific knowledge and organize this knowledge into patterns that enable superior performance in domain-related tasks (98). An expert is more successful at selecting appropriate strategies and is able to identify the most relevant information to make decisions (99; 97). Past studies in personnel selection reveal that students incorporate more irrelevant aspects in screening decisions than do recruiters (100; 101). Because of their reliance on unimportant criterion, students have been regarded as a convenient, yet inappropriate subject group for examining resumes (102). Additionally, experts consider resume items indicative of future organizational performance as more important than novices (103; 100).

Students are consistently more lenient and give higher overall ratings to resumes than do recruiters (20; 104; 105; 106). The frequency and replicability of this finding suggests an underlying root cause. To explain this phenomenon, several hypotheses have been proposed. Early theories have suggested that underlying differences in category width between recruiters may explain differences in selection decisions between recruiters (107). Category width refers to the inclusivity of a category according to an individual, leading to differences in what a person considers to be a good representative of that category. For instance, a broader definition of the category "ideal candidate" offers one potential explanation for the leniency shown by student reviewers. A similar theory is that students and recruiters define different cutoff points when assessing the acceptability of a candidate (104). Others posit that students are more likely to give higher ratings to fellow students because they are like themselves (105). Students may also not fully understand the degree of competence expected of them from the workforce (106). As such, it is likely that students will move more resumes to the next hiring level than will recruiters.

The amount of time recruiters spend screening resumes has not been extensively researched. Resume screening is a highly idiosyncratic practice (108), which may explain the lack of research. An early study found that recruiters for accounting, banking, sales, office administration, management training, and management information systems spent between 30-120 seconds screening each resume (23). A more recent study involving human resources and business graduate students spent an average of 16 seconds when reviewing an administrative assistant resume (109). Experts are able to solve problems faster because they use the best strategies (97), so it seems likely that recruiters will spend less time screening resumes than students.

3.1.2 Applicant Fit

A large portion of a recruiters' job consists of narrowing down vast applicant pools to identify the most qualified candidates for the position in the question. To accomplish this, recruiters partially rely on the concept of fit (110). There are two distinct yet commonly recognized types of fit.

- **Person-Job (P-J) Fit:** The degree of equivalence between the knowledge, skills, and abilities possessed by the applicant and demanded by the position (111).

- **Person-Organization (P-O) Fit:** The congruence and overall compatibility between an applicant and an organization (112).

Although applicant fit is more commonly applied to the interview stage of the hiring process (49; 113), recent evidence suggests that recruiter assessments of fit begin during the resume screening stage (114). While recruiters will have both a distinct position and company culture they can visualize while reviewing resumes, students will have neither. Instead, students will only be able to speculate on how well an applicant will fit the job and company they envision.

4. DATA COLLECTION AND PROCESSING*

4.1 Participants

Students participating in the study were recruited through emails and short recruitment speeches at the beginning of computer science classes. All students that participated in the study were undergraduate computer science majors. In total, 77 undergraduates were recruited for the study.

Recruiters were recruited at STEM career fairs on college campuses, at industry fairs, and at employers' offices. In all, 221 recruiters participated in the study. All recruiters in the study hire software engineers and had prior experience evaluating computer science resumes. The industry of the recruiters can be seen in Table 4.1.

Table 4.1: Recruiter Industries

Industry	**Freq**	**%**
Computer systems design & services	46	23.5
Finance, insurance, real estate, & rental leasing	28	14.3
Professional, scientific, & professional services	22	11.2
Industrial & miscellaneous chemicals and/or petroleum	14	7.1
Public administration	13	6.6
Information & communications	11	5.6
Business support services including employment support services	9	4.6
Administrative & other support services	6	3.1
Educational, health, & social services	6	3.1
Other Industries	41	20.9

Note: Since this is a human subjects experiment, approval was obtained by the IRB. Approval obtained by TAMU IRB under RB numbers IRB2017-0079D and IRB2015-0183D.

4.2 Experimental Process

The experimental process was run on two separate populations. In the first experiment, students completed the study in empty study spaces and classrooms and utilized Tobii X2-60 eye-trackers. In the second experiment, recruiters completed the study in private booths at career fairs and various office spaces and used Tobii Spectrum eye-trackers. The eye trackers used in both studies were set up as shown in Figure 4.2.

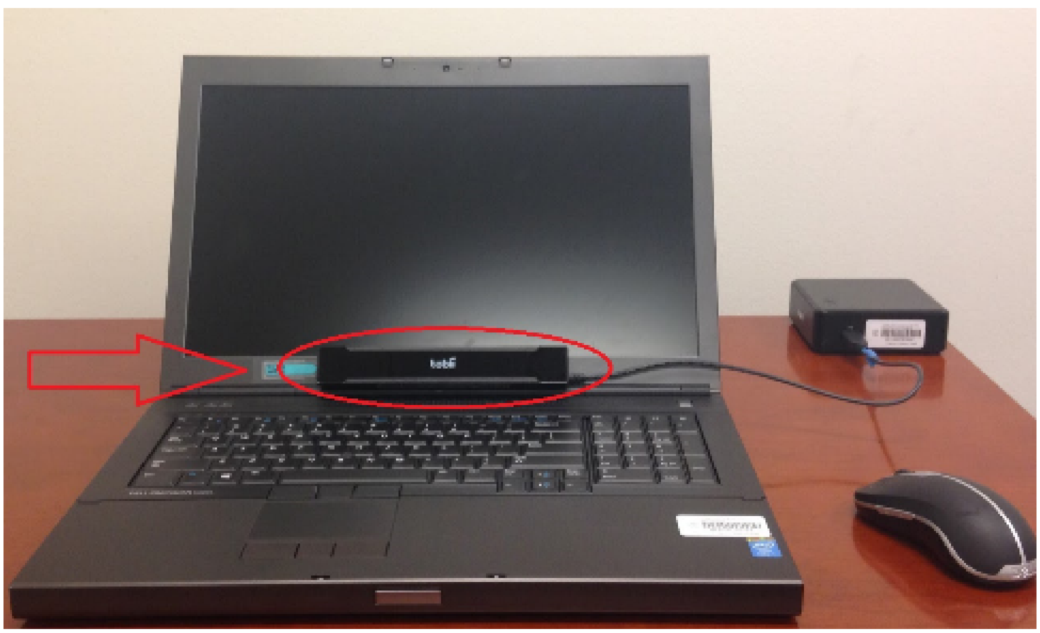

Figure 4.1: General eye tracker setup

All participants signed a consent form prior to participation in the study. Each participant was informed that they could drop out at any point without penalty and were asked if they had any questions prior to proceeding with the study. The eye trackers were then calibrated to the participant. Next, participants were given verbal instructions as well as written instructions on screen. Participants were first presented 5 example resumes as a means of orienting themselves to the task. They were then shown 30 resumes to review at their own pace. For each resume, participants had the option to select a checkbox to indicate whether or not they would move the resume to the next level.

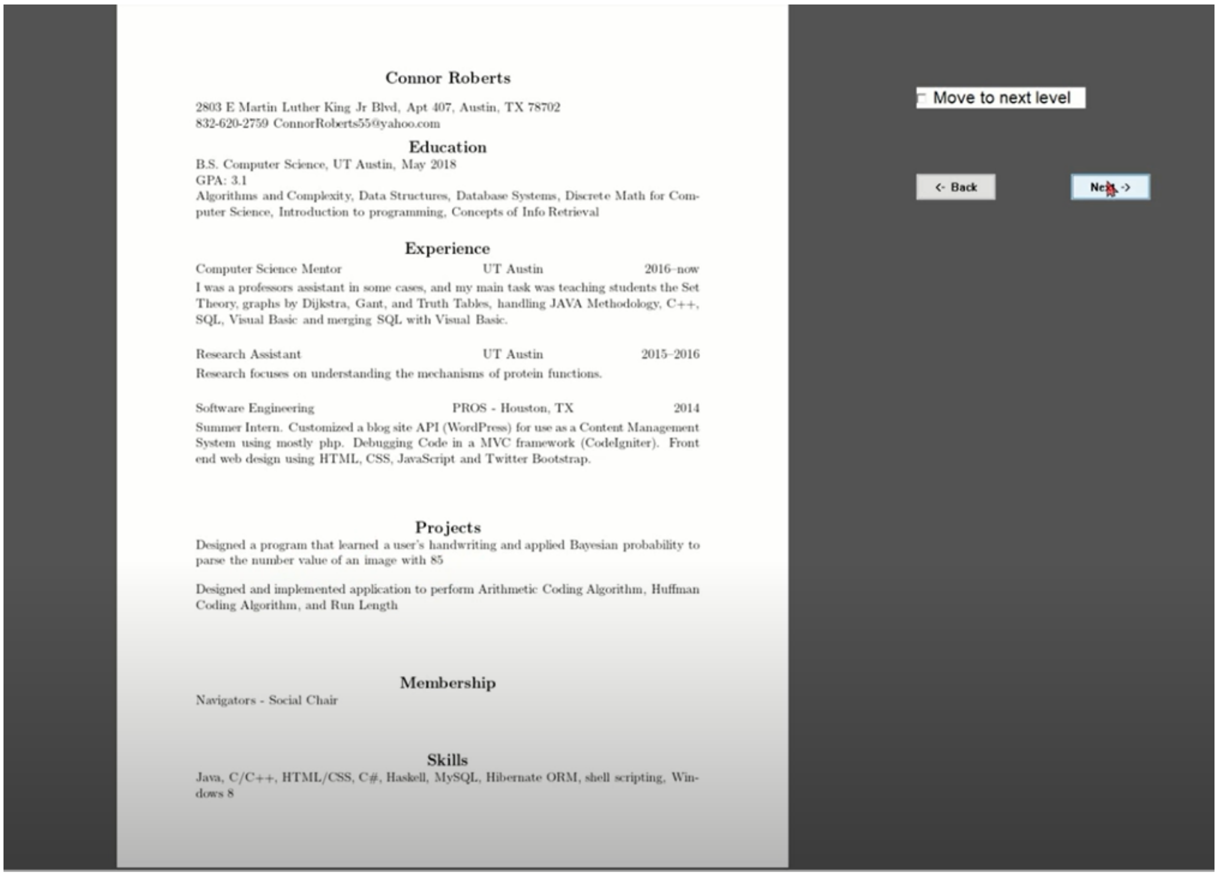

Figure 4.2: Participant View

After rating all the resumes, participants were asked what job they were thinking of while reviewing the resumes. Then resumes were brought back in a second round. If students had moved a resume to the next level, they were asked to answer three questions about the resumes. Recruiters were asked three questions about each resume regardless of whether or not they moved a resume to the next level:

1. Please rate the quality or "hireability" of the previous candidate.

2. What type of position do you think this candidate will most likely end up in?

3. What starting salary would you guess that this candidate would receive?

After the screening process was completed, participants answered a short demographics survey on the computer. The study itself was self-paced and completed using a mouse and keyboard. Students were given $20 and recruiters were given $50 for their participation in the study. The data collected were then de-identified to ensure the anonymity of the participants.

4.3 Study Combination

Not all participants were able to be used for the study. Since the studies were not initially designed with comparison in mind, some resume items shown to recruiters and to students had slight differences. For instance, for work experience, clubs, and skills there were entries unique to either students or recruiters, thereby making some resumes shown to either students or recruiters theoretically impossible to be shown to the other. To preserve the integrity of the resumes being compared between studies, any resume with one of these exclusive entries was removed, and a subset of comparable resumes from each study was used for statistical analysis. This limited the total usable participants to 73 computer science undergraduates and 197 recruiters. Demographics information for the remaining participants used in the combined study analysis is shown in Table 4.2.

4.4 Resume Generation

All resumes were unique and randomly generated using techniques as described in (115). Resumes in both experiments used five primary sections. At the top of resumes was Education; this section contained information about an applicant's college, degree, GPA, and coursework. Coursework was not always listed on the resume, but college, degree, and GPA appeared on every resume. College and degree were each held constant. GPA ranged from 2.2 to 4.0 with an average GPA of 3.3 on resumes. Below the Education section was the Experience and Projects sections. These sections contained between 0-3 different internships (average 2) and 0-3 projects (average 1) respectively. The next section, Membership, contained extracurricular activities such as club

Table 4.2: Demographics & Outcomes of Resume Reviewers

Category	Response	Recruiter	Student	Sig Dif
Gender	Male	54.31%	84.93%	Yes
	Female	44.67%	15.07%	Yes
	Other	1.02%	0%	Yes
Race	White	80.02%	54.79%	Yes
	Asian	7.61%	31.51%	Yes
	Black	7.10%	5.48%	Yes
	Native American/Hawaiian Islander	1.02%	2.74%	Yes
	Other/Prefer Not to Say	4.06%	5.48%	No
Ethnicity	Hispanic/Latino	17.3%	21.9%	Yes
	Not Hispanic/Latino	82.5%	78.1%	Yes
Total Participants:		197	73	

All results are two-sided two sample t tests between the number of each category for recruiter and students. Significance is marked at the .05 level.

involvement and any fraternity or sorority involvement. The last section, Skills, listed between 0-15 technical and non-technical skills. An example resume generated is shown is in Figure 4.3.

4.4.1 Benefits of Randomization

In traditional resume studies, participants are shown the same several resumes to assess. This is positive in some respects such as enabling matched-pairs statistical testing and intraclass correlation calculation. However, this approach falls victim to template bias, as described in (115). Template bias refers to the statistical problem that arises from the use of repeated variable groupings. Essentially, if variables are packaged into repeated bundles then the effects observed from statistical testing may arise from the bundle of characteristics rather than from the specific characteristics intended to be tested. By incorporating randomization in the resume items shown, the repeated bundling of specific characteristics is removed. For the purposes of this study, the randomization aspect provides a means of isolating the effects caused by specific resume items.

While recruiters were never specifically instructed on the precise position they were hiring for, recruiters were asked what position they were thinking of when screening the resumes.

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Education

B.S. Computer Science, Texas A&M University, May 2019
GPA: 2.7

Experience

SAS Programmer Summer Intern — Sterling Life Sciences - Houston, TX — 2018
Used SAS to design quality checks for questionnaires. Quickly learned a new programming language. Developed abilities to work as part of the team.

Summer Camp Counselor — Pali Overnight Adventures — 2017
Duties included, but were not limited to: Cared for 20 six to eight year olds. Served as a music instructor teaching guitar in a specialty "Rock Star" camp. Worked in the recording studio with Logic Pro.

Computer Lab Assistant — Texas A&M University — 2015–2017
Assisted students with programming and exam review questions Installed new software onto lab computers Helped with troubleshooting of lab printers

Projects

Multiplayer 3D space combat simulator game created primarily in C++. Main Menu was created in Java. Game Graphics were rendered using OpenSceneGraph.

Web Crawler: Wrote a crawler for a small web, designed an index structure, and wrote a search engine (abstract syntax tree) to handle queries.

Membership

Catholic Students Association - Treasurer
Texas Aggie Democrats - Web Master

Skills

C/C++, Javascript, Python, Haskell, Ruby on Rails, VBA under Excel, Qt, CISCO CCNA, Reliable

Figure 4.3: Example Resume

Table 4.3: Positions Recruiters Considered

Position	Frequency
Software Developer	145
Web Developer	44
App Developer	21
Data Scientist	20
Management	19
Quality Assurance	13
Internship	12
Tech Support	12
Business Analyst	9
Cybersecurity	8
Technician	8
Consulting	6

5. RECRUITER AND STUDENT SCREENING DECISIONS*

5.1 Recruiter Survey

All recruiters involved in the study were surveyed to determine which characteristics they were looking for on entry-level computer science resumes. Recruiters were able to select as many or as few resume characteristics as they deemed necessary. Students were not asked this question. The results of the survey are tallied in Table 5.1 and shown graphically in Figure 5.1.

Table 5.1: Recruiter Survey Table

Characteristic	Frequency	%
Work Experience	165	83.3
Projects	132	66.7
GPA	115	58.1
Specific Skills	73	36.9
Leadership	53	26.8
Distinctiveness	24	12.1
Other	18	9.09
Public Service	14	7.07

Over three-quarters of the recruiters surveyed indicated that prior work experience was a characteristic of importance when screening entry-level computer science resumes. Over half considered projects and GPA to be important factors during the screening process as well. Interestingly,

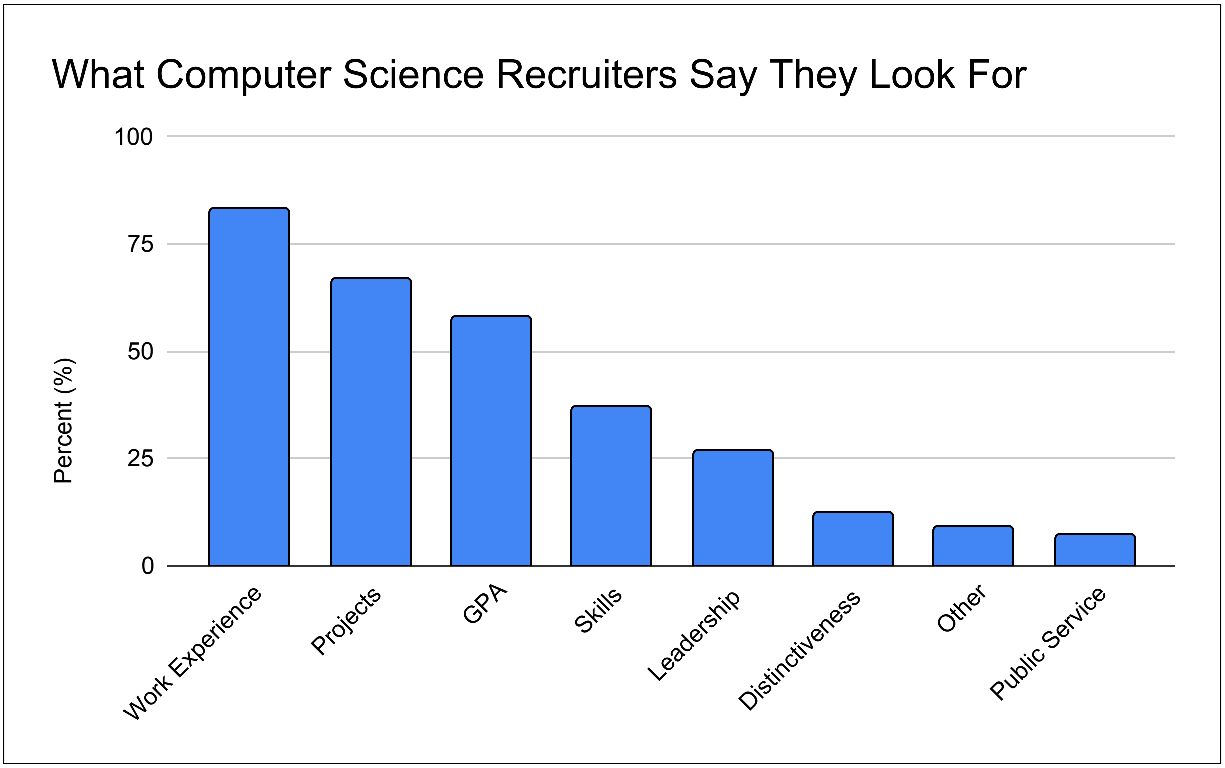


Figure 5.1: Recruiter Survey

projects, which are far from established in terms of the volume of research supporting their inclusion on entry-level resumes, were mentioned more frequently than GPA. Specific skills and leadership positions were cited by over a quarter of the recruiters polled. Few recruiters selected distinctiveness, public service, or other characteristics as important determinants in resume screening outcomes.

5.2 Preliminary Statistical Analysis and Considerations

5.2.1 Clustered Data

As a result of each participant in the student and recruiter study screening 30 resumes, each subject had 30 observations. Observations within a single subject are not independent of one another. Following the merge of the two studies, the number of observations for recruiters and students fell to 836 and 324 respectively. However, there were still instances of multiple observations coming from single subjects. To adjust for these cases, when possible, the data was clustered for statistical testing. The clustering as described here is not to be confused with cluster analysis. Instead, this clustering refers to a concept more commonly utilized in neuroscience, clustered data (116). Clustering was applied to all regression models including interaction testing.

5.2.2 Evaluating Leniency

Prior to going into deeper analysis, the simplest test to perform is one comparing the student and recruiter populations propensity to move a resume to the next level. The variable indicating whether or not a participant is a recruiter or student, and the outcome variable which indicates whether or not a resume is able to move to the next level are both binary variables. Since both the independent and dependent variables are binary, the most appropriate statistical test to use is one which allows a comparison of proportions.

In this case it is not possible to account for data clustering as mentioned above when performing either a two-sample Z proportions test or a chi-square test of independence. This is because calculating either a two-sample Z proportions test or chi-square test of independence, while factoring in clustered data, requires calculating the intraclass correlation coefficient (117). For the purposes of this calculation, the data will be assumed to be independent.

Given that the number of observations within the recruiter and student groups are relatively small (both less than 1000), an arguably superior test to use in this case is the Fisher's exact test. As mentioned in the expertise section, past studies comparing the ability of recruiters and students to review resumes found students to be more lenient in their resume screening. Accordingly, this presumes a directionality in the test results and interpretation. Though it is not uncommon for researchers to use two-sided tests to reach directional conclusions, this is not strictly a statistically correct practice (118). In order to determine whether or not students were more likely to move resumes to the next level than recruiters, a one-tailed Fisher's exact test was used. The contingency table used for the calculation is Table 5.2 and is shown below.

Table 5.2: Resumes Moved to the Next Level

MoveToNext	Recruiters	Students	Total
0	462	155	617
1	374	169	543
Total	836	324	1160

MoveToNext is a binary variable indicating whether or not a resume is moved to the next level of the hiring process, with 1 representing resumes that were moved to the next level and 0 representing resumes that were not. Student is a binary variable indicating whether or not a subject was a student or not, with 0 indicating the subject was a recruiter and 1 indicating the subject was a student.

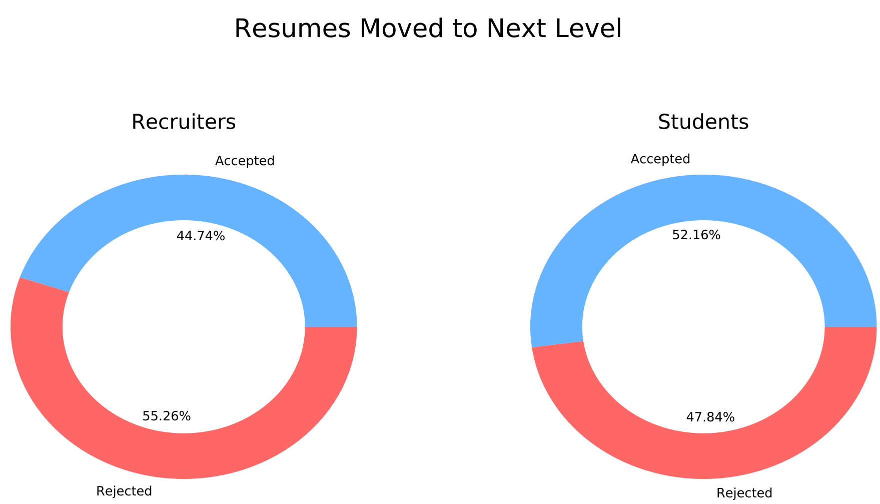


Figure 5.2: MovetToNext Visual Comparison

As can be surmised from Table 5.2, or observed from Figure 5.2, a resume shown to a student was moved to the next level 52.2% of the time. A resume shown to a recruiter was moved to the next level 44.7% of the time. A one-sided Fishers exact test was conducted with the following null and alternative hypotheses.

H_0 : Students were just as likely or less likely than recruiters to move resumes to the next level

H_a : Students were more likely than recruiters to move resumes to the next level

The resulting P value from the one-sided Fisher's exact test was .014. To avoid increasing the Type I error (false positive) chance within the one-sided test, it is recommended to halve the α value before comparing the resulting p-value (119). Following this precaution, $.014 < .025$, so the null hypothesis is rejected. Students were significantly more likely to move resumes to the next level than recruiters.

In accordance with past research studies comparing students to recruiters, students were more lenient than recruiters when screening resumes (20; 104; 105; 106). Less clear is the precise reason as to why this phenomenon occurs. Theories proposed range from differences in category width (107), similarity to themselves (105), and a lack of understanding the competence expected in the workplace (106). Another possibility not mentioned could be differences in the ideas of fit between students and recruiters. Recruiters are known to have idiosyncratic ideas of which qualities reflect good P-J or P-O fit among candidates (120). The issue is likely only worse for students who lack both a job and company from which to determine how well a fictitious applicant would fit in the position. For the purposes of this study however, students being more lenient implies there are fundamental differences between how students and recruiters screen resumes.

5.3 Section Based Regression Model

Since students and recruiters were shown completely different, randomized resumes, it was not possible to simply investigate which particular resumes were generally moved on by the recruiters or students. Instead, a regression model was generated to determine which resume items contributed most to a resumes success. In this case a resume being successful simply means that the person screening the resume selected the check mark on the "move to next level" checkbox when participating in the study. For this problem, an ordinary least squares (OLS) in a Linear Probability Model (LPM) was used to determine which items on the resume best accounted for why a resume was moved to the next level. (Probit and logit estimations provide similar results; OLS is provided for convenience of interpretation.)

It was reasoned that since recruiters set the real-world standard in regards to selecting which resumes continue in the hiring process, the coefficients associated with the recruiters would be a realistic assessment for the true value of the resume item.

The study combination process considerably reduced the number of work experiences, skills, and clubs that appeared on resumes. Some instances within categories appeared too infrequently to run a regression on all the individual items. While all resumes had a GPA ranging from 2.2-4.0, not all randomly generated resumes had courses, work experience, Greek life, clubs, skills, or projects. To work around this issue, initially the majority of items were grouped as 0/1 variables, the idea being to test the value that the presence or absence of resume items had on the overall screening. The equation was defined as follows:

5.3.1 Equation

Move To Next = $\beta_1 GPA_{r,p}$ + $\beta_2 AnyCourselist_{r,p}$ + $\beta_3 AnyJob_{r,p}$ + $\beta_4 AnyFratSor_{r,p}$ + $\beta_5 AnyClub_{r,p}$ + $\beta_6 AnyTechSkill_{r,p}$ + $\beta_7 AnyNontechSkill_{r,p}$ + $\beta_8 AnyProject_{r,p}$ + $\epsilon_{r,p}$

Move To Next is a binary variable indicating that the participants believe the resume should be moved to the next level in the screening process, as defined by the participant. GPA is a categorical variable spanning from 2.2 to 4.0. AnyCourselist is a 0/1 variable indicating whether or not the resume provides a list of courses in the education section. AnyJob is a 0/1 variable indicating whether or not the resume lists work experience. In some cases, AnyJob was further separated into 0/1 variables for retail experience (e.g. cashier), irrelevant internships (e.g. Fine Arts Summer Intern), academic internships (e.g. REU Internship), technician experience (e.g. Field Service Technician), and software experience (e.g. Programming Intern) to determine the effects of different types of work experience. AnyFratSor is a 0/1 variable indicating whether or not the resume lists at least one fraternity or sorority. AnyClub is a 0/1 variable indicating whether or not the resume lists at least one club membership. AnyTechSkill is a 0/1 variable indicating whether or not the resume lists at least one technical skill. Technical skills included programming languages such as Java, as well as software such as the game engine Unity. AnyNontechSkill is a 0/1 variable indicating whether or not the resume lists at least one non-technical skill. Non-technical skills included listing skills such as "hardworking" and being a "quick learner". AnyProject is a 0/1 variable indicating whether or not the resume lists a project.

5.3.2 Results

The results of the above regression are displayed in Table 5.3.

All interaction testing was calculated by generating models using the equation 5.1 shown below and evaluating the P values associated with the interaction term. Interaction testing is used in this case to establish whether or not a participant being a student has a significant effect on an explanatory variable. This provides evidence that students treated a resume item differently than recruiters.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \epsilon \tag{5.1}$$

In the equation, y represents the MoveToNext variable approximation, β_0 is the intercept, $beta_1$ is the slope of the Student variable, x_1 is the 0/1 value of the Student variable, $beta_2$ is the slope of the Any* variable, x_2 is the value of the Any* variable, $beta_3$ is the slope of the interaction variable created by multiplying the student variable by the Any* variable, and $epsilon$ is the error term.

5.3.3 General Findings

Overall, students were moderately successful at screening resumes as compared to recruiters. However, observing the P values in the interaction column in Table 5.3, it can be concluded that the student and work experience terms interact, meaning that students do treat work experience significantly differently than recruiters. Alternatively, using Figure 5.3 one can graphically confirm

Table 5.3: Resume Item Weights

Variable	**(1) Recruiters**	**(2) Students**	**(3) Interaction**
Work Experience	0.303***	0.507***	0.174**
	(0.0507)	(0.0816)	(0.0697)
GPA	0.291***	0.266***	-0.039
	(0.0318)	(0.0493)	(0.6001)
Technical Skills	0.198***	0.145*	-0.072
	(0.0568)	(0.0491)	(0.0966)
Projects	0.184***	0.260***	0.081
	(0.0323)	(0.0514)	(0.07266)
Fraternity/Sorority	0.0841**	-0.0292	-0.065
	(0.0363)	(0.0565)	(0.0785)
Clubs	0.0814**	0.0566	-0.059
	(0.0324)	(0.0614)	(0.0684)
Courses	0.0356	0.0585	0.037
	(0.0349)	(0.0436)	(0.0687)
Non-Technical Skills	-0.0433	-0.0272	0.020
	(0.0335)	(0.0486)	(0.0655)
Constants	-1.129***	-1.087***	
	(0.114)	(0.154)	
Observations	836	324	
R-squared	0.191	0.247	

Robust standard errors in parenthesis
*** p<0.01, ** p<0.05, *p<0.1

that the 95% confidence intervals for the slopes of the work experience regression models do not overlap. The work experience variable as it is here is noting how recruiters and students judge the presence or absence of work experience. For a resume containing at least one work experience, the student model improved the probability of a resume being moved to the next level by 50.7 percentage points, whereas the recruiter model only improved the percent chance by 30.3 percentage points. Students were either more harsh when resumes did not list any type of previous work experience, overly accepting of resumes that did list work experience, or a combination of these ideas. Recruiters may be more considerate of the quality of previous experiences or deem work experience as less centralizing than students.

The results of the regression also align fairly well with the recruiter survey results in Section

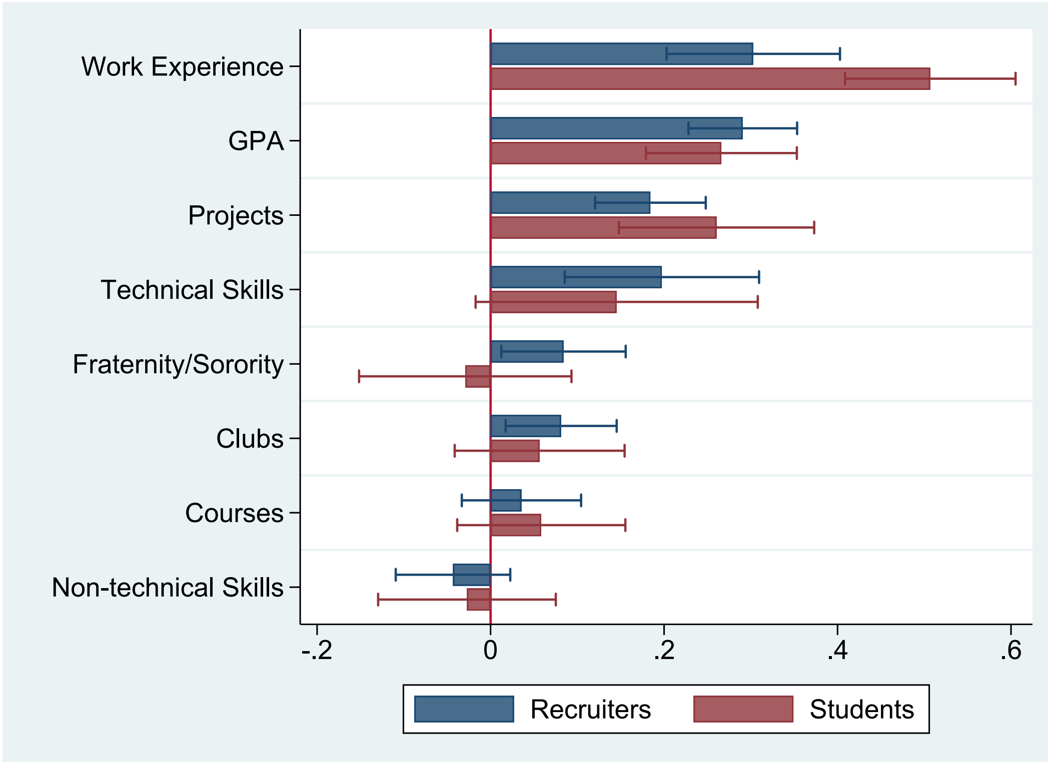


Figure 5.3: Participant View ©2022 IEEE

5.1. As expected, work experience, GPA, technical skills, and projects top the survey results and account for a relatively large amount of the regression model as compared to alternative resume characteristics.

5.3.4 Model Limitations

While this model provides some insights into how students and recruiters screen resumes, this model has a few notable weaknesses. First, the R-squared value is a little low at .191 and .247 for the recruiter and student models respectively. One reason for this is the oversimplified versions of the variables as they are defined in the regression. As mentioned in Section 5.3, the process of combining the two studies limited the number of times some specific instances of resume items were displayed on resumes. Since many of the items appeared too infrequently to run a regression including dummies for all the items, the items were combined into categories. The primary weakness of this design decision is that all work experiences, technical skills, projects, and clubs were assumed to be identical. Assuming that a relevant work experience from a renowned company and a work experience from an unrelated field carry the same weight in a recruiter's eyes is inferentially dubious. To investigate this further, these sections were broken down into smaller groupings which should provide insights into which aspects of these resume items are the most influential to resume screening outcomes.

5.4 Improving The Regression Model

5.4.1 Recategorization of Variables

The AnyJob variable present in both the recruiter and student regression models was further divided into its component parts. By observing the possible work experiences that could potentially appear on resumes, different categories emerged from the data based on the type of experience. These categories were as follows: Webdev Experience, Software Experience, Irrelevant Internship, Academic Internship, Technician Experience, and Retail Experience. By replacing AnyJob in the regression with these subcategories, the contribution of each can be quantified to shed light on which of these categories contributed the most to a resumes success. Additionally, the number of work experiences on a resume was added to resumes. The number of work experiences ranged from 0-3. While creating additional categories for work experience would likely improve the R-squared further, this would also increase the risk of overfitting either model.

GPA is the only non-binary variable present in the regression, instead the value ranges from 2.2 - 4.0, with the mean shown to recruiters being 3.28 and the students 3.27. The distribution of GPAs shown to each group is shown in Figure 5.4. While it would be possible to bin GPA into different categories by range such as [2.2 - 3.0), [3.0 - 3.6), [3.6 - 4.0] ; converting GPA from a continuous variable to a discrete variable loses information. In general, dichotomising continuous variables into variables is a discouraged practice because it reduces the overall statistical power when detecting relationships (121; 122). Instead, GPA was converted into a 0-1 continuous variable by the subtracting 2.2 from the GPA. The GPA' range was from 0-1.8 with this change. This has no effect on the model other than converting the slope to a more comparable form.

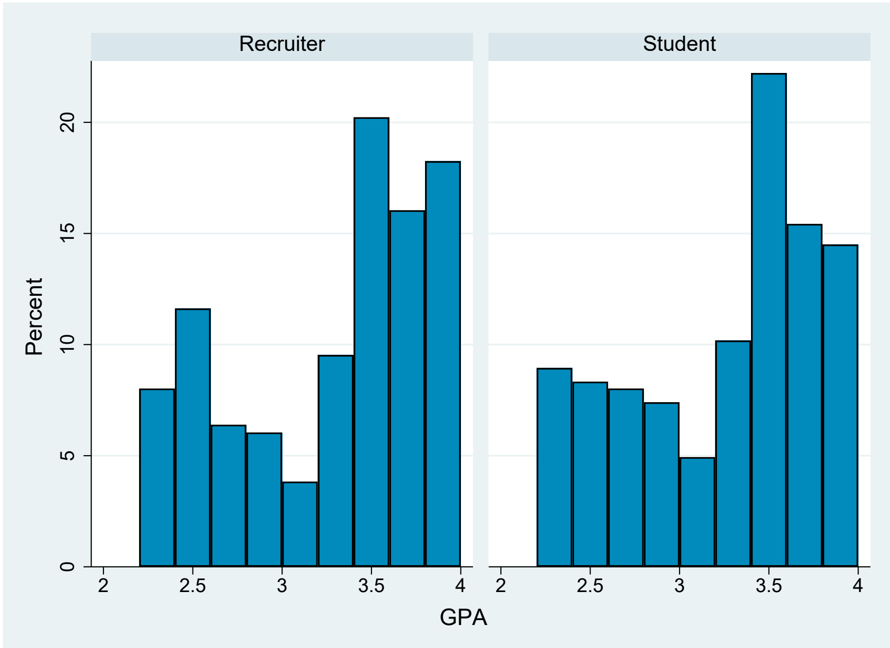


Figure 5.4: GPA Distribution

The AnyProject variable was also further separated into component parts. Projects displayed a less obvious pattern than did work experience, however, three categories were selected. The new categories of projects were: Class Project (0/1 denoting any project completed in class), Game Project (0/1 denoting any project that involved coding a game), and Personal Project (0/1 denoting any project not done in school and not a game). A variable was also added to count the number of projects present on resumes. The number of projects ranged from 0-3.

Previously, AnyTechSkill represented a 0/1 variable that marked when any technical skill appeared on a resume. However, the number of technical skills on resumes could be 0 or in the range of 5-15. The categorical version of AnyTechSkill was not capturing the disparity between listing 5 skills and 15, which would likely be evaluated differently by students and recruiters alike. To address this, AnyTechSkill was converted into a continuous variable known as NumTechSkill which counts the number of technical skills listed in the Skills section of the resume. The number of technical skills was also divided by 5 to aid with interpretation, converting the range from 5-15 to 1-3.

The remaining variables were either already split (Membership section became AnyClub and FratSor, Non-Technical Skills was already split from Technical Skills) or were not able to be divided further (AnyCourseList).

5.4.2 Improved Regression Equation

Factoring in the changes made in section 5.4.1, the new regression model is formed.

Move To Next = $\beta_1 GPA_{r,p}$ + $\beta_2 AnyCourselist_{r,p}$ + $\beta_3 AnyFratSor_{r,p}$ + $\beta_4 AnyClub_{r,p}$ + $\beta_5 NumTechSkill_{r,p}$ + $\beta_7 AnyNontechSkill_{r,p}$ + $\beta_8 AnyGameProj_{r,p}$ + $\beta_9 AnyClassProj_{r,p}$ + $\beta_{10} AnyPersonalProj_{r,p}$ + $\beta_{11} AnyWebJob_{r,p}$ + $\beta_{12} AnySoftJob_{r,p}$ + $\beta_{13} AnyIrrelJob_{r,p}$ + $\beta_{14} AnyTechJob_{r,p}$ + $\beta_{15} AnyAcadJob_{r,p}$ + $\beta_{16} NumJobs_{r,p}$ + $\beta_{17} NumProjects_{r,p}$ + $\epsilon_{r,p}$

Many of the variables are identical to their descriptions in section 5.3.1. The changes are shown in Table 5.4 and the new variable descriptions are in Table 5.5.

Original	Replacement
GPA	GPA'
AnyTechSkill	NumTechSkill
AnyProject	NumProjects, AnyGameProj, AnyClassProj, AnyPersonalProj
AnyJob	NumJobs, AnyWebJob, AnySoftJob, AnyIrrelJob, AnyTechJob, AnyAcadJob

Table 5.4: Changes to regression model

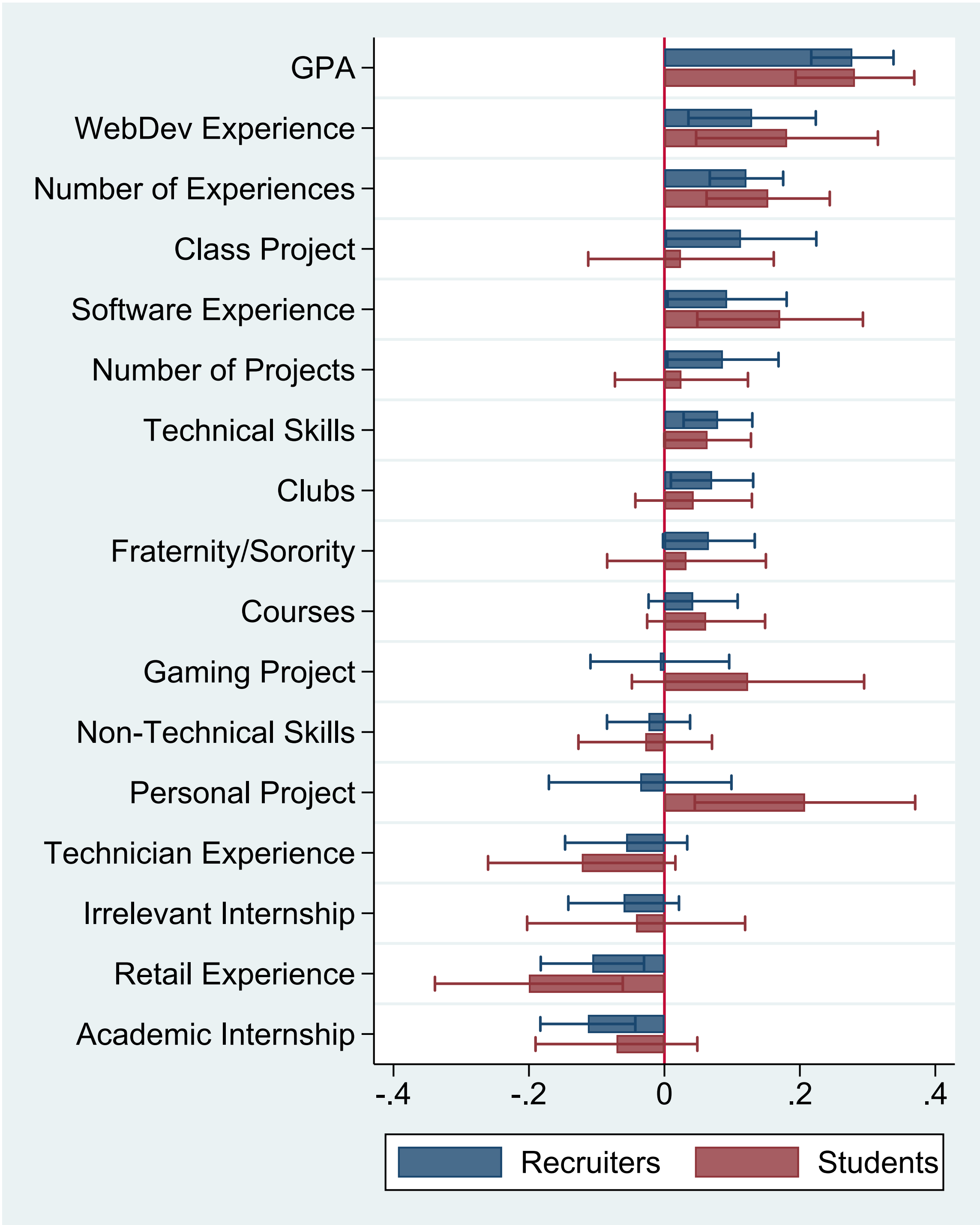


Figure 5.5: Items Influencing Recruiter Screening Decisions

Variable	Range	Description
GPA’	0-1	Continuous 0-1 version of GPA
NumTechSkill	0 , 1-3	Number of technical skills on resume
NumProjects	0-3	Number of projects on a resume
AnyGameProj	0/1	At least one gaming project on resume
AnyClassProj	0/1	At least one school project on resume
AnyPersonalProj	0/1	At least one project not school or game related on resume
NumJobs	0-3	Number of experiences on a resume
AnyWebJob	0/1	At least one web dev experience on resume
AnySoftJob	0/1	At least one software dev experience on resume
AnyIrrelJob	0/1	At least one irrelevant internship on resume
AnyTechJob	0/1	At least one technician experience on resume
AnyAcadJob	0/1	At least one academic internship on resume

Table 5.5: New Variable Descriptions

5.4.3 Tables and Figures

5.4.4 Interpretation and Comparison to Original Model

5.4.4.1 GPA

The results of the improved regression model indicate that GPA had the largest influence in both recruiter and student models in any one factor. The difference between a student having a GPA of 2.2 and 4.0 was about 50.0 percentage points in the probability of being moved to the next level by recruiters. The relationship between a higher GPA and an increase in the probability was linear for both the recruiter and student models. Alternative models resulted in model fit. For each 0.10 increase in GPA, the probability of being moved to the next level by recruiters improved by 2.78 percentage points. A table for some common GPA values and the associated improvement in chances in being moved to the next level for recruiters and students is shown below.

The student and recruiter model results align remarkably well, suggesting students’ view of

Table 5.6: Improved Resume Item Weights

Variable	**(1) Recruiters**	**(2) Students**	**(3) Interaction**
GPA	0.278***	0.281***	-0.0349
	(0.0308)	(0.0439)	(0.1081)
Web Dev Experience	0.129***	0.181***	0.0404
	(0.0477)	(0.0673)	(0.0822)
Number of Experiences	0.121***	0.153***	0.0423
	(0.0275)	(0.0456)	(0.0281)
Class Project	0.113***	0.0245	-0.120
	(0.0563)	(0.0687)	(0.0799)
Software Dev Experience	0.0926**	0.171***	0.0739
	(0.0446)	(0.0613)	(0.0635)
Number of Projects	0.0864**	0.0252	0.0264
	(0.0416)	(0.0493)	(0.0311)
Technical Skills	0.0790***	0.0637*	-0.0204
	(0.0257)	(0.0321)	(0.0456)
Clubs	0.0703**	0.0431	-0.0592
	(0.0308)	(0.0432)	(0.0684)
Fraternity/Sorority	0.0657*	0.0327	-0.0647
	(0.0343)	(0.0588)	(0.0785)
Courses	0.0424	0.0616	.0371
	(0.0334)	(0.0437)	(0.0687)
Gaming Project	-0.00679	0.123	0.162*
	(0.0519)	(0.0860)	(0.0824)
Non-Technical Skill	-0.0234	-0.0284	0.0203
	(0.0311)	(0.0495)	(0.0655)
Personal Project	-0.0358	0.208**	0.136**
	(0.0325)	(0.0519)	(0.0669)
Technician Experience	-0.0565	-0.122*	0.0118
	(0.0457)	(0.0694)	(0.0752)
Irrelevant Internship	-0.0602	-0.0418	0.0949
	(0.0414)	(0.0807)	(0.0929)
Retail Experience	-0.106***	-0.200	-0.0965
	(0.0386)	(0.0696)	(0.0696)
Academic Internship	-0.113***	-0.0708	0.0858
	(0.0355)	(0.0599)	(0.0646)
Constants	-0.408***	-0.413***	
	(0.0614)	(0.0734)	
Observations	836	324	
R-squared	0.267	0.361	

Robust standard errors in parenthesis

*** p<0.01, ** p<0.05, *p<0.1

Note: Interaction effects in the form Student * Variable

GPA	Rec Increase (%)	Stu Increase (%)
4.00	50.0	50.6
3.75	43.0	43.6
3.50	36.1	36.5
3.25	29.1	29.5
3.00	22.2	22.5
2.75	15.3	15.5
2.50	8.33	8.44
2.25	1.39	1.41

GPA in resume screening is quite accurate to real-world expectations. While a high GPA alone does not guarantee a resume will move on, it certainly helps.

5.4.4.2 Work Experience

Notably, while students and recruiters view the presence of any work experience on resumes differently as seen in the original model, they did not treat any of the work experience categories significantly differently from one another. This finding suggests that there is not a specific type of work experience that was overestimated or underestimated by students. Rather, the difference arises from the cumulative effect of evaluating these work experiences slightly different from each other.

The different types of work experiences are shown in Figure 5.6. When interpreting this figure, it is important to recall that the values of the associated slopes are impacted by the the number of work experiences variable, which had a slope of .129 for recruiters and .153 for students. For instance, a resume with a retail experience also must have had at least one work experience. Even though the slope associated with retail experience is negative for recruiters (-.106), the value added by having one work experience offsets this (.121) resulting in an overall slightly positive effect. Just not as positive as if the work experience was a software-related experience.

The only significant, positive types of work experiences were web development and software industry experiences. Technician experience and irrelevant internships, both had slightly negative slopes for both the student and recruiter models, but were insignificant. Retail experience and academic internship experiences both had significant negative slopes. As mentioned in the previous

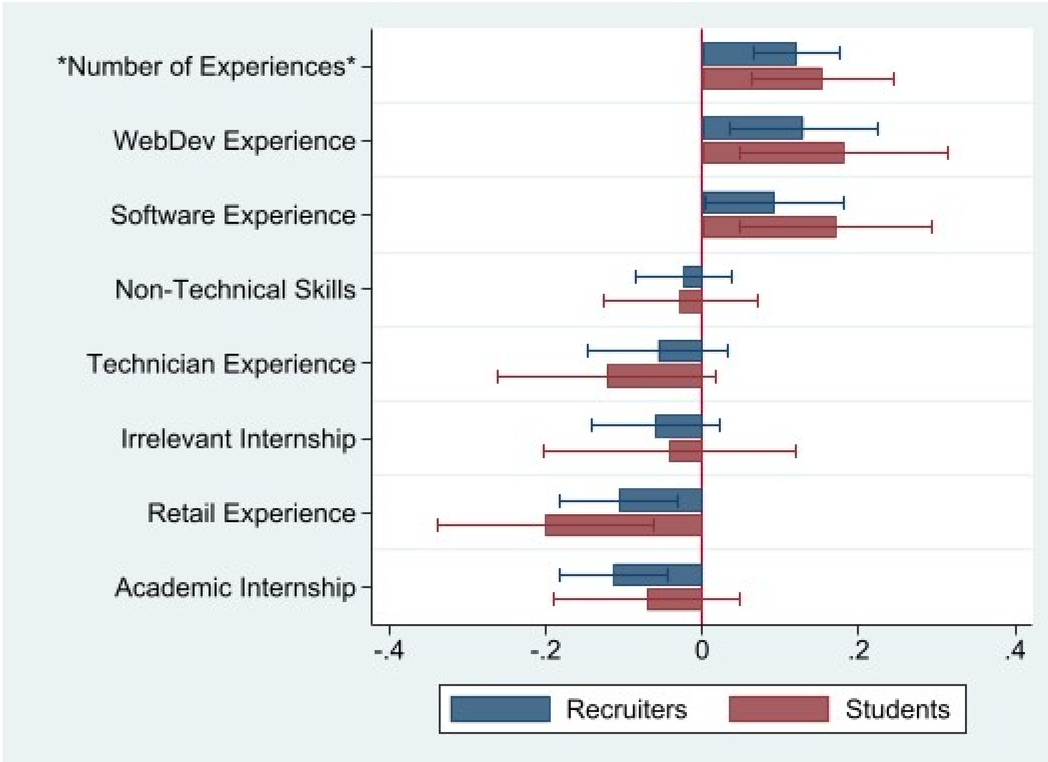


Figure 5.6: Types of Work Experience

paragraph, the negative slope in these cases is canceled out for recruiters by the positive effect associated with having a work experience for recruiters. The only case where this is not true is for a retail experience in the student model, where the negative effect of having a retail experience outweighs the positive effect of having a work experience.

5.4.4.3 Projects

In contrast to work experience, while the original model determined students and recruiters had similar views of the value of having or leaving off projects from resumes, separating projects into categories revealed some differences in evaluations between recruiters and students. As can be seen in Figure 5.7, these changes do not appear graphically using confidence intervals, but can be observed using interaction testing. While confidence intervals that do not overlap will always be statistically significantly different, the reverse is not necessarily true (123). Reliance on confidence interval overlap is convenient, but it is also overly conservative, resulting in Type II

(False Negative) errors (124; 125).

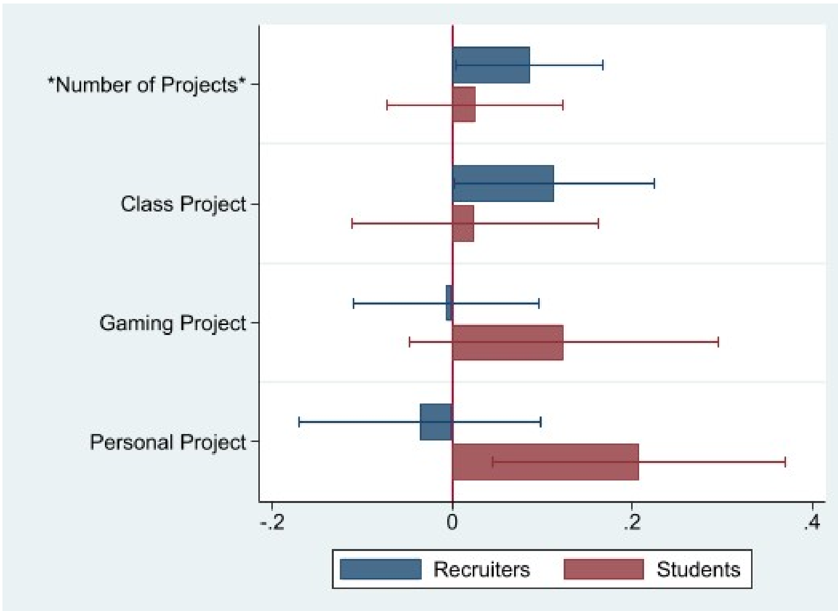


Figure 5.7: Types of Projects

Similar to work experience, the number of projects variable (.086 for recruiters and .113 for students) also had an effect on the slope values of the different types of projects. According to the interaction testing, students considered both gaming projects and personal projects to be significantly more valuable on resumes than did recruiters. The slopes associated with gaming projects and personal projects are also in opposite directions between students and recruiters. Class projects were the only type of project that had a significantly positive effect on the recruiter model. This may be partially explained by the fact that many class projects were completed in teams. The recruiter evaluation of personal projects is also different than anticipated. This may be partly attributed to the varying quality of personal projects.

5.4.4.4 Skills

The number of technical skills was also found to significantly contribute to the quality of a resume. To read technical skills as on Figure 5.8, recall that technical skills was divided by 5. The maximum number of technical skills that could be listed on a resume was 15. With this in mind, the maximum amount technical skills could contribute is 23.7 percentage points for recruiters and 19.1 percentage points for students. Technical skills were an important factor, and as such, likely merit inclusion on computer science resumes.

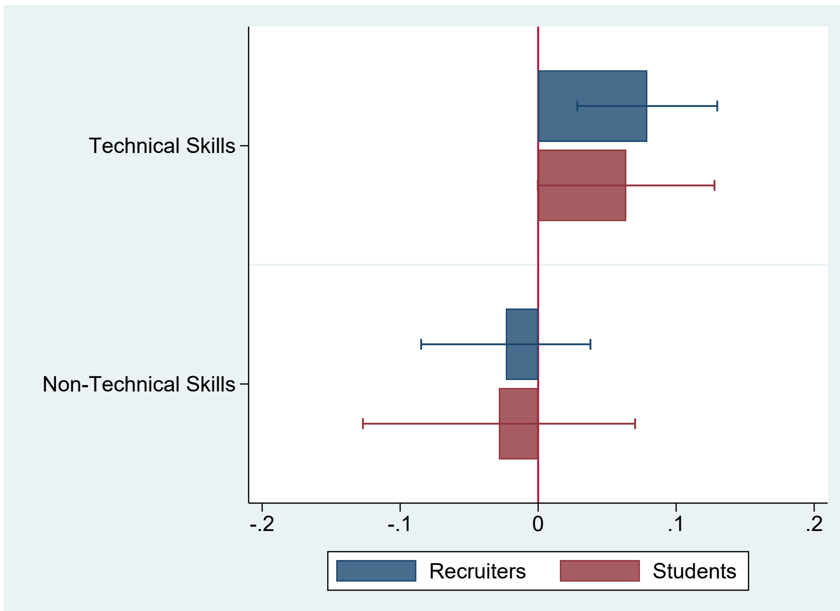


Figure 5.8: Technical & Non-Technical Skills

Listing any non-technical skills was not associated with improvement in chances to be moved to the next level. In fact the slope is negative, though insignificant. This should not be interpreted as non-technical skills being less important than technical skills, or that non-technical skills are undesirable. However, this finding does suggest that specifically listing out non-technical skills on the resume does little to prove to recruiters that a student truly possesses those attributes.

5.4.4.5 Membership

The membership category includes listing any clubs on the resume as well as fraternity/sorority involvement. Recruiters and students generally agreed on that including information related to club and fraternity/sorority participation were beneficial to the overall resume quality.

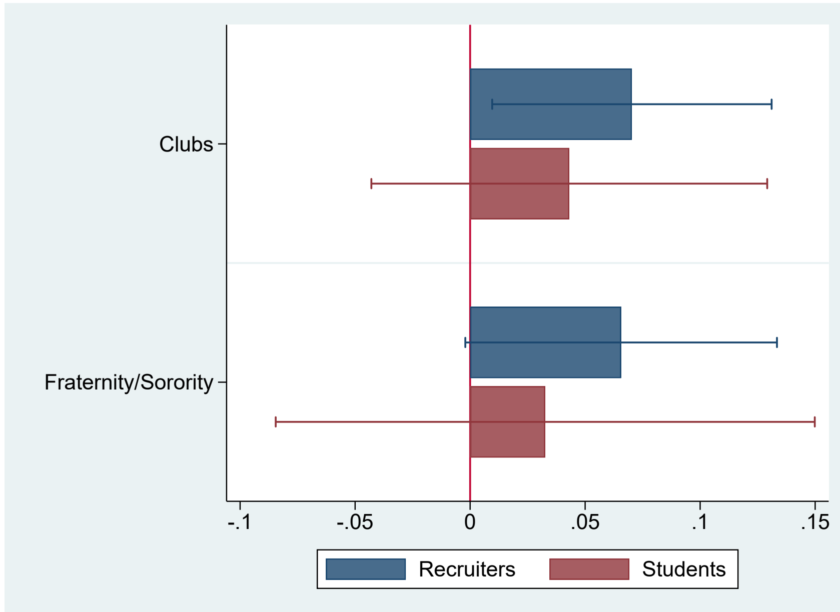


Figure 5.9: Membership Section

Neither clubs nor fraternity/sorority involvement significantly impacted the student resume screening level. However, club involvement did have a slightly positive, significant effect in the recruiter model. Clubs may warrant inclusion on resumes, but they are less influential than the other factors mentioned prior.

5.4.4.6 Courses

Listing coursework was not significant for either the student or recruiter model. Though listing courses did not work against resumes, it also did not seem to have much of an effect on the success or failure of resumes. There are likely cases where a specific course provides the knowledge desired by a particular position, and does significantly impact the probability of a resume being moved to the next level. However, scenarios such as this are beyond the scope of this experiment.

5.4.5 Within Group Comparison

5.4.5.1 Interrater Reliability

Interrater reliability is defined as the relative consistency of ratings provided by multiple raters and their judgements of multiple targets (126). In effect, this provides a way of quantifying the

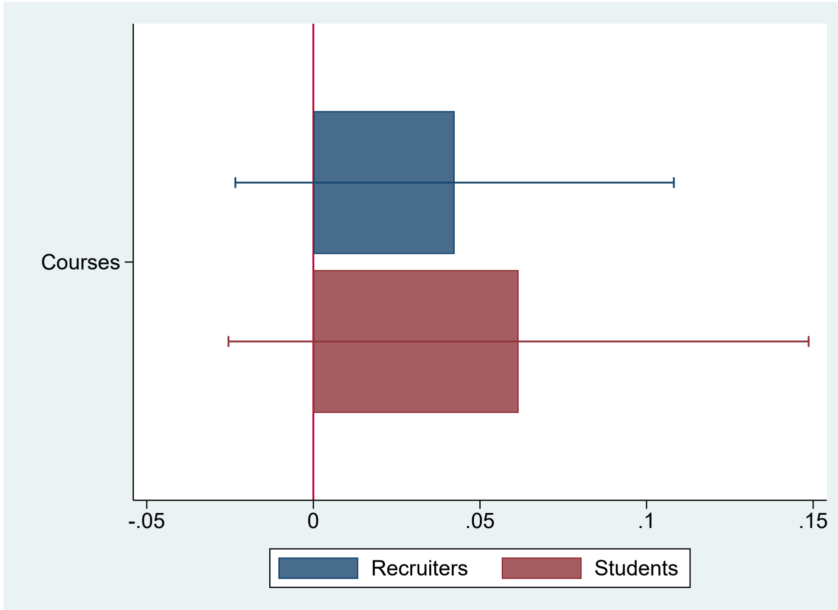


Figure 5.10: Listing Courses

degree of agreement between raters (127). An interrater reliability of above .60 is generally considered to be good (14; 8; 33).

In past studies, the interrater reliability of recruiters has been higher than for students. An early study involving recruiters and students rating the suitability of 24 accounting resumes found that recruiters had an interrater reliability of .68 whereas students had an interrater reliability of .48 (20). A more recent Belgian study found that recuiters and students rating CVs had an interrater reliabilities of .88 and .81 respectively. Based on these experiments, the contrasting results makes hypothesizing that either students or recruiters are likely to have screen resumes more similarly to each other difficult.

In this study, determining the interrater reliability could provide additional insights into how similar recruiters were to one another and if students could be similarly consistent in their resume screening. Unfortunately, this calculation is not possible for this experiment due to the experimental setup. In order to calculate the intraclass correlation coefficient (ICC), or any statistic that represents the interrater reliability, there must be common targets between judges from which to determine similarity. Since this study has randomized resumes as its targets and no two resumes involved were identical, this calculation is not possible to compute.

5.4.5.2 Inferences from the Data

One alternative method is to view how accurately the models are able to predict student or recruiter screening decisions. The R-squared value of the student model is nearly .1 higher than that of the recruiter model, suggesting the students were more consistent in their screening. This also suggests that students were more alike in their resume screening than were recruiters. A possible reason for this is the students being a more homogeneous group. Unlike recruiters which came from different backgrounds, all the participating students were from the same university and were computer science majors.

5.4.6 Addressing the R-squared

The new regression models have improved R-squared values, suggesting that the new models fit the data better than the original section based regression. The recruiter model R-squared improved from .191 to .267, which is a 39.8% improvement over the original model. The student model R-squared improved from .247 to .361, demonstrating even greater improvement than the recruiter model, improving 46.2%.

Of possible concern regarding the recruiter and student regression models is the relatively low R-squared values held by each. Even with the improved versions of the model, these R-square values are still low. However, though the R-squared values may appear fairly small, R-squared values tend to be smaller in social science statistical models. The complex, multidimensional nature of modeling human behavior makes explaining a large amount of the variance difficult. For instance, take the article "A variance explanation paradox: When a little is a lot" by Abelson (128). In this paper, batting average was used to predict whether or not a baseball player would land a hit. The aim of the study being to determine the extent to which player skill influences player performance. The resulting R-squared from the model was $< .01$. Despite the low R-squared, the results were still meaningful. The effects could still be felt over time. More skilled players still landed hits more often than less skilled players. Similarly, we claim that resumes with a larger number of desirable items will be more likely to be moved onto the next level than those with less. This study does not claim to explain all of the factors that go into a resume moving onto the next level, rather, it seeks to quantify the influence held by the resume items within a job seekers control. Incorporating the advice within this paper should improve a job seeker's chances at moving a resume to the next level, but it certainly will not guarantee it.

6. EYE TRACKING

6.1 Brief Introduction to Eye Tracking

Eye tracking is a research tool used for recording eye movement and gaze location during task completion over time (129). It has been used for a wide variety of purposes including, but not limited to decision making (130; 131), reading (132; 133), learning (134; 135), and economics research (136; 109). Although the link between mind and eye may be imperfect in some cases (137), the focus of the eye indicates visual attention, which is regarded as a good indicator of mental processing (129; 138).

6.1.1 Eye Movements

Within the eye tracking field, the two basic types of eye movement relevant for this research are fixations and saccades.

6.1.1.1 Fixations

A fixation is defined as the time in which the eyes positions remain relatively fixed and new information is gathered from the visual stimulus (133). Fixations exhibit a rather large degree of variability and range from 50 ms to longer than 600 ms for reading tasks (133). A list of some average fixation ranges associated with reading tasks from (133) is shown below.

Task	Fixation Duration (ms)
Silent Reading	225-250
Oral Reading	275-325
Scene Perception	260-330
Visual Search	180-275

There is also a large body of evidence to suggest fixations differ between experts and novices. A cross-domain meta-analysis of eye tracking research found that experts tend to have shorter fixation durations, more fixations on relevant areas, and less fixations on irrelevant areas than did non-experts (139). Recruiters as experts in this experiment may exhibit these differences.

6.1.1.2 Saccades

A saccade is the actual movement of the eye between fixation points (133), during which time vision is suppressed (140). It is worth noting, that while visuals are suppressed during a saccade, there is evidence to suggest cognitive processing is not (141). Depending on the task, saccades tend to range from 30-50 ms (142) and in reading tasks tend to span from 6-9 letters (133).

6.1.2 Eye Trackers

Screen-based eyetrackers, as used in this experiment, typically rely on pupil center corneal reflection (PCCR) to capture and record eye tracking data (143). PCCR works by shining a near-infrared light and using the reflection to identify the pupil center and illuminator reflection on the cornea (143; 144). From this positional information, the participant's gaze is calculated (144).

The initial study involving students utilized Tobii X2-60 eye trackers, whereas the second recruiter study utilized Tobii Spectrum eye trackers. Some basic specifications are shown in Table 6.1 below from sources (145; 146).

Table 6.1: Eye Tracker Specs Comparison

	Tobii X2-60 Compact	Tobii Pro Spectrum
Sample Frequency (Hz)	60	300 [1]
Accuracy (°)	.4	.3
Precision (° RMS)	.32	.06
Latency (ms)	< 35	< 2.5

[1] Also available in 60, 120, 150, 600 or 1200 Hz

Considering the improvements to accuracy, precision, and latency the Tobii Pro Spectrum is essentially an upgrade to the Tobii X2-60 Compact. However, the biggest obstacle when comparing data gathered between the two is the difference in sample frequency. The Spectrum takes 5 times as many samples as the Compact given the same amount of time. At each moment an eye tracker takes a sample, a gaze point is generated. This gaze point contains information specifying the location of the eye's focus in terms of pixels and millimeters.

6.2 Calculating Resume Screening Time

To determine the amount of time resumes were screened, the total number of gaze points were tallied for each subject and resume pairing. The number of seconds represented per gaze point was calculated by converting the sample frequency of each tracker using $T = \frac{1}{f}$, where T is seconds per sample (sps) and f is sample frequency.

	Tobii X2-60 Compact	Tobii Pro Spectrum
T (sps)	.01667	.00333

Gaze points were then converted into time units using the following simple equation $Time = GazePoints * T$. The results of the student and recruiter eye tracking times are shown in Table 6.2.

Recruiters on average spent significantly less time screening resumes (19.97 sec) than did students (23.05 sec). Recruiters also spent significantly less time screening resumes that they decided to move to the next level (23.35 sec) than did students (27.17 sec). These findings in themselves are not particularly surprising. Experts tend to use better, more efficient strategies than do novices for domain-related tasks (98; 97). The task of resume screening follows this line of thinking. Slightly more surprising, recruiters (17.19 sec) and students (18.48 sec) did not spend significantly longer than one another when viewing resumes they decided not to move to the next level. Speculatively, it seems that determining which resumes are inadequate is a simpler task. The high standard deviation for both the recruiter and student screening times further supports the notion that resume screening is a highly idiosyncratic practice (108).

Table 6.2: Resume Screen Time

Resumes	Recruiters		Students		t-statistic	P value
	Mean	SD	Mean	SD		
All	19.97	14.83	23.05	15.95	t(1007) = 2.98	**.0029**
Accepted	23.35	15.49	27.17	15.58	t(477) = 2.57	**.0105**
Rejected	17.19	13.68	18.48	15.13	t(528) = .949	.3430

Mean and standard deviations are time in seconds.

P values were calculated using two-sided t tests. Significant P values are in bold.

Additional t tests were run within the recruiter and student samples to determine whether or not significantly more time was spent viewing resumes they would accept or reject. Recruiters spent significantly more time screening resumes they accepted (M= 23.35, SD= 15.49) than they rejected (M= 17.19, SD= 13.68), t(691) = 5.55, p < .0000. Students also spent significantly more time screening resumes they accepted (M= 27.17, SD= 15.58) than they rejected (M= 18.48, SD 15.13), t(314) = 5.02, p < .0000. The faster task performance seen by both groups for rejections as well the similar overall task speed between groups when looking at a rejected resume suggests that it is easier to identify an inadequate resume than a quality one.

6.3 AOI-Based Analysis

6.3.1 AOI Creation

One methodology that eye tracking researchers use to analyze eye tracking data is by creating areas of interest (AOI). AOI are useful in that they can be used to to quantify whether and for how long a participant looked at a particular region (147).

For the purposes of this experiement, resumes were separated into 8 different rectangular AOI sections. Each AOI was created to surround a particular section of the resume. The descriptions for each section are found in Table 6.3. An example resume with the AOI fitted is shown in Figure 6.1.

Table 6.3: AOI Descriptions

AOI	Description	Dimensions (px)*
Introduction	Name on resume	[743, 46, 1176, 117]
Address	Address, phone number, and email	[600, 118, 1143, 167]
Education	Degree, college, GPA, and courses	[600, 168, 1309, 293]
Experience	Previous work experiences and descriptions	[600, 294, 1309, 639]
Projects	List of completed projects	[600, 640, 1309, 834]
Membership	Clubs involvement, fraternity or sorority membership	[600, 835, 1118, 931]
Skills	Programming languages, software, and soft skills	[600, 932, 1309, 1018]
Outside	Any gaze not in one of the other AOI	

* Dimensions are ordered [Left, Top, Right, Bottom]

6.3.2 Dwell Time

Dwell is defined as the total amount of time spent looking within an AOI including all fixations and saccades (148). Greater dwell times are associated with increased levels of interest in the AOI

(148).

To find the time each participant spent in an AOI, the number of gaze points falling within the AOI bounds were tallied. The number of gaze points was then multiplied by the number of seconds per sample for the eye tracker used to determine the total amount of a time a participants' gaze fell within an AOI. The amount of time students and recruiters spent in an AOI sheds light on the overall screening behavior of the participants.

Table 6.4: Dwell Time Comparison

AOI	Recruiter (sec)	Student (sec)	P Value
Intro	0.205	0.244	0.2174
Address	0.560	0.494	0.1490
Education	2.820	2.637	0.2734
Experience	10.18	11.43	0.0522
Projects	2.168	3.463	**0.0000**
Membership	0.677	0.767	0.1470
Skills	0.814	0.787	0.7996
Outside	2.600	3.226	**0.0008**

The table shows that students spent longer looking at the Projects AOI and the Outside AOI. Students viewing the Projects AOI longer is not particularly surprising given the differences between students and recruiters in their evaluations of different types of projects. Students viewing the Outside AOI longer may be the result of students spending more time considering whether or not to move a resume to the next level.

Though interesting to compare the amount of time students and recruiters spent in each resume section, students spent overall more time screening resumes than did recruiters. Therefore it is far from surprising that students spent longer than recruiters screening some of the AOI. Rather than only compare the amount of time a participant was scanning each AOI, it also is of interest to compare the proportion of time recruiters and students spent screening each AOI.

Table 6.5: Proportion of Dwell Time in AOI

AOI	Recruiter (%)	Student (%)	P Value
Intro	1.21	1.44	0.3141
Address	3.37	2.65	**0.0130**
Education	17.12	14.03	**0.0004**
Experience	45.83	45.09	0.6055
Projects	9.38	12.40	**0.0002**
Membership	3.62	3.69	0.8162
Skills	3.84	3.33	0.2501
Outside	15.62	17.38	0.0714

Recruiters spent a greater proportion of their screening time considering Address and Education than did students. The idea that recruiters spent proportionally more time considering the address has roots in the theory of fit mentioned previously. While students may dismiss the address when reviewing resumes, a recruiter has an actual company with a real location to consider as part of the resume screening. The increase in proportion of time spent viewing the education section is interesting, because this section also contains information that may not interest students when screening resumes, such as expected graduation date.

Students spent a significantly larger portion of their screening time viewing the Project section on resumes. This finding corroborates the result from the total time spent in each AOI. For all other sections, (Intro, Experience, Membership, Outside), students and recruiters spent a comparable proportion of their screening time viewing.

6.3.3 Fixations Within AOI

6.3.3.1 Number of Fixations

The number of fixations, alternatively referred to as fixation frequency or fixation count, refers to the tallied number of fixations on a stimulus (147). It is possible to utilize the number of fixations on both the entire stimulus as well as in each AOI.

To calculate the number of fixations, each unique instance of a fixation falling within the bounds of an AOI was tallied. The results are shown in Table 6.6.

Table 6.6: Average Number of Fixations Table

AOI	Recruiter	Student	P Value
Intro	0.77	0.67	0.3809
Address	2.09	1.62	**0.0090**
Education	10.23	8.52	**0.0047**
Experience	37.38	35.87	0.5239
Projects	8.03	10.17	**0.0386**
Membership	2.62	2.04	**0.0096**
Skills	3.00	2.24	**0.0450**
Outside	5.32	6.56	**0.0006**
Total	69.426	67.684	0.6340

As noted by Holmqvist, though valid, fixation count is not necessarily the optimal choice when comparing two groups that did not spend the same amount of time observing the stimulus (147). It is also possible calculate the proportion of fixations falling within each AOI by simply dividing an AOI fixation count by the total fixation count.

Table 6.7: Proportion of Fixations Table

AOI	Recruiter (%)	Student (%)	P Value
Intro	1.30	1.53	0.4328
Address	3.50	2.98	0.1277
Education	18.03	15.88	**0.0343**
Experience	48.58	46.67	0.2295
Projects	10.20	11.91	0.0649
Membership	4.20	3.39	**0.0449**
Skills	4.08	3.33	0.1059
Outside	10.12	14.32	**0.0000**

6.3.3.2 Fixation Duration

Fixation duration refers to the average length of time each fixation lasts. In a meta-study of expertise and eye movements, it was found that experts tend to have consistently higher average fixation duration than non-experts (149).

All of the mean fixation durations fall within typically reported ranges of 150 to 300 msec (148). Notably every AOI was significantly different between students and recruiters. Recruiters had longer mean fixations for every AOI. Though longer fixation durations for experts is consistent with literature (149), the sheer magnitude of difference here suggests that the different eye trackers used may also have played a role.

6.4 Heatmap Generation & Analysis

Among the more common methods for visualizing eye tracking data is the heatmap. Heatmaps are two-dimensional representations of data wherein fixation data (either the fixation count or fixation duration) is aggregated and displayed with varying amounts of color and opacity dependent on the amount of fixation data present (150; 151).

Fixation count heatmaps were generated for the purpose of determining precisely where on

Table 6.8: Mean Fixation Duration

AOI	Recruiters		Students		P Value
	Mean (ms)	95% CI (ms)	Mean (ms)	95% CI (ms)	
Intro	239	227-251	178	158-198	**0.0000**
Address	256	246-265	207	190-224	**0.0000**
Education	238	232-243	193	183-202	**0.0000**
Experience	227	224-231	171	165-177	**0.0000**
Projects	214	208-220	152	143-162	**0.0000**
Membership	215	209-222	157	146-169	**0.0000**
Skills	215	209-221	150	141-159	**0.0000**
Outside	277	268-287	217	203-230	**0.0000**
Total	238	233-242	177	170-184	**0.0000**

resumes recruiters and students were looking. Heatmaps provide an easy to understand visual for comparing different screening strategies. All heatmaps shown were created using Python. The fixation counts were binned based on their pixel coordinates and assigned a color gradient based on their value. The fixation count bins were then passed through a Gaussian filter to blur the rectangular bounds and create a more accurate overall picture of where fixations were most prominent. Values below the set threshold were replaced with NaN. A resume image from the study was placed under the heat map to show where the fixations were present. It should be noted that since resumes were randomized, the resumes shown are only some of the resumes actually screened and not the only the resume involved in collecting the fixation counts. The purpose of adding an example resume below the heatmap is merely to show where the fixations were most concentrated.

[h]

As can be seen from Figure 6.4 and Figure 6.5, the heatmaps created from the recruiter and student data are remarkably similar. Students and recruiters appear to have found common areas that drew their fixations. Work experience and GPA seem to dominate the scan paths of both students and recruiters. Notably, recruiters spent far greater time with the first entry for work experience. The average number of work experiences listed for recruiters was 2.4. This suggests that it might be best for students to list their most impressive work experiences first.

Among the more interesting findings from the heatmap is that the primary locations of fixations do not entirely align with the recruiter survey from Section 5.1. In the survey, work experience was the most frequently mentioned criteria followed by projects, and GPA which was mentioned by 58% of the recruiters. Based on the number of fixations, it seems GPA was looked at more often than any section other than work experience. The heatmap also aligns better with the coefficients from the regressions. Perhaps GPA matters even more to recruiters than they realize.

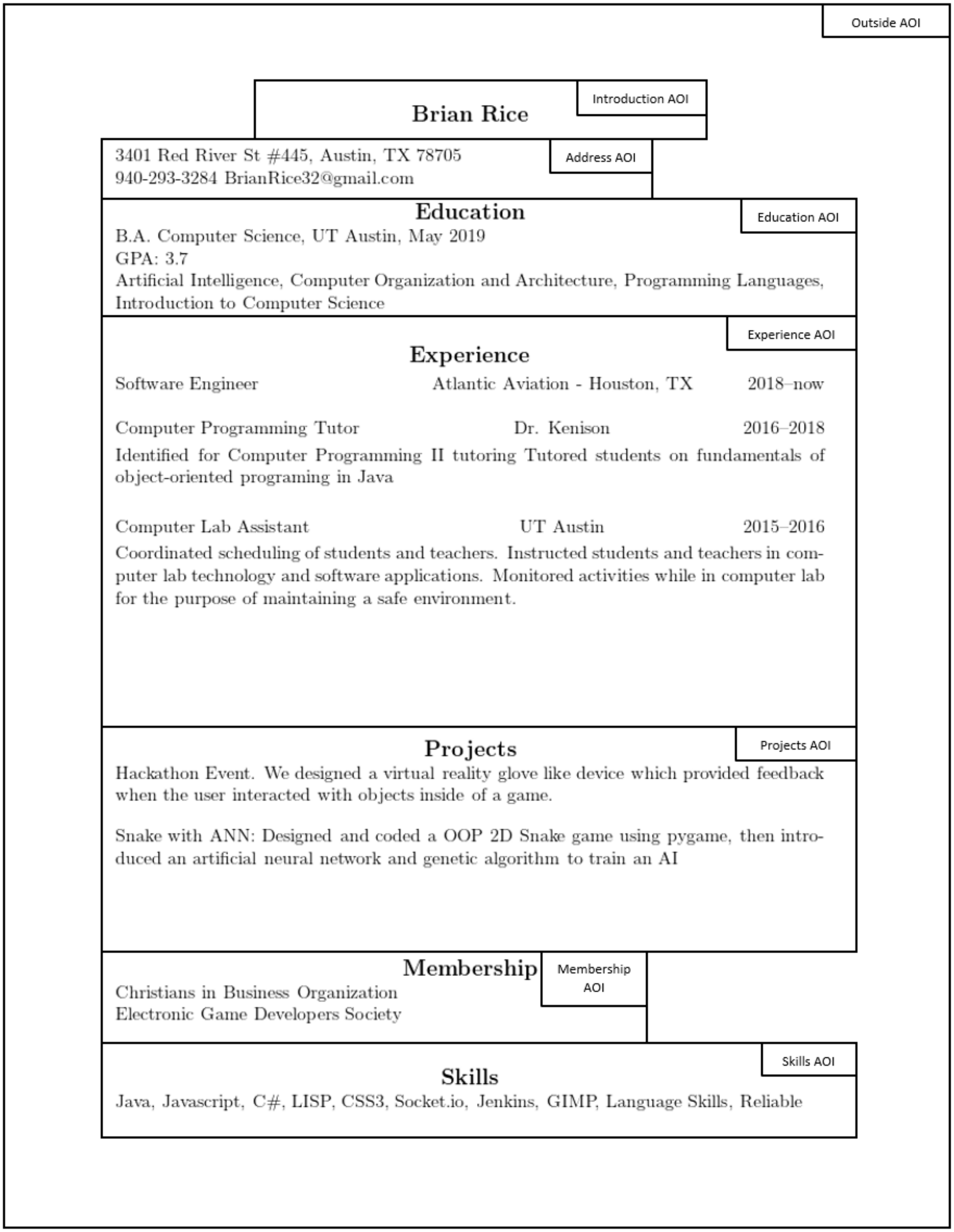


Figure 6.1: AOI Zones

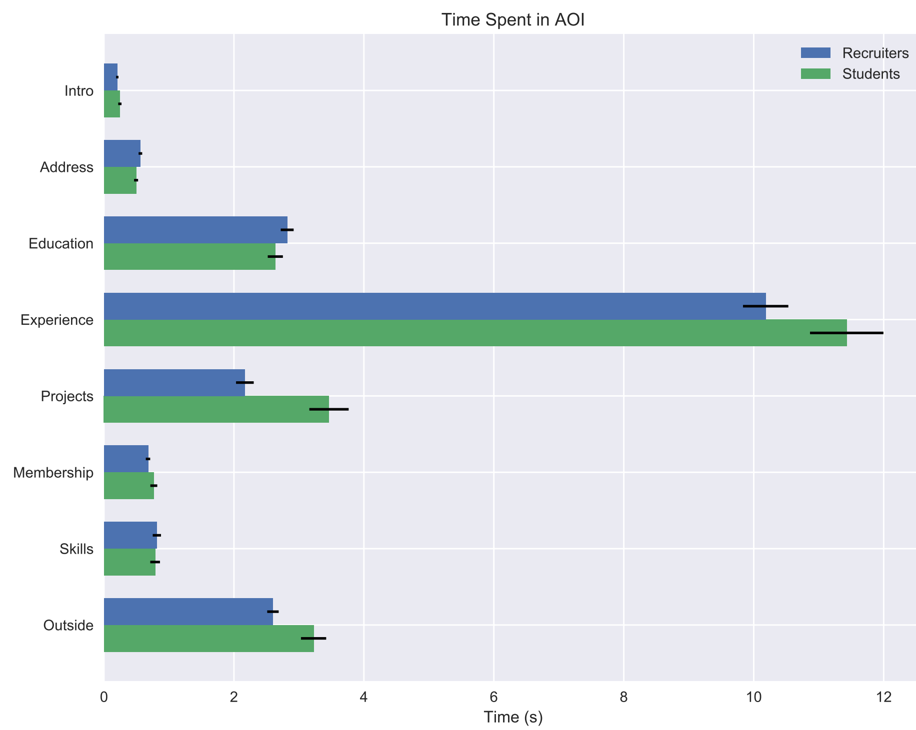


Figure 6.2: AOI Time Comparison

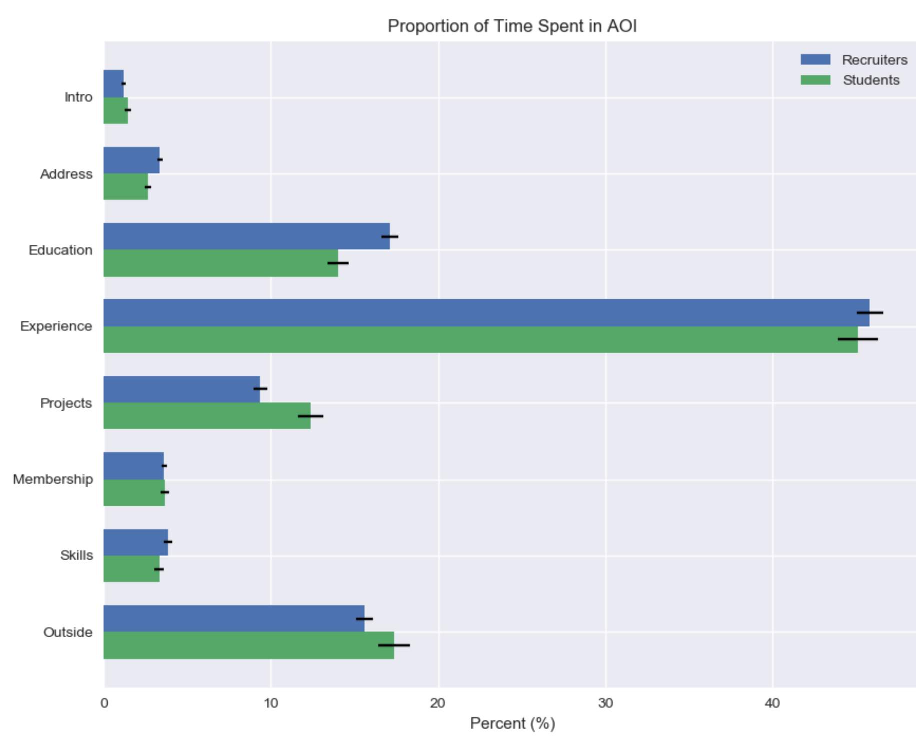
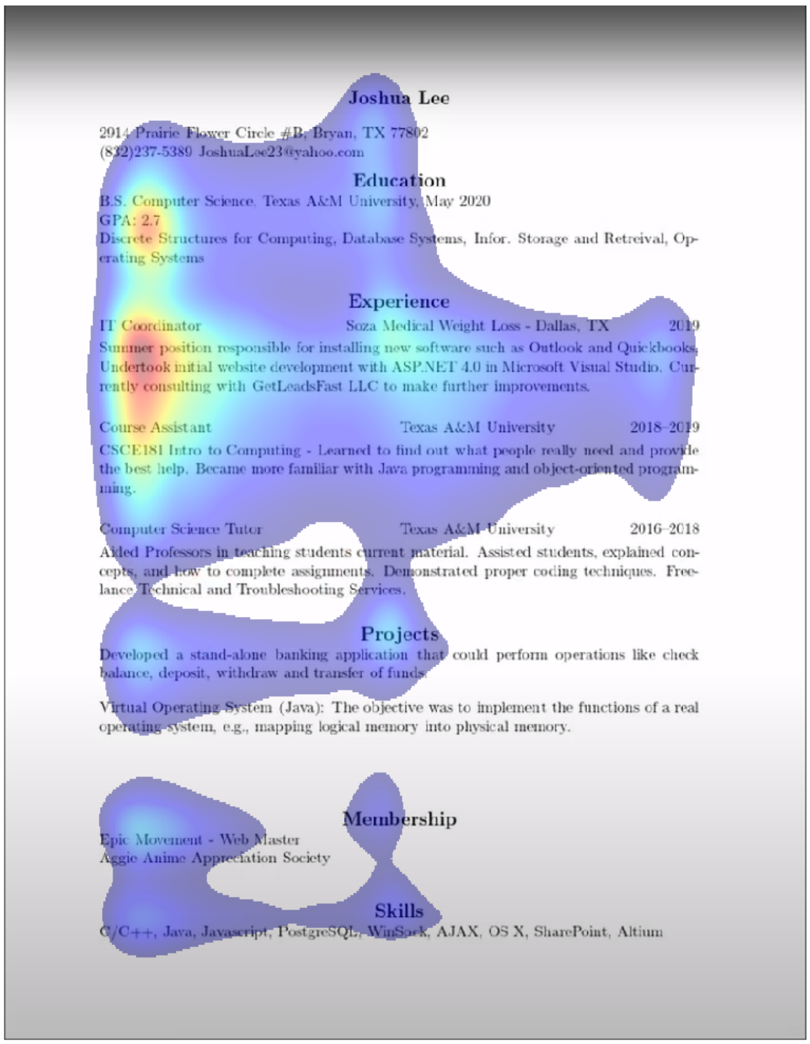


Figure 6.3: AOI Proportion of Time Comparison
Note: Standard Errors are Error Bars



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Education

B.S. Computer Science, Texas A&M University, May 2020
GPA: 2.7
Discrete Structures for Computing, Database Systems, Infor. Storage and Retreival, Operating Systems

Experience

IT Coordinator | Soza Medical Weight Loss - Dallas, TX | 2019

Summer position responsible for installing new software such as Outlook and Quickbooks. Undertook initial website development with ASP.NET 4.0 in Microsoft Visual Studio. Currently consulting with GetLeadsFast LLC to make further improvements.

Course Assistant | Texas A&M University | 2018–2019

CSCE181 Intro to Computing - Learned to find out what people really need and provide the best help. Became more familiar with Java programming and object-oriented programming.

Computer Science Tutor | Texas A&M University | 2016–2018

Aided Professors in teaching students current material. Assisted students, explained concepts, and how to complete assignments. Demonstrated proper coding techniques. Freelance Technical and Troubleshooting Services.

Projects

Developed a stand-alone banking application that could perform operations like check balance, deposit, withdraw and transfer of funds.

Virtual Operating System (Java): The objective was to implement the functions of a real operating system, e.g., mapping logical memory into physical memory.

Membership

Epic Movement - Web Master
Aggie Anime Appreciation Society

Skills

C/C++, Java, Javascript, PostgreSQL, WinSock, AJAX, OS X, SharePoint, Altium

Figure 6.4: Recruiter Heatmap

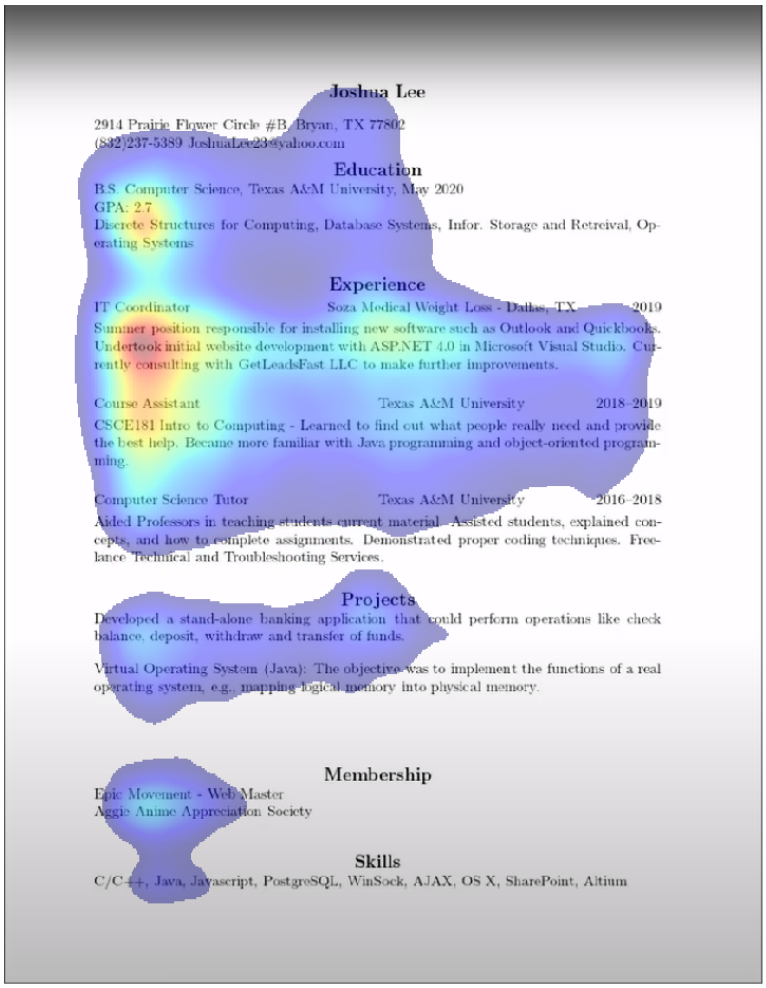

Figure 6.5: Student Heatmap

7. FUTURE WORK*

For so long as there are competitive job applications, there will always be a need for current, relevant information on how best to leverage ones' skills and abilities. Though the findings in this work are applicable now, it is likely that one day the recommendations presented here will need to be supplemented with new research. Future work should continue to investigate the best practices to aid those wishing to enter the industry.

Among the more alarming discoveries while conducting this research was the lack of recent resume studies within STEM. Without a scientific backing, advice for job applications too often becomes anecdotal and suffers from the follies associated.

Future studies could delve more into the eye tracking aspects of comparing students and recruiters. In this study, the majority of observations for both recruiters and students had to be dropped to ensure a faithful comparison between the studies being compared. A similar analysis in isolation of solely the recruiter data set as well as the student data set would certainly warrant additional investigation either following this framework, or more ideally expanding upon it.

8. CONCLUSION*

8.1 Research Questions Revisited

1. **Which items on entry-level computer science resumes most directly influence screening decisions?**

   The items that carry the most weight on entry-level computer science resumes are relevant work experiences, GPA, projects (particularly those that demonstrate the ability to work in a team), and technical skills.

2. **What gaps exist between computer science students' and their recruiters' perceptions of entry-level computer science resumes?**

   Students were overall too likely to consider resumes a high enough quality to move to the next level of the hiring process. Additionally, students overestimated the value added to a resume by the presence of at least one work experience. Students also overestimated the value of personal projects and gaming projects on resumes.

3. **Do computer science students and recruiters exhibit similar resume screening behavior?**

   Overall students spent significantly more time screening resumes than did recruiters. Students were similar in regard to the locations of their fixations, but were found to be fairly different using different eye tracking metrics. Most notably, students had far lower mean fixation durations than did recruiters in every AOI. Students also spent proportionally less dwell time in Address and Education AOI and more time in the Projects AOI. Additionally, students had significantly lower proportions of fixations in Education and Membership AOI and significantly higher Outside the AOI than did recruiters.

8.2 Recommendations for CS Students

The following advice is for creating entry-level computer science resumes and may not apply to other majors.

- Relevant work experiences are ideal, but any work experience is better than listing none. List your most impressive first.
- GPA is an important factor, the higher the better.
- Projects are good to include, but be mindful of their quality.
- Technical skills should be listed.
- Extracurriculars may add slightly to the resume quality, but likely will contribute less than the resume items listed above.
- Adding relevant coursework may benefit a resume, but generally does make much difference.
- Listing a non-technical skill does not convince a recruiter that skill is actually present.

8.3 Recommendations for CS Education

There are a few possible ways educational staff might address any misunderstandings students have regarding their resumes. First, resume writing skill workshops can be effective in improving the quality of resumes [77]. As such, providing resume workshops for students might be an effective way to clarify industry resume expectations. Additionally, despite its importance to acquiring a job in industry, the ability to write an effective resume is not a skill typically addressed within CS coursework [78]. Even the most recently created curriculum guide for CS only lists one course (professional development seminar) that takes resume writing into consideration [79]. Professional development courses such as this may warrant additional emphasis in the CS curriculum to minimize student knowledge gaps of industry expectations and hone relevant industry skills such as resume writing.

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