Examining the Use of Online Platforms for Employment: A Survey of U.S. Job Seekers

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ABSTRACT

Online employment resources are now as important as offline personal and professional networks, which have been pivotal in finding employment. However, it is unclear, which specific online resources are key to employment and how job seekers take advantage of them. Therefore, in an online survey of 768 job seekers, we investigated which online platforms, specific job search phases, behaviors, and job search strategies job seekers used in their job search, and which of these were associated with positive outcomes. We examined whether these results correlated with demographic factors and found differences in online platform use among income, gender, years of education, and race. Our results suggest that higher-income job seekers were more likely to use different strategies and more likely to get callbacks than lower-income job seekers. We raise new questions around demographics and technology and discuss the need for practitioners to design for a wider variety of job seekers.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**;

KEYWORDS

Employment, internet, social media, job seekers, Socio-demographic factors

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1 INTRODUCTION

The Internet is an advantageous resource for those seeking employment. It can be accessed with little cost, allows multiple job applications to be sent, and can help job seekers highlight their experience and skills [70]. Although not advanced, job search on the Internet requires some level of digital literacy. The coronavirus outbreak (COVID-19) resulted in a loss of over 700,000 jobs across the United States, the biggest job loss since the 2007-2009 recession [50]. Before COVID-19, the majority of people who were unemployed included those without a college degree, racial and ethnic minorities, women, and people with disabilities [6, 51–53], which means that these groups in particular were most likely further disadvantaged because of the pandemic. Therefore, understanding technology's role in their job search, its advantages and shortcomings before the pandemic, is beneficial to understand opportunities to provide employment support at a time of limited face-to-face contact.

A 2015 Pew Report found that 79% of recent job seekers depended on online information and 34% stated that the Internet was the *most important resource* in their most recent job search [59]. It is intriguing that the Internet was cited as more important than social networks given that decades of literature support the importance of offline social networks in job search success [48, 65]. However, the Pew report did not provide details of the specific applications that job seekers used online for job search and the specific role of technologies in the job search process remains unexplored [65]. Literature about Internet job search outcomes is also limited [1, 13, 27, 61, 62]. While the use of online resources was most represented among individuals with a college degree or higher, those who earned less than a college education were far less confident in performing job-related tasks such as highlighting employment skills in social media, creating a professional resume, or even completing a job application online [59]. It's unclear how Internet use for job search varies across social class [65], particularly for many low-income populations [67]. More recent HCI literature suggests that social media platforms like Facebook, Instagram, and Glassdoor have been used for job search among low-resourced job seekers [67]; however, this research was conducted qualitatively in one region in the United States (U.S.). The extent to which this research generalizes, the details of how these platforms are used among low-resourced job seekers, and whether they have been effective is unclear. To begin to address these gaps, we conducted a Qualtrics survey from April 28 to May 10, 2020 of 768 job seekers living and conducting their job search in the U.S. We raised the following research questions (RQs):

- **RQ1:** Which social media and other online platforms do job seekers use in their job search[1]?
- **RQ2:** Which social media and other online platforms do job seekers use to conduct specific job search phases and behaviors?
- **RQ3:** What type of job search strategies do those job seekers using social media and other online platforms engage in and which are associated with positive job outcomes?
- **RQ4:** How does one's level of perceived social support correlate to their use of social media and other online platforms used in their employment process?
- **RQ1-4-demographic:** Finally, we investigated how research questions 1-4 vary by demographic factors such as race, income, educational status, and geographic location [64].

We confirm differences in social media usage for employment among demographics, including income, gender, years of education, and race. Overall, higher-income job seekers were more likely to use different strategies and more likely to get callbacks than lower-income job seekers. Such differences in usage mirror broader socioeconomic inequalities across demographic groups. However, our work provides a deeper understanding of social media use for employment among job seekers in the U.S. Surprisingly, our work suggests that "typical" employment sites like Indeed and LinkedIn might not be as effective as Q&A platforms. We found Q&A platforms to be used for more exploratory strategies, which surprisingly, were used predominantly by high-income populations. Our findings suggest examining qualitatively specific barriers that might prevent low-income job seekers from using these platforms in an exploratory way. While our data does not allow us to conclude that more training is needed to support platform use in lower-income populations, our results do suggest that platform perceptions (e.g., professional versus non-professional sites) may drive usage, which confirms prior research [22]. Thinking about platform inclusivity entails thinking beyond training users to use platforms in the way they were designed. Our work suggests that inequality could be amplified when digital employment platforms are designed and marketed to specific job seekers, especially "professionals" or white-collar workers. Companies, practitioners, and designers could change their marketing and even their design strategies to include lower-waged job seekers or blue-collar workers. For instance, Indeed in its marketing aims to be inclusive while LinkedIn targets professional job seekers.

Our key contribution to the field is the validation of past HCI qualitative findings through quantitative research, which targets a large number of low-wage job seekers. Broadly, our work makes both empirical and practical contributions by extending and contributing to the existing HCI literature on employment (e.g., [12, 22–24, 55]), design for inclusion and diversity (e.g., [25, 28, 36, 43]), and the broad discourse on social and digital inequality (e.g., [35, 54, 57, 68]). We also contribute recommendations for future research and uncover specific questions to address in the future.

[1]We defined job search in our survey as any behavior that supports obtaining a (new) job. This could include but was not limited to searching for available jobs, clarifying goals (e.g., what type of job do I want?), preparing for or getting advice from someone about job applications, the job application process, or information about a specific job.

2 RELATED WORK

We begin by highlighting technology's role in the job search process and how bias in the job search is associated with demographic factors such as race/ethnicity, gender, age, income, and education. We then draw from Wanberg et al. comprehensive review of empirical job search literature and focus on general job search behavior and job search strategies used offline. We describe our expected contributions to this and relevant HCI literature, particularly as it relates to understanding how traditional offline job search behaviors and strategies transfer to online contexts.

2.1 Technology Use, Employment, and the Digital Divide

People of all ages are spending more time online searching for jobs [30, 59]. A 2015 nationally representative survey of 2,001 U.S. adults 18 and over, conducted by Pew, found that of the 33% of Americans who had searched for a job from 2013-2015, roughly 79% depended on online information [59]. Thirty four percent (34%) stated that the information and resources they found online was their most important resource. Of the 65% of Americans who used social media, 35% had used social media to search for or research jobs and 21% had applied to jobs they initially heard about through social media. In fact, 13% of social media users contributed *landing jobs* to their social media presence. However, a recent study indicates that low-resource and less-educated job seekers perceived managing their social media presence as unnecessary given the types of jobs they were seeking [22]. Although the Pew study provided insights on the distribution of job seekers that turn to the Internet to support their job search, the study did not uncover specific online platforms or behaviors employed in this process. In fact, little job search research has investigated the behaviors and sources job seekers use online [65, 67](RQ 1). The survey results along with prior research suggest inequalities in peoples' education and existing skills such as digital literacy (RQ1-4 demographic). We extend this work by identifying the demographic differences in how individuals use technology for employment, and which technologies individuals use. We also discuss the need for policies to intervene to prevent such inequalities from pervading online as well.

As suggested earlier, the employment impact on marginalized groups was magnified post-COVID-19. Social-distancing and reduced operations of many social organizations required people to stay-at-home and rely on technology. Therefore, understanding the role of online platforms in their job search before the pandemic, is beneficial to provide employment support at a time of limited face-to-face contact. However, the use of online resources for employment has been found to be inversely related to the respondent's education level [59]. In other words, those with less than a college degree are less confident in performing job-related tasks online. In fact, a qualitative study of 11 low-resourced job seekers found that while the Internet provided resources beneficial to finding relevant jobs, such resources did not increase their chances of securing employment [67]. The job seekers in this study who showed successful use of online resources were those who were already skilled and had the resources to succeed in the job search. While earlier studies cited the Internet as discriminatory against individuals who do not have regular Internet access [2], 81% of individuals in the U.S. have access to a smart phone with Internet access [11]. However, despite such gains in technology and Internet adoption, the digital divide persists. Lower-income Americans, younger adults, and non-whites, for example, are more likely to be "smartphone-only" Internet users, or smartphone dependent [11]. This is also consistent with a past survey that found that lower-income smartphone owners were likely to use their smartphones for the job search [59]. On the contrary, only 5% of households earning $100,000 or more were smartphone dependent. Because use is also likely to be correlated with a proclivity for using new technologies [62], we expect to see differences in the types of job search sites used among different social class groups. The specific role of technologies in the job search process remains unexplored [65], particularly for many low-income populations [67]. This survey aims to bridge this gap. We aim to uncover specific ways that such inequalities pervade the online job search process today. Before understanding how traditional job search translates in online contexts, we must understand traditional offline job search behaviors and strategies, and the importance of social support.

2.2 Job Search Behavior and Strategies and Social Networks

Job search behaviors are the actions required to find a job [5] and job seekers employ multiple job search strategies that correlate to job search outcomes. Job search behaviors have been classified into two phases: preparatory or active [5]. Behaviors in the preparatory phase include exploring careers, searching jobs, finding job information, advertising skills, preparing resumes, and reflecting on the job search process. Behaviors in the active phase include applying for jobs, getting advice, getting referrals, and seeking training opportunities. While preparatory behaviors are presumed to be completed before active job search behaviors, individuals cycle back and forth between the two as needed [65]. When compared to preparatory job search, active job search has a stronger relationship to job finding and quality of employment [63]. Wanberg, Ali and Csillag conjecture that this is because active behaviors involve applying for positions [65]. There is limited research on how people use *online* platforms in different job search phases (RQ2).

Individuals, however, engage in different job search *strategies* and prior findings show that job search strategies correlate to job search outcomes. Three categories of job search strategies include focused, exploratory, and haphazard. Job search behaviors targeting one's job search around specific goals are more focused while those relating to a broader search and openness to different possibilities are exploratory. Past research found that exploratory strategies led to people receiving more offers while focused strategies led to greater job satisfaction [18]. On the other hand, haphazard strategies, which lack focus or clear plans, have been found to be negatively related to job search satisfaction and number of offers [18]. How job search behavior strategies correlate to internal and external job outcomes in *online* contexts is an open question (RQ3). Our investigation extends prior literature by investigating the strategies used by job seekers using online platforms for employment, variances across demographic factors, and how job seekers' use of certain platforms relate to their job search strategies (RQ2 and 3-demographic).

Networking via family, friends, or attending offline networking events is a popular strategy used in the job search. In fact, Wanberg et al. found in their review that mobilizing *offline* social networks plays an essential role in finding employment and the quality of employment (i.e., job search success) [65]. This is consistent with Granovetter's classic study that found that 56% of their sample of 282 professionals found jobs through their social contacts [48]. However, a 2015 Pew Report found that 79% of recent job seekers depended on online information and 34% stated that the Internet was the *most important resource* in their most recent job search [59], which was rated higher than traditional offline forms of networking. Still, prior research identifies the importance of understanding whether certain people benefit more or less from the use of interventions, like the Internet, for networking [66]. This leaves an open question related to understanding what online platforms offer in terms of providing network support (RQ4). Our work investigates the job search strategies and behaviors that are more likely to be used when leveraging online platforms, whether such platforms are associated with marshalling social networks, and how these factors vary by demographics (RQ2-4-demographic).

3 METHODS

Our survey consisted of a national sample of U.S. adults and was administered from April 28 to May 10, 2020. We recruited participants through a Qualtrics[2] survey panel, which enabled us to, with its distribution feature, target respondents. Qualtrics was also more economical in terms of time, effort, and cost, than building our own collection tool. For context, respondents sign up for panels, enter information about themselves, and receive surveys they qualify for. Because our survey targeted people who used tech for job search and Qualtrics respondents only require basic website navigation, we did not see tech proficiency as a limitation. In the following subsections we discuss the details of our survey design, describe our application selection process, and data analysis.

3.1 Survey Design

Our survey[3] contained a total of 71 questions. While this represents an atypically high number of survey questions, surveys allow for flexibility, mitigate recall bias, and allow respondents to answer at their convenience. This is also less obtrusive and may be more appropriate during COVID-19 pandemic conditions than before. To ensure demographic representation based on the U.S. census, we screened participants based on income and oversampled participants earning an income of less than $30K per year, given that these populations can often be hard to reach [69]. Eligible respondents who consented to our study were then required to complete four survey sections: 1) use of online platforms, 2) job search strategies and job search outcomes, 3) perceived social support, and 4) demographic factors. For eligibility, we ensured that respondents were 18 and older, non-students, and were looking for work. We also

[2]Qualtrics is a web-based survey tool used to conduct survey research; details can be found as supplementary material and on their website: https://www.qualtrics.com/.
[3]The survey materials are available as supplementary material.

screened for the length of time job seekers searched for jobs. Because we designed our survey well before nationwide stay-at-home orders due to the coronavirus outbreak, we excluded participants who had been unemployed for less than three months and whose jobs were recently impacted by the pandemic. Finally, we screened for respondents' use of social media for job search and excluded those who had not used social media in this way.

3.1.1 Use of Online Platforms. To gauge job seekers' use of *online* platforms, we asked "*In the past 3 months, have you used the following online sites in your job search?*" The online platforms, which we discuss in the next subsection, included Facebook Groups, Facebook, Twitter, Instagram, LinkedIn, Career Builder, Indeed, Q&A, YouTube, and Company websites. [4] We then asked job seekers to select which of the following nine job search behaviors, if any, that they had done in the past 3 months: exploring careers, searching jobs, finding information, advertising skills, reflecting, applying for jobs, getting advice, getting referrals, and seeking training. For each job behavior selected, we asked the frequency in which, or how often (never, once a month or less, a few times a month, once a week, a few times a week, and daily) they used the selected platforms for each selected behavior. [5] We randomized the order of the selected job search behaviors, and the order of platforms.

3.1.2 Job Search Strategies and Job Search Outcomes. We asked respondents about the nature of their job search and outcomes to examine whether and how strategies correlate with job search success. We leveraged items from the Information Search Strategies Scale to assess respondents' job search strategies [18]. This scale has been used in prior studies to assess whether job search strategies are *focused*, *exploratory*, or *haphazard* [60]. Respondents were asked to rate their agreement with 11 statements related to the focused (e.g., "*I gathered information only for job openings that looked like what I wanted*"), exploratory (e.g., "*I tried to get my resume out to as many organizations as possible*"), and haphazard (e.g., "*My approach to gathering job-related information could be described as random*") nature of their most recent job search. Participants' agreement was assessed in 5-point Likert scales ranging from Strongly Disagree to Strongly Agree. To gauge the success of job search outcomes, we asked respondents about the number of callbacks they received in the past 6 months.

3.1.3 Perceived Social Support. We measured social support by borrowing 11 of the 12 items from Cohen's social support scale, which is a classic and widely accepted measure of social support [14, 15]. Social support was assessed using 4-point agreement Likert scales (Definitely False to Definitely True), including items like "*If I was stranded 10 miles from home, there is someone I could call who could come and get me*" and "*There is someone I can turn to for advice about handling problems with my family.*" We did not include the item, "*If I wanted to go on a trip for a day (for example, to the country or mountains), I would have a hard time finding someone to go with me*," as we perceived this as irrelevant for the purpose of our study.

3.1.4 Demographic Factors. Finally, to investigate the role of demographic factors in job search, we asked respondents for their race, income, educational status, gender, and geographic location. Household income was specified based on increments of $10k starting from less than $10k up to $59,999 and then from $90k-$99,999, and $100k or more. Respondents also had the option to select "Prefer not to say." To allow us to have flexibility around income partitions based on the number of responses, we created two buckets: $60k - $74,999 and $75k - $89,999. Our goal was to analyze how, if at all, job search strategies, platform use, and job search outcomes differed among low-income and mid/high-income individuals. Thus, we asked Qualtrics to ensure a quota of at least 250 low-income and 250 high-income respondents[6]. We also captured respondents' highest grade of education completed, which ranged from less than high school to doctorate degree. Finally, we collected respondents' zip codes, which we discuss in detail later.

3.2 Selection of Employment Applications

We took a comprehensive approach to determine which set of applications to include in our survey. We identified the most popular online platforms used for employment based on popular press and drew from a case study of the most popular social media tools used by recruitment organizations [8], and sites mentioned in past relevant HCI research. We were mindful of the types of behaviors that job seekers *could* perform on each site and ensured that the platforms accounted for the job search behaviors identified in our related work. However, it is unclear how such tools are actually used in the job search—those who use digital tools often use them in unintended ways. Therefore, we classified those sites not explicitly designed for employment purposes as *non-career related sites*. Collectively, we identified ten online platforms (see Table 1). Half of them were classified as non-career related: Facebook, Facebook Groups, Twitter, Instagram, and YouTube. Sites designed to enable job seekers to search and apply for jobs, find information about each jobs, and advertise their skills included: CareerBuilder, Company Websites, Indeed, and LinkedIn. While job search sites like CareerBuilder, Indeed, and Monster from a job seeker perspective might appear to be the same, there are key differences between them [34]. According to popular press, Indeed and Monster are most similar in that they include more candidates without a college education than CareerBuilder, and they both cater to those with only a high school education and temporary job seekers. CareerBuilder does not include such candidates and we chose to include it because of this clear distinction. We chose to include Indeed over Monster because Indeed includes work-at-home jobs, contract positions, *and* volunteer work and is essentially the most inclusive job posting board. While Facebook was designed to connect family and friends, there were reports from popular press that suggested its use for job search purposes [16] and the platform recently included a job board feature. While Facebook was designed to connect family and friends, LinkedIn was designed primarily to connect professionals.

[4] We also included a survey question about their offline resources used in the past 3 months; however, these results were excluded from our analysis because they fell outside the scope of this work.

[5] Assume a job seeker selected Facebook and Indeed as the platforms they use for job search and they also selected *exploring careers* as one behavior they did in the prior question. They would then be prompted with "*In the past 3 months, how often did you use Facebook to explore future careers?*" They would then be asked about their frequency of using Indeed for the job search behavior.

[6] Lower-income was defined as having an annual income lower than $30,000 while higher-income was defined as having an annual income higher than $75,000.

	Preparatory Phase				Active Phase				
	Explore Careers	Search Job	Find Information	Advertise Skills	Reflect	Apply For Jobs	Get Advice	Get Referrals	Seek Training
Facebook Group							×	×	
Facebook		×	×	×		×			
Twitter		×		×					
Instagram		×		×					
LinkedIn		×	×	×		×			
Career Builder		×	×	×		×			
Indeed		×	×	×		×			
Q&A	×						×		
YouTube			×						×
Company Website		×	×	×		×			

Table 1: Selection of employment applications and the job-related behaviors they support.

Both social media platforms enable job seekers to showcase their work and professional networks.

Facebook Groups enable job seekers to get advice and possibly seek referrals. Similarly, Instagram and Twitter are two popular social media platforms not inherently associated with employment but have been used for employment purposes according to popular press [17, 29]. Job seekers can use Twitter to spotlight their professional profile, follow institutions and professionals, and send private messages to those with mentorship potential [17]. Unlike LinkedIn, Facebook, and Twitter, Instagram is entirely visual and can be used to establish a job seeker’s personal brand or showcase their work. Instagram users can follow companies who are hiring and learn more about company and/or employee culture [29]. YouTube is a video sharing platform that can be beneficial for job seekers to seek training and for employers to provide information about their organizations and vacancies. Finally, Q&A sites like Glassdoor, Quora and Reddit, enable job seekers to explore careers, get advice, and ask specific career-related questions. Glassdoor is a website that allows former and current employees to review their experiences interviewing with and working for companies anonymously. It also provides a way to share salary information and for job seekers to search and apply for jobs. Unlike Glassdoor, neither Quora nor Reddit were designed explicitly for career-related purposes. Quora is a popular Q&A platform providing direct answers to questions, and many of them are employment and career related. Finally, Reddit contains countless subreddits related to employment such as /r/employment and /r/jobs that have been created solely for the purpose of sharing employment-related content. From a recruitment perspective, many organizations use LinkedIn, YouTube, Twitter, and Facebook [8] to advertise their positions and search for job candidates.

Finally, we drew from past HCI research that investigated how low-resourced job seekers navigated the employment process and the sites they reported using [67]. Indeed and Facebook were the most popular sites reported; a small number of job seekers also reported using Craigslist. Only one participant reported using Facebook, Facebook Groups, and Instagram. Google was also popular but quite broad for the purposes of our study. Another study, which envisioned job sites that would address the needs of similar populations found that their participants did *not* use LinkedIn because the site was designed for professionals and they did not identify with this group [22]. Our investigation aims to uncover whether these past findings generalize across a larger number job seekers and across geographic regions.

3.3 Data Analysis

The survey took participants on average slightly over 26 minutes (SD = 79.97 minutes). This average is abnormally high because a participant spent 1,770 minutes[7] (29.5 hours) on the survey. This was the longest reported duration. The shortest time to complete was reported at 2.5 minutes (or 156 seconds). Qualtrics managed compensation, which was $5 per participant. The survey was sent to a total of 1,797 panelists; however, after Qualtrics removed incomplete responses, invalid responses, and responses that were completed in a time deemed too quickly to be reliable, we had a total of 776 robust responses (43% valid). The research team assessed all responses and removed 8 additional responses that we deemed invalid. The criteria for exclusion included: contradicting responses, what we identified as random responses and questionably large numbers of job offers and job interviews received. We also removed respondents who used non-U.S. job sites or provided data that they were living outside of the U.S. As such, we had 768 robust and valid responses for analysis.

3.3.1 Measures. We used the following measures in our analysis and describe how each measure was calculated below: personal platform engagement, platform frequency, platform popularity, three job search strategies, job search outcomes, social support, and a series of demographic factors. We describe how each measure was calculated in the following paragraphs.

- *Individual Platform Use.* A job seeker’s platform use U was the average frequency of their use of an online platform to conduct job search behaviors. Assuming participant x had selected any choice except for Never, or m of the nine job search behaviors with a platform p, then participant x’s frequencies using p for the m behaviors were defined as $f_{x,p,1}, ..., f_{x,p,m}$. The f’s were x’s responses to the survey, coded as the following numeric values: Once a month=1,

[7] It is likely that this participant forgot to close their browser or managed multiple tasks while completing the survey

A few times a month=2, Once a week=4, A few times a week=10, and Daily=30. Participant x's engagement in p was then measured as: $U_{x,p} = (f_{x,p,1} + ... + f_{x,p,m})/m$.

- *Overall Platform Frequency.* A platform's overall frequency F was the average personal platform engagement of those who had used a platform *in a phase.* Assuming a platform p was used by n job seekers in a phase, and frequencies of a job seeker x who had used p for m behaviors in a phase were $f_{x,p,1}, ..., f_{x,p,m}$. Then x's personal use of p in a phase was calculated as $U_{x,p} = (f_{x,p,1} + ... + f_{x,p,m})/m$. The overall platform frequency F of p in a phase was $F_p = (U_{1,p} + ... + U_{n,p})/n$. The frequency f's were coded in the same way we described in the paragraph above. To clarify, some participants did not conduct any job search behaviors for a phase. These participants were excluded from the overall platform frequency calculation for that certain phase.
- *Overall Platform Popularity.* A platform's overall popularity P was the proportion of job seekers who used the platform in a phase. Assuming the number of total valid respondents was N, and a platform p was used by n participants in a phase. Then platform p's overall popularity in that certain phase was measured as $P_p = n/N$.
- *Job Search Strategies.* The level of job search strategies were three numeric variables. Each of the three strategies (focused, exploratory, and haphazard) was assessed as the mean of participants' ratings of associated statements (Strongly Disagree = 1; Strongly Agree = 5). For example, the level of focused strategy was the mean of participants' responses to the corresponding statements of focused job search nature.
- *Job Search Outcomes.* Job search outcomes was measured as a binary variable based on whether job seekers received callbacks from employers or not. This follows past employment-related audit studies [46].
- *Social Support.* The level of social support was a numeric variable, which was measured as the mean of participants' responses to the 11 items of Cohen's Social Support Scale [14, 15].
- *Demographic Factors.* We used the following demographic factors in our analysis: age, education, gender, income, race, and location. Age, education, and income were numeric variables. We calculated education by coding participants' highest grade of education into the number of years of education. As stated earlier, we gave respondents 10 numerical income intervals to choose from (i.e. "$10,000-$19,999") and the option "Prefer not to say." When analyzing income, we took the average of respondents' selected income interval excluding those who preferred not to disclose. In other words, if a respondent chose "$10,000-$19,999" as their income, we coded this as "$15,000." Following Pew research, we bracketed respondents' income into lower-income (lower than $30,000), mid-income ($30,000 to $74,999), and higher-income (higher than $75,000) [56]. We calculated gender, race, and location as categorical variables. We used participants' zip codes to categorize their location into the following four U.S. regions: the Midwest, the Northeast, the South, and the West.[8]

3.3.2 Statistical Techniques.

We used descriptive statistics and statistical modeling to analyze relationships between job seekers' engagement with online platforms, perceived social support, job search strategies, and the other variables of interest. For RQ3, we investigated whether adopting different job search strategies was associated with different outcomes by running a series of nested logistic regression models with the same outcome (i.e., receiving a callback or not) and demographic variables and job search strategies as predictors. We also examined whether job seekers' demographic variables moderate the impact of job search strategies on job search outcomes through adding interactions between job search strategies and various demographic variables into the model. To examine the relationship between online platform use and job seekers' perceived social support (RQ4), we ran a linear regression model with social support as the outcome, and individual platform engagement and demographic variables as input variables. To understand how individual demographics moderate the relationship between platform engagement and social support, we then added interactions between platform engagement and income into the model.

4 RESULTS

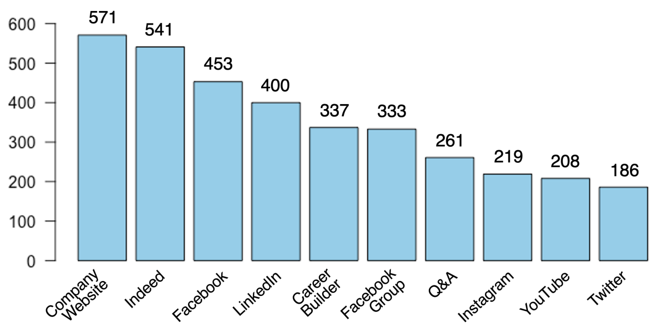
As stated earlier, we had 768 valid responses. The majority (59.6%) of our respondents were women, White (69.5%), had no more than a college degree (81.8%), and earned an annual income of less than $30K (49.1%). More than half of our respondents (53.6%) were between the ages of 31-50 (average age = 40.59, SD = 12.40). All respondents reported searching for jobs and 65.5% reported being unemployed. Another significant percentage of respondents reported being self-employed (16.4%), underemployed (11.8%), and/or retired, military, unable to work, or other specific status such as being pregnant or semi-retired (12.2%). A small percentage (5.1%) reported being homemakers. In the sections that follow, we address each of our research questions. The detailed breakdown of respondents' online platform use is included in Table 6 of the Appendix.

4.1 RQ1: Platform Use

Respondents reported using over 10 different social media and other online platforms in their job search. Unsurprisingly, the most used online platforms included Company-specific websites and Indeed (See Figure 1). These were followed by Facebook, LinkedIn, CareerBuilder, and Facebook Groups. The least used sites for the job search process included Twitter, Instagram, and YouTube. Q&A sites, like GlassDoor, were also not frequently used. Respondents included sites outside of the options provided. The most frequently mentioned options included Zip Recuiter (N=24), Monster (N=18), Craigslist (N=15), Google (N=15), and Snagajob (N=7).

Figure 2 illustrates the correlation coefficients associated with the use of ten platforms. Overall, the use of all platforms tend to be

[8] We followed the U.S. Census Bureau for guidance and divided the states into four regions: the Northeast (ME, MA, RI, CT, NJ, PA, NY, VT, NH), the Midwest (MI, OH, IN, IL, WI, MN, IA, MO, KS, NE, SD, ND), the South (DE, MD, VA, WV, KY, NC, SC, TN, GA, FL, AL, MS, AR, LA, TX, OK, DC), and the West (MT, ID, WY, CO, NM, AZ, UT, NV, CA, OR, WA, AK, HI) [10].



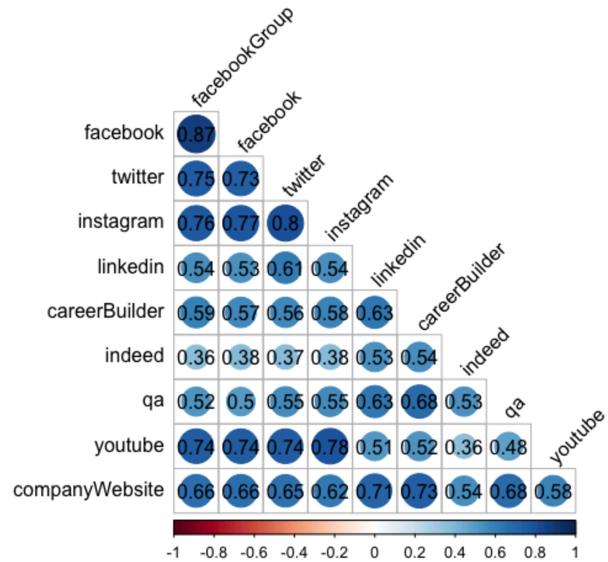


Figure 1: [Left] How many respondents used each platform for their job search?

Figure 2: [Right] Correlation between platforms

positively correlated with each other. In particular, we see that non-career-oriented social media platforms (i.e., Facebook Group, Facebook, Twitter, Instagram, and YouTube) have moderate to strong positive correlations with one another ($r \geq 0.73$). Therefore, in the rest of the paper, we aggregate them into a single variable, *non-career-oriented social media* platforms, in the linear regression analysis. The use of company websites has moderate positive correlations with the use of LinkedIn ($r = 0.60$) and Career Builder ($r = 0.64$). This implies that if people use company websites more often, they also appear generally more inclined to use LinkedIn and Career Builder. In addition, the correlations between Indeed and other investigated platforms are positive but relatively weak ($0.25 \leq r \leq 0.43$). Thus, there was no single categorical variable for career-related websites.

We examined the relationship between the frequency of online platform use and demographic variables — income, education, gender, race and ethnicity, age, and location (see Table 2). We found that income, years of education, gender, and age are strong predictors for the use of all the platforms besides Indeed. In particular, individuals with higher income and educational attainment tend to use these platforms more frequently. Compared to women respondents, men tend to use online platforms for job search more frequently, especially non-career social media platforms ($\beta = 3.365$ times per month, $95\%CI = [2.400, 4.331]$, $p < 0.001$). In addition, we found that age was marginally negatively correlated with the frequency of using LinkedIn, Q&A forums, company websites, and non-career social media for the purpose of job search. In fact, our results show that the use of Indeed was not significantly correlated with any demographic variables. This suggests that Indeed was used broadly across demographic groups.

4.2 RQ2: Platform Behaviors

Figure 3 shows that most participants used all platforms for all job search behaviors, including job search reflection. However, career exploration, followed by searching and applying for jobs, and finding job information were the most common behaviors conducted on the platforms. In general, the investigated online platforms were used less frequently for job search behaviors like getting advice, getting referrals, and seeking training.

However, whether someone uses a platform or not, does not show how frequently or intensively they engage with the platform. Twitch, a live streaming platform for gamers, for example, might not be used by a large number of people online (i.e., not "popular" among the general public); however, those who *do* use Twitch, might engage with the platform intensively. Thus, to grasp the full picture of participants' use of online platforms in preparatory and active job search phases (RQ2), we focused on both 1) how popular each platform was (i.e., what percentage of respondents chose to engage with each platform) and 2) how frequently each platform was used (i.e., when engaging with certain platforms, how often they used the platform). As such, we used the quadrant plots to illustrate each platform's Overall Frequency Score and Overall Popularity Score (see Figure 4 and Figures 5-8 in the Appendix) [26]. When plotting this quadrant diagram among all the respondents (see Figure 5 in the Appendix), we found that the selected online platforms were more popular and more frequently used in people's preparatory phase than in the active phase.

We then broke down the use of online platforms for the preparatory and active phases of job search by respondents' income level (see Figure 4). Overall, we found that both the usage frequency and the popularity of each platform increase as income increases. This suggests that higher income individuals utilize online platforms

	LinkedIn		Career Builder		Indeed	
	β	*CI*	β	*CI*	β	*CI*
(Intercept)	3.825^{***}	[2.391, 5.259]	3.894^{***}	[2.545, 5.244]	7.959^{***}	[6.212, 9.706]
Income	0.425^{***}	[0.251, 0.599]	0.348^{***}	[0.184, 0.512]	-0.012	[-0.224, 0.200]
Education	0.773^{***}	[0.536, 1.009]	0.314^{**}	[0.092, 0.536]	$0.251\cdot$	[-0.037, 0.539]
Man	1.801^{**}	[0.691, 2.911]	1.833^{***}	[0.789, 2.877]	-0.850	[-2.202, 0.502]
Asian	-1.044	[-3.249, 1.161]	-1.730	[-3.804, 0.344]	$-2.373\cdot$	[-5.059, 0.313]
African American	-0.230	[-1.947, 1.487]	0.793	[-0.822, 2.409]	0.010	[-2.082, 2.101]
American Indian	-1.087	[-6.575, 4.402]	-2.602	[-7.765, 2.562]	-1.354	[-8.041, 5.332]
Hispanic	-0.551	[-2.808, 1.706]	-1.297	[-3.420, 0.827]	0.136	[-2.613, 2.886]
Multiracial	-0.178	[-2.559, 2.203]	-0.634	[-2.874, 1.606]	-0.043	[-2.943, 2.858]
Age	-0.058^{**}	[-0.101, -0.014]	-0.011	[-0.052, 0.030]	-0.032	[-0.085, 0.021]
Northeast	0.947	[-0.813, 2.707]	-0.275	[-1.931, 1.381]	-0.011	[-2.155, 2.133]
South	0.607	[-0.988, 2.201]	-0.601	[-2.101, 0.899]	-0.680	[-2.623, 1.262]
West	0.184	[-1.602, 1.970]	-0.889	[-2.569, 0.791]	-0.819	[-2.994, 1.357]
Adjusted R^2	0.196		0.101		-0.003	

	Non-career Social Media		Q&A		Company Website	
	β	*CI*	β	*CI*	β	*CI*
(Intercept)	2.483^{***}	[1.235, 3.731]	2.696^{***}	[1.471, 3.921]	5.343^{***}	[3.969, 6.717]
Income	0.335^{***}	[0.184, 0.487]	0.312^{***}	[0.164, 0.461]	0.299^{***}	[0.132, 0.465]
Education	0.462^{***}	[0.256, 0.667]	0.274^{**}	[0.072, 0.475]	0.418^{***}	[0.192, 0.645]
Man	3.365^{***}	[2.400, 4.331]	0.699	[-0.249, 1.647]	2.102^{***}	[1.039, 3.166]
Asian	-1.300	[-3.219, 0.618]	$-1.643\cdot$	[-3.526, 0.241]	$-1.845\cdot$	[-3.958, 0.267]
African American	-1.010	[-2.503, 0.484]	-0.891	[-2.358, 0.576]	$-1.411\cdot$	[-3.056, 0.234]
American Indian	-0.590	[-5.366, 4.185]	-2.712	[-7.400, 1.976]	-1.470	[-6.728, 3.789]
Hispanic	0.253	[-1.710, 2.217]	-2.496^{*}	[-4.424, -0.568]	-1.703	[-3.866, 0.459]
Multiracial	-3.171^{**}	[-5.243, -1.100]	$-1.742\cdot$	[-3.776, 0.292]	$-2.020\cdot$	[-4.301, 0.261]
Age	-0.090^{***}	[-0.128, -0.052]	-0.056^{**}	[-0.094, -0.019]	-0.062^{**}	[-0.104, -0.020]
Northeast	0.845	[-0.687, 2.376]	0.162	[-1.341, 1.666]	0.054	[-1.632, 1.741]
South	0.839	[-0.548, 2.226]	0.823	[-0.539, 2.185]	-0.065	[-1.592, 1.463]
West	0.713	[-0.841, 2.267]	0.559	[-0.967, 2.085]	-0.144	[-1.855, 1.568]
Adjusted R^2	0.210		0.089		0.120	

$^{***}\ p < .001$; $^{**}\ p < .01$; $^{*}\ p < .05$; $.\ p < .1$

Table 2: Linear regression model results for changes in the frequency of platform use associated with individuals' income, education, gender, race, age, and location

more in both preparatory and active job search phases. In addition, we found that Indeed was the most popular and most frequently used platform for lower income individuals, but it was neither popular nor frequently used for higher income respondents. Aligning with results presented in the previous section that the frequency of using Indeed is not correlated with demographic variables, the absolute popularity and frequency of using Indeed is similar across different income groups. However, Indeed plays a different role in people's job search based on their income level. More specifically, Indeed tended to be the most important tool to support lower-income individual's job search, but higher-income people did not solely rely on Indeed for their job search online. The trend of using LinkedIn, however, has the opposite pattern. For lower-income individuals, both the popularity and the usage frequency of LinkedIn are lower than the average, but those scores are higher than the average for higher-income individuals. In addition, we found similar trends when we broke down the use of online platforms by respondents' gender and race (see Figure 7 and 8 included in Appendix) — the average popularity and frequency of using varied platforms are higher among men than women, and among white individuals than non-white individuals.

Unlike the trend we identified in income, gender, and race, we found that the use of varied online platforms for job search among those with some college education is lower than both those with high school diploma or less and those with bachelor's degrees or higher (see Figure 6 in the Appendix for reference). The decline in platform use for those with some college education may be due to the nature of associate degree training in the U.S. Individuals with associate degrees train for specific jobs such as nursing and manufacturing, which suggests the need to follow specific job search channels. Such specificity in job search might not be necessary for those with lower or higher educational attainment leaving online platforms a better option for these job seekers.

4.3 RQ3: Job Search Strategies and Outcomes

Our third research question sought to investigate the type of job search strategies job seekers using social media and other online platforms engaged in and which strategies were associated with positive job outcomes. To address this question, we first investigated whether adopting different job search strategies was associated with different outcomes, and found that it was. Table 3 presents logistic regressions on all the respondents with the outcome of whether they reported receiving callbacks in the past 60 days (with 1 = received at least one callback, 0 = received no callback). The key takeaway here is that both exploratory and focused strategies were positively associated with the increase in the odds of getting callbacks. As shown in Table 3a, if an individual's exploratory strategy score were to increase by 1 unit (out of 5) and other variables are held constant, the odds of getting a callback would be 61.0% higher ($95\% CI = [1.303, 1.998]$, $p < 0.001$). Similarly, each single unit increase in one's focused strategy score is associated with 47.4% increase in the possibility of getting callbacks ($95\% CI = [1.159, 1.880]$, $p < 0.01$). Table 3b and Table 3c examine whether one's income level and education level influences the impact of job search strategy on

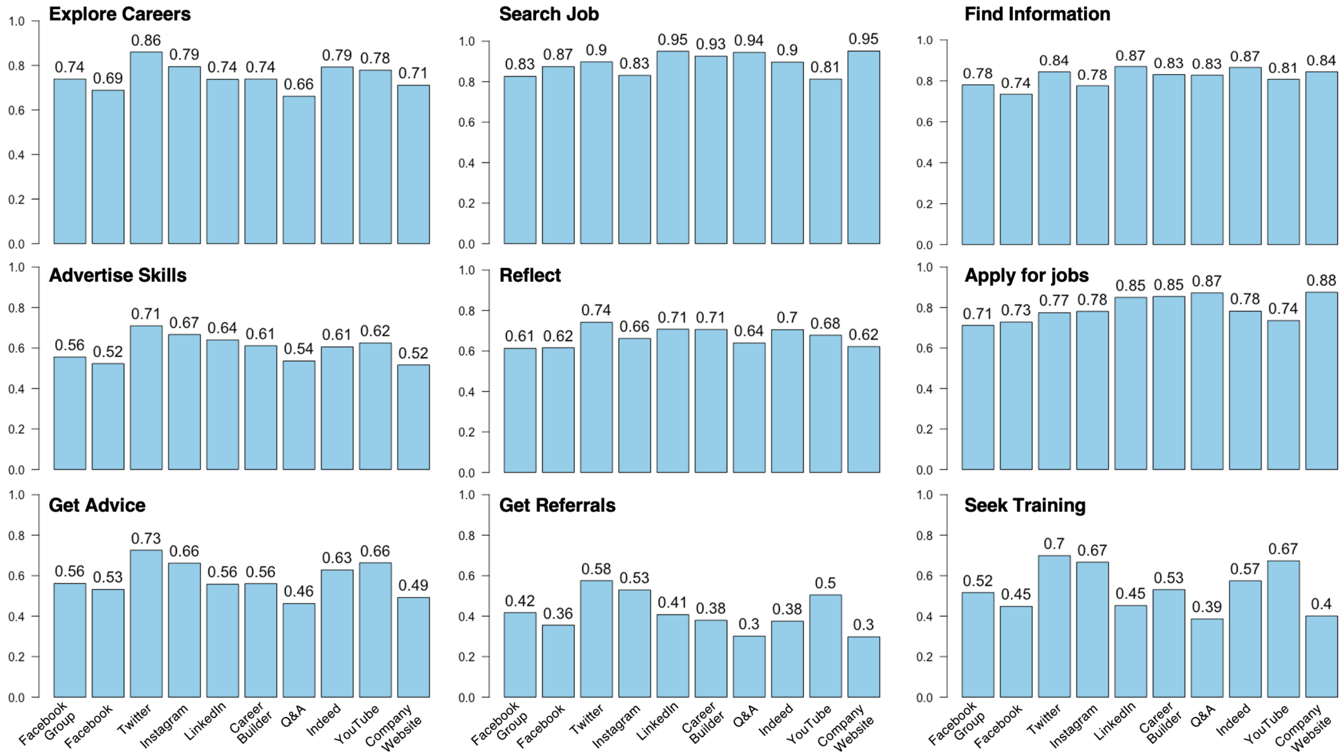


Figure 3: Among those who reported using each platform, what percentage are using them to engage in each job search behavior?

job seeking outcomes. Interestingly, our model suggests that for every 10K increase in income, there is a 7.9% increase in the odds of getting at least one callback when adopting the exploratory strategy and a 12.7% increase when adopting the focused strategy. More research is needed to understand whether there is a greater number of higher-paying jobs than lower-paying ones, and/or whether adopting exploratory and focused strategies can be more effective in helping higher-income job seekers get callbacks. These strategies were less effective in helping job seekers with lower incomes to get callbacks.

Using linear regression, we examined the correlations between three job search strategies — haphazard, exploratory, and focused — with the use of various online platforms. A key takeaway was that people with more education and who were older were less haphazard in their searches. That said, in our sample, men with higher incomes reported adopting more exploratory strategies. Two additional takeaways were that the use of non-career-oriented social media was positively associated with all strategies and the use of Q&A sites and company websites were significantly associated with exploratory strategies.

4.4 RQ4: Social Support

We examined the relationship between online platform use and perceived social support. Table 5a presents the influence of the demographic factors income, educational attainment, race, gender, age, and location, on perceived level of support. In short, when taking white women, who represented our average participants[9], and all other variables stay the same, people with higher income tend to have higher perceived social support level ($\beta = 0.042$, $95\%CI = [0.027, 0.056]$, $p < 0.001$)[10], and men tend to have lower perceived social support than women ($\beta = -0.120$, $95\%CI = [-0.213, -0.027]$, $p < 0.05$).

Table 5b shows that using non-career-oriented social media platforms is associated with *reductions* in perceived social support ($\beta = -0.012$, $p < 0.01$), while the use of Indeed is associated with a *marginal increase* in perceived social support ($\beta = 0.005$, $p < 0.1$). Since no causal relationship was investigated in our survey, one possible explanation is that when one's frequency of using non-career social media platforms increases from never (0 times per month) to every day (30 times per month), their perceived social support level decreases because they spend less time seeking support using their offline resources. Another possible explanation is that individuals with higher perceived social support are less likely to leverage non-career-oriented social media platforms for

[9]A 41-year-old white woman in the Midwest.

[10]The intercept value of 2.982 is the perceived support level (out of 4) for the average person in our sample using the mean amount of all the online platforms for job search behaviors. We found that the coefficient of income is additive ($\beta = 0.042$) with statistical significance. This suggests that if person A's income is 10K higher than person B's, the perceived level of support of person A would be higher than person B's, but only to a small degree ($\beta = 0.042$). An otherwise identical white woman whose income is 10K higher than average would have a perceived support level of 3.024 (2.982 + 0.042).

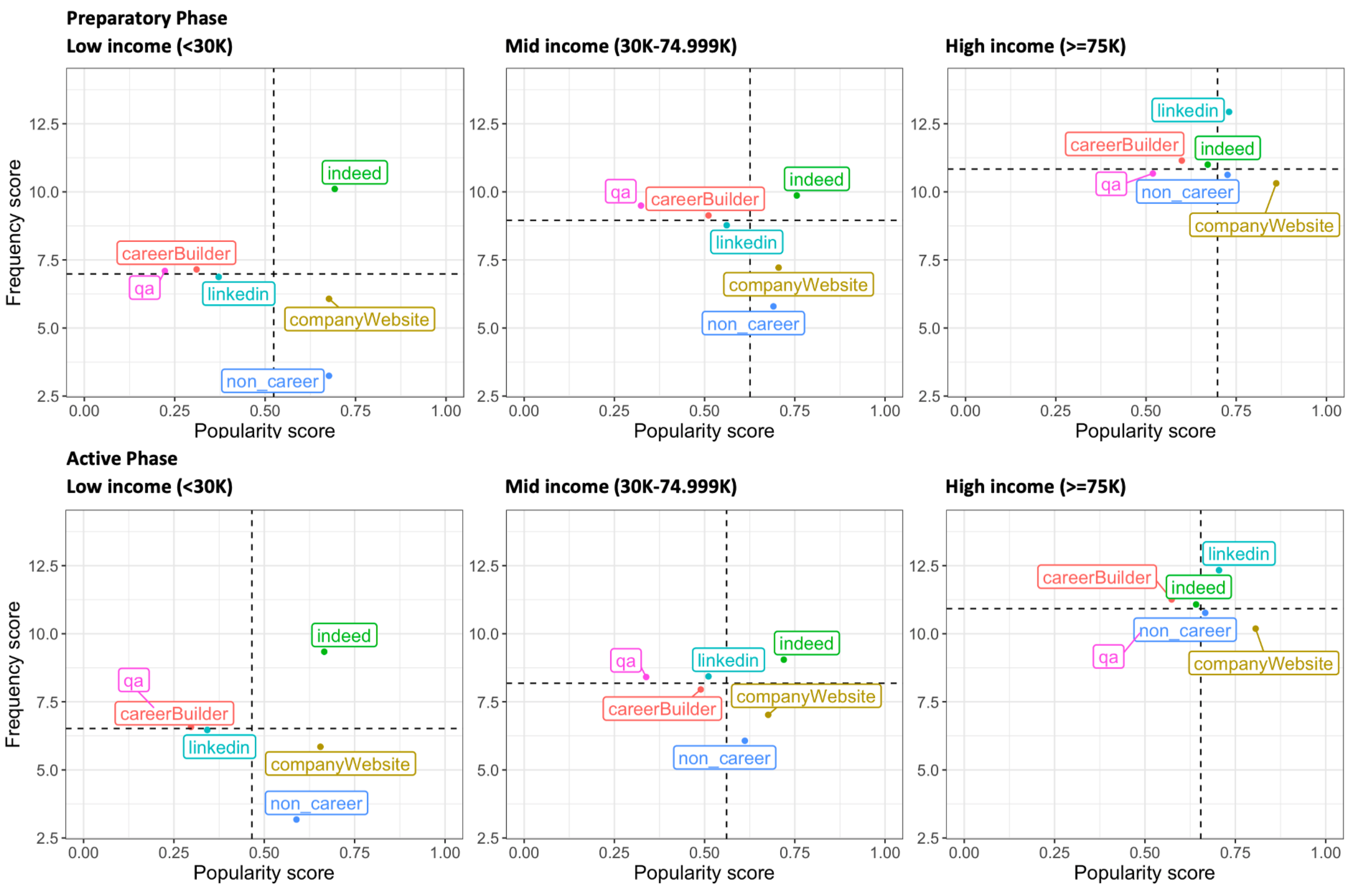


Figure 4: Per income level, which of the platforms were the most "popular", and which were used most intensely in each phase?

this purpose. We did not find significant correlations between a job seeker's perceived social support and their use of LinkedIn, Career Builder, Q&A forums, and company websites.

Table 5c examines whether income moderates the impact of online platform use on perceived social support. For individuals with higher income, the correlation between their perceived social support and use of non-career-oriented platforms decreases. This result potentially suggests that the less time those with higher incomes use non-career social media, the higher social support they perceive. It could also suggest that the more support those with higher incomes perceive, the fewer social media platforms they use. One possible way to interpret this trend is that those with higher incomes tend to have access to more social support, which leads to their less frequent use of non-career-oriented social media for the purpose of job search. In contrast, the interaction between using LinkedIn and income indicates that the correlation between one's use of LinkedIn and perceived social support increases as the income level increases. This suggests that, for individuals with lower income, the use of LinkedIn is less associated with the provision of social support.

5 DISCUSSION

While we extend past research to better understand a wider range of job seeker strategies (i.e., not solely low-income job seekers), our approach allows for generalizability. As we highlighted in our related work, a large majority of the past research in this area is qualitative in nature and another novelty of our work is that it increases the generalizability of these past findings [65]. Before diving into our discussion, and the contributions of our work, we summarize our findings to address our research questions. We found that job seekers used all 10 of the online platforms in their job search that we proposed as well as others (i.e., Zip Recruiter, Monster, Craigslist, Google, and Snagajob). Interestingly, the use of Indeed was consistent across demographic groups. Taking a closer look into demographics, we found that men and younger adults tend to use online platforms more often in general. In addition, income and education were strongly correlated with the frequency of using online platforms for job search—individuals with higher income and educational attainment appear to use online platforms more frequently[11] (RQ1, RQ1-demographic). We also found that both the

[11] While not central to our work, we found that income was also positively correlated with educational attainment and gender. Our results revealed racial income gaps (i.e., an average Black person's income was 7.7K (16%) lower than an average White person's ($p < 0.05$)). Unfortunately, such discrepancies align with past research. A recent study

	3a. Base Model		3b. Interaction Model with income		3b. Interaction Model with education	
	β	*CI*	*β*	*CI*	*β*	*CI*
(Intercept)	0.040***	[0.013, 0.121]	0.024***	[0.007, 0.078]	0.040***	[0.013, 0.120]
Income	1.065*	[1.012, 1.121]	0.517***	[0.370, 0.709]	1.059*	[1.006, 1.115]
Education	1.054	[0.983, 1.130]	1.029	[0.959, 1.105]	0.726	[0.485, 1.073]
Man	1.199	[0.862, 1.666]	1.093	[0.780, 1.528]	1.168	[0.838, 1.627]
Asian	0.857	[0.448, 1.649]	0.858	[0.445, 1.652]	0.868	[0.451, 1.681]
African American	0.895	[0.545, 1.470]	0.959	[0.583, 1.575]	0.930	[0.566, 1.528]
American Indian	0.450	[0.058, 2.455]	0.386	[0.052, 1.960]	0.446	[0.058, 2.361]
Hispanic	1.425	[0.740, 2.803]	1.475	[0.768, 2.887]	1.432	[0.745, 2.809]
Multiracial	1.426	[0.723, 2.870]	1.531	[0.773, 3.089]	1.420	[0.722, 2.847]
Age	0.987*	[0.974, 0.999]	0.987	[0.975, 1.000]	0.987·	[0.975, 1.000]
Northeast	0.778	[0.466, 1.296]	0.757	[0.450, 1.269]	0.782	[0.467, 1.305]
South	0.769	[0.484, 1.220]	0.725	[0.456, 1.150]	0.750	[0.472, 1.189]
West	0.881	[0.523, 1.481]	0.826	[0.488, 1.394]	0.851	[0.504, 1.433]
Strategies						
strategy_haphazard	1.150·	[0.977, 1.353]	1.132	[0.957, 1.340]	1.144	[0.971, 1.349]
strategy_exploratory	1.610***	[1.303, 1.998]	1.686***	[1.355, 2.109]	1.610***	[1.302, 1.999]
strategy_focused	1.474**	[1.159, 1.880]	1.654***	[1.288, 2.136]	1.483**	[1.164, 1.893]
Interaction with income						
Income:strategy_haphazard			1.010	[0.963, 1.059]		
Income:strategy_exploratory			1.079*	[1.018, 1.147]		
Income:strategy_focused			1.127**	[1.050, 1.212]		
Interaction with education						
Education:strategy_haphazard					0.983	[0.922, 1.048]
Education:strategy_exploratory					1.062	[0.980, 1.153]
Education:strategy_focused					1.060	[0.967, 1.162]
Adjusted R^2	0.071		0.094		0.092	

*** $p < .001$; ** $p < .01$; * $p < .05$; . $p < .1$

Table 3: Logistic regression results for odds of receiving a call-back associated with job search strategies and demographic variables.

	4a. Haphazard Search		4b. Exploratory Search		4c. Focused Search	
	β	*CI*	*β*	*CI*	*β*	*CI*
(Intercept)	2.967***	[2.765, 3.168]	3.148***	[3.001, 3.296]	3.336***	[3.197, 3.476]
Income	0.008	[-0.016, 0.031]	0.019*	[0.001, 0.036]	0.012	[-0.005, 0.028]
Education	−0.034*	[-0.066, -0.002]	0.002	[-0.021, 0.026]	0.015	[-0.007, 0.037]
Man	0.020	[-0.132, 0.172]	0.139*	[0.027, 0.250]	0.060	[-0.046, 0.166]
Asian	−0.036	[-0.327, 0.255]	0.035	[-0.178, 0.248]	0.112	[-0.091, 0.314]
African American	0.068	[-0.160, 0.296]	0.049	[-0.118, 0.215]	0.028	[-0.130, 0.186]
American Indian	0.250	[-0.473, 0.974]	−0.103	[-0.633, 0.427]	−0.263	[-0.766, 0.239]
Hispanic	−0.123	[-0.422, 0.177]	0.317**	[0.098, 0.537]	0.112	[-0.095, 0.321]
Multiracial	0.119	[-0.197, 0.436]	−0.045	[-0.277, 0.186]	0.039	[-0.181, 0.259]
Age	−0.006·	[-0.012, 0.000]	0.000	[-0.004, 0.005]	0.006**	[0.002, 0.010]
Northeast	0.042	[-0.275, 0.190]	0.002	[-0.169, 0.172]	0.007	[-0.155, 0.168]
South	−0.016	[-0.227, 0.195]	0.149·	[-0.006, 0.303]	0.069	[-0.078, 0.215]
West	−0.018	[-0.254, 0.218]	−0.004	[-0.177, 0.169]	0.071	[-0.093, 0.235]
Online platform						
Non-Career	0.050***	[0.036, 0.064]	0.015**	[0.005, 0.025]	0.031***	[0.022, 0.041]
LinkedIn	−0.002	[-0.014, 0.010]	0.005	[-0.004, 0.014]	0.002	[-0.007, 0.010]
Career Builder	−0.014·	[-0.028, 0.000]	0.003	[-0.007, 0.014]	−0.012*	[-0.022, -0.002]
Indeed	0.000	[-0.009, 0.009]	0.003	[-0.004, 0.010]	0.002	[-0.005, 0.008]
Q&A	−0.001	[-0.013, 0.015]	0.017***	[0.007, 0.027]	0.002	[-0.008, 0.011]
Company Website	−0.004	[-0.019, 0.010]	0.020***	[0.009, 0.030]	0.011*	[0.001, 0.021]
Adjusted R^2	0.074		0.253		0.158	

*** $p < .001$; ** $p < .01$; * $p < .05$; . $p < .1$

Table 4: Association between job search strategies and online platform use.

popularity and the frequency of using online platforms increase as income increases, and a similar increase can be seen across gender and race (RQ2, RQ2-demographic). In terms of strategies, our results suggest that as income increases, exploratory and focused strategies were found to be more positively associated with the odds of getting at least one callback (RQ3, RQ3-demographic). Finally, our results suggest that more frequent use of non-career-oriented social media platforms is associated with *reductions* in perceived social support, while more frequent use of Indeed is associated with a *marginal increase* in perceived social support (RQ4). Interestingly, the use of LinkedIn, Career Builder, Q&A forums, and company websites in

found such income gaps to be more than double the amount suggested by our findings (i.e., Blacks reportedly earn 38% less than Whites on average [31]) outside of a digital context [31].

	a. Model with control variables		**b. Model with control variables and online platform use**		**c. Model with control variables, online platform use, and interaction between online platform use and income**	
	β	*CI*	β	*CI*	β	*CI*
(Intercept)	2.982***	[2.862, 3.101]	2.914***	[2.787, 3.040]	2.911***	[2.785, 3.038]
Income	0.042***	[0.027, 0.056]	0.042***	[0.027, 0.057]	0.047***	[0.028, 0.065]
Education	0.002	[-0.018, 0.022]	0.001	[-0.020, 0.021]	0.002	[-0.018, 0.023]
Man	−0.120*	[-0.213, -0.027]	−0.097*	[-0.193, -0.001]	−0.104*	[-0.200, -0.008]
Asian	−0.171·	[-0.356, 0.013]	−0.155·	[-0.338, 0.029]	−0.165·	[-0.349, 0.020]
African American	−0.042	[-0.185, 0.102]	−0.045	[-0.189, 0.098]	−0.055	[-0.200, 0.089]
American Indian	−0.336	[-0.794, 0.123]	−0.316	[-0.772, 0.140]	−0.328	[-0.782, 0.126]
Hispanic	0.071	[-0.117, 0.260]	0.091	[-0.098, 0.279]	0.089	[-0.100, 0.277]
Multiracial	0.012	[-0.187, 0.210]	−0.011	[-0.210, 0.189]	−0.013	[-0.212, 0.186]
Age	0.001	[-0.003, 0.004]	0.000	[-0.003, 0.004]	0.000	[-0.004, 0.004]
Northeast	−0.095	[-0.242, 0.052]	−0.087	[-0.233, 0.060]	−0.092	[-0.239, 0.055]
South	−0.095	[-0.228, 0.039]	−0.081	[-0.214, 0.052]	−0.075	[-0.208, 0.058]
West	−0.081	[-0.230, 0.069]	−0.065	[-0.214, 0.083]	−0.059	[-0.209, 0.090]
Online platform use						
Non-Career			−0.012**	[-0.021, -0.003]	−0.007	[-0.016, 0.003]
Linkedin			0.002	[-0.005, 0.010]	−0.001	[-0.009, 0.008]
Career Builder			0.002	[-0.007, 0.011]	0.000	[-0.009, 0.009]
Indeed			0.005·	[-0.0003, 0.011]	0.005	[-0.001, 0.010]
Q&A			0.001	[-0.008, 0.009]	0.000	[-0.009, 0.010]
Company Website			0.007	[-0.002, 0.016]	0.008	[-0.002, 0.017]
Interaction with Income						
Income:Non-Career					−0.003**	[-0.005, -0.001]
Income:LinkedIn					0.002*	[0.000, 0.004]
Income:Career Builder					0.002	[0.000, 0.004]
Income:Indeed					−0.001	[-0.003, 0.000]
Income:Q&A					0.000	[-0.002, 0.002]
Income:Company Website					0.000	[-0.003, 0.002]
Adjusted R-squared	0.057		0.069		0.080	

$^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$; $.\ p < .1$

Table 5: Changes in support levels associated with online platform use and income.

general did not appear to influence an individual's perceived social support level.

Although more research is needed to confirm our findings, our results, when situated into prior literature, suggest that those with higher incomes tend to have higher perceived social support [32], which might lead to their less frequent use of non-career-oriented social media for the purpose of job search. In contrast, the interaction between using LinkedIn and income indicates that the correlation between one's use of LinkedIn and perceived social support increases as the income level increases. This suggests that, for individuals with lower income, the use of LinkedIn is less associated with the provision of social support (RQ4, RQ4-demographic). An underlying finding of our work is that higher-income job seekers were more likely to get callbacks and use different strategies than lower-income job seekers.

In the subsections that follow, we further situate our findings into existing research. We explain how our demographic trends are consistent with and extend past findings and raise new questions for future work. We conclude by contributing strategies to better support those falling into demographics underserved by these tools and presenting actionable design suggestions for those designing future digital employment tools.

5.1 Understanding Demographic Trends in Usage

Our results show interesting demographic trends in usage. We found that gender, age, and additionally, income and years of education, which are highly correlated, are strong predictors for the use of all platforms *except* Indeed. First, and perhaps unsurprisingly, we found that men tend to use online platforms for job search more frequently (especially non-career platforms) and that age is marginally negatively correlated with the frequency of using all platforms except Indeed and Career Builder. This is somewhat consistent with past research that suggests that adult women tend to use the Internet more often as a communication tool and that the likelihood and frequency of Internet usage decreases with age [3, 4, 71]. Hoffman et al. also found that self-efficacy drives more online activity such as content creation (e.g., social content, skilled content, political content) and self-efficacy was noticeably higher for men, younger users, and highly educated users [39]. Many social media platforms, as designed, require content creation to market and "brand" oneself. Perhaps this, and the fact that men and younger users are online more, explain why they tend to use online platforms for employment more. However, while we must consider how these sites might inherently appeal to certain groups based on age and gender, we take a closer look at how these sites might tailor to other demographics like income, education, and ultimately, race.

As early as 1998, the year Internet job search questions were introduced in the Current Population Survey (CPS), job seekers have reported using the Internet for job search [45]. A decade later, job search tools were said to only have supplemented the traditional hiring process and not used as a replacement [42]. It became clear that the use of the tools was dependent on the skill level and education of the target audience who were primarily job seekers with higher computer literacy and technical expertise, and who were seeking higher-paying jobs (e.g., engineering, information technology, finance, accounting). Therefore, those seeking minimum wage and low-skilled jobs were not the best candidates for online job search due to low computer literacy and use rates. In fact, almost another decade later, Pew's 2015 nationally representative survey found that the use of online resources for employment was inversely related to the respondents' level of education [59]. Those with less than a college degree were indeed less confident in performing job-related tasks online. An HCI-related study of low-resourced job seekers found that while Internet resources provided beneficial resources, these resources did not increase their chances of securing employment [67]. Our results, unfortunately confirm and extend these findings while uncovering details regarding the types of and differences in tools used.

Our results also suggests that for lower-income individuals, the use of LinkedIn is less associated with the provision of social support. Considering that LinkedIn is marketed as a professional networking site, our finding mirrors Zillien and Hargittai's work that suggests that higher socio-economic Internet users engage more often in Internet activities that are capital-enhancing, while lower socio-economic classes use the Internet in less productive ways [71]. We glean from past literature on Black-White income inequality on why this might exist. Gordils et al. argue that people's awareness of income inequality has the potential to make group differences salient and highlight the scarcity of subsequent resources in question (e.g., income, housing, employment, jobs) [31]. This awareness evokes perceptions of competition between groups (in their work, Black versus White group competition) and as a result, heightened perceptions of other race-based outcomes like discrimination. These authors argue that the stratification of "Us" versus "Them" becomes more salient as the awareness of the inequalities increases. Drawing from their findings and from past HCI research that suggests that lower-income job perceive sites like LinkedIn as professional, and not designed for them [22], we argue that the design of some websites might be leading to this type of "Us versus Them" thinking [7]. In other words, job seekers are more likely to use the employment platforms that they identify with, which could be based on demographic factors such as income, education, age or even job type. There are certain cues on LinkedIn—it aims for job seekers to "Make the most of your *professional* [emphasis added] life"—that might lead job seekers to draw this conclusion. This "Us versus Them" thinking could also be associated with perceptions of competition. Gordils et al. argue that such perceptions are associated with interracial competition, which is associated with racial income inequality [31].

Interestingly, our initial investigation of employment platforms revealed LinkedIn and CareerBuilder to be the only sites that were tailored to specific job seekers (i.e., professionals) [34]. This might explain why higher-income job seekers used more tools than lower-income job seekers overall. There were no demographic differences in the usage of Indeed, which was the most inclusive job platform as described by popular media [34]. Drawing from our related work and results, it is clear Indeed in its marketing aims to be inclusive while LinkedIn targets professional job seekers. In fact, LinkedIn co-founder Allen Blue has stated ambitions to sign up the growing number of blue-collar workers on the site after shedding its "elitist image" [41]. According to the article, in addition to increased revenue, having this data could help employers plan where to build a redistribution center or factory. Going forward, research, practitioners, and designers could simply change their marketing and design strategies to include lower-waged job seekers. The possibility of such inclusion could avoid leading to such divisions in thinking. Further, the COVID-19 pandemic has forced job seekers to use what was before intended to be a supplement to job search but now is required, which leaves such biases to further propagate into the system. Our work highlights the importance for practitioners to not only be more inclusive to job seekers across demographic groups, but to consider designing tools that tailor specifically to blue-collar or low-wage workers and their employers. Such tools have been widely explored in HCI and CSCW work [19, 20, 25, 37, 38, 40, 46, 67].

5.2 Rethinking the Design of Digital Employment Tools and Job Search Strategies

Perhaps unsurprisingly, job seekers' most common behaviors included career exploration, searching and applying for jobs, and finding job search information. In general, the average popularity and frequency scores were lower for the active phase of the job search than the preparatory stage. This suggests the importance of online platforms for information-seeking. However, this also suggests opportunities for job seekers to leverage these platforms for more active job search behaviors such as getting advice, getting referrals, and seeking training—behaviors that were used less frequently and behaviors that past research suggests could be beneficial for marginalized job seekers.

Situating our findings into Wheeler and Dillahunt's, while Indeed is beneficial for lower-income job seekers' abilities to *find* jobs, it might be less useful for helping lower-income job seekers to *land* jobs [67]. These authors suggest the need to support lower-income job seekers in receiving referrals, seeking training/skill-building, and creating and revising online profiles. Our results also suggest providing support for referrals, training, and additionally advice. Their work suggests that offline social connections were most beneficial for their participants in terms of landing jobs. Interestingly, our findings reveal that lower-income job seekers' use of non-career oriented social media was more associated with perceived social support. This perhaps shows that the use of non-career-oriented social medias mirrors one's offline network—those who already have stronger offline social connections are more likely to find social media more useful and thus use them more. Or alternatively, social media could be an opportunity to foster social connections for lower-income individuals, especially for those who do not have strong offline connections. Going forward, researchers should investigate how social platforms could influence job seekers' perceived social support levels, especially for lower-income individuals, and whether connecting them to job seekers who share similar experiences could increase perceived social support. However, as suggested earlier, it is important that the sites themselves convey a sense of inclusivity and that they support a wide range of users.

Our findings suggest moving job seekers toward exploratory and focused job searches. Recall from our related work that behaviors targeting one's job search around specific goals are more focused while those relating to a broader search and openness to different possibilities are exploratory. Our results showed that focused and exploratory strategies are both positively associated with the increase in the odds of getting callbacks when used in an *online* context. We also found that older job seekers were associated with using more focused searches suggesting that as we age, our job searches might be more targeted and goal-oriented. The association between focused and exploratory strategies and callbacks align with prior research that found that focused and exploratory *offline* searches led to people receiving more offers [18, 44]. Koen et al. argue that people using exploratory strategies tend to apply for more jobs and search for longer periods [44], which explains why they might receive more offers.

What is interesting about our findings is that they suggest that "typical" employment sites like Indeed and LinkedIn might not be as effective as Q&A platforms and that job seekers used Q&A platforms for more exploratory strategies. These platforms surprisingly were used predominantly by high-income populations. Such sites might benefit low-income job seekers but were not being used in this way.

Given these findings, more efforts should be made to move job seekers toward exploratory and focused job searches and we provide several concrete design recommendations for such efforts. Q&A platforms as employment tools are less explored in low-income contexts although Marlow and Dabbish [49] have documented the benefit of sites like Stack Overflow for professional programmers. Developers at sites like Indeed could provide job information from, or nudge users to view outside sources (Q&A sites, employer pages, O*NET, LinkedIn) and remind job seekers to be open to new opportunities (e.g., recommending jobs 10 miles versus 5 miles away). Opportunities to use Q&A sites for employment information should be made more visible in general. Given Q&A sites are used more for higher-income people, we should consider opportunities to imagine how Q&A platforms could be better designed to reach lower-wage job seekers and be beneficial to their needs. Such platforms could create new ways for information retrieval and resource seeking, which is different from traditional online mentoring and support platforms.

Following Crossley and Highhouse [18], we further suggest designers focus on skills versus specific job titles to foster online exploratory searches. HCI researchers proposed SkillsIdentifier, a tool to help job seekers "identify and communicate their current skill set [22, p.7]. They then implemented the tool and conducted a lab study of it among 20 U.S.-based job seekers primarily consisting of racial minorities [21]. Their findings suggested that the tool helped with the process of career planning and aiding job seekers in making career transitions (arguably a result of exploring new careers). While this tool did not directly suggest new and potential job titles to job seekers, it indirectly did so by providing a drop-down suggesting job titles as job seekers entered their current jobs (e.g., finding health, human resources, or executive administrative assistant when searching for "assistant"). Building on this, we suggest that designers provide alternative job recommendations based on job seekers' skill set (e.g., job seekers with strong communication skills are candidates for event organizers and human resource specialists). HCI researchers investigating the needs of lower-income job seekers have also proposed concepts that ask job seekers to input their "dream jobs" as a way to provide career pathways [23], which could lead to a more *focused* job search. Other researchers focusing on crowd workers have proposed reimagining online crowdwork platforms to support crowd workers' reskilling and changing of career path [58], which could also lead to a more focused job search. Moving forward, a qualitative investigation of those job seekers who used Q&A sites is needed to fully understand how they made use of these platforms and which platforms they used.

6 LIMITATIONS AND FUTURE WORK

We discuss the limitations of our work. First, while our results confirm and extend past research findings related to social media and online platform use for employment, a key limitation is our inability to provide detailed explanations of our results. When possible, we drew from past literature; however, surveys are most useful for showing trends and this is a known limitation. Second, our survey was limited to a U.S. audience and while our sample sizes across race were imbalanced, for the most part, they corresponded with that of the U.S. (See Table 6 in the Appendix). Future work is necessary to understand how and whether our work generalizes across non-U.S. regions. Further investigations could examine whether the online employment platforms used in our study are also used in an international context. And, if so, are they used in the same way? Finally, another limitation of our study is the *multiple-comparisons problem*, which occurs when a dataset is used to fit multiple statistical models. We did not adapt post-hoc tests such as the Bonferroni correction to address this problem, because we viewed our survey as exploratory; our results contribute new questions and hypotheses to raise for future research.

While past research suggests the importance of social support in the job search [33], we did not find this to be especially salient in our results. We speculate that the measures used to assess individuals' perceived social support might be outdated and thus not tailored to the employment or contexts that have been transformed by technology. These scales were created well before the introduction of smart phones, social media, and online employment platforms. Perceived social support today, might not be the same as it was then. Thus, while one of the most common scales used today to measure perceived social support in HCI research (e.g., [14, 15]), the scales might be outdated, which leaves another opportunity for future work.

7 CONCLUSION

To conclude, we conducted an online survey of 768 U.S.-based job seekers to better understand their use of social media and other online platforms for their job search and how this correlated with demographic factors. Our results uncovered ways in which socioeconomic inequality across demographic groups persists in online contexts and we urge practitioners to rethink how perceptions of design might lead to divisions in thinking and exclusion in usage. Given that employers use social media and other online platforms for hiring [47], their usage of these sites might be inherently biased and lead to persistent inequities in hiring. Our findings make empirical and practical contributions, recommendations for practitioners, and contribute questions for future research.

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APPENDIX OVERVIEW

We've included our survey materials as a part of our supplementary material. Note that we included a survey question about job seekers' use of online *and* offline resources in the past 3 months; however, these results were excluded from our analysis because they fell outside the scope of this work. The rest of our appendix includes the following tables and graphs that might be useful for the more curious reader:

- Table 6: Detailed breakdown of online platform use by demographics;
- Table 7: Negative binomial regression results for changes in number of received call-backs associated with strategies and demographic variables;
- Figure 5: Platform behaviors in preparatory and active phases;
- Figures 6-8: Platform behaviors by education, gender, and race;

	Total	FB Grp	FB	TW	IG	LI	CB	ID	QA	YT	Comp. Web
Woman	458 (59.6%)	157 (20.4%)	245 (31.9%)	52 (6.8%)	93 (12.1%)	225 (29.3%)	180 (23.4%)	349 (45.4%)	146 (19.0%)	83 (10.8%)	335 (43.6%)
Man	307 (40.0%)	174 (22.7%)	205 (26.7%)	134 (17.4%)	126 (16.4%)	175 (22.8%)	156 (20.3%)	190 (24.7%)	114 (14.8%)	125 (16.3%)	235 (30.6%)
Prefer not to Say or Self describe	3 (0.4%)	2 (0.3%)	3 (0.4%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (0.1%)	2 (0.3%)	1 (0.1%)	0 (0.0%)	1 (0.1%)
White	534 (69.5%)	255 (33.2%)	338 (44.0%)	142 (18.5%)	150 (19.5%)	280 (36.5%)	246 (32.0%)	379 (49.3%)	195 (25.4%)	146 (19.0%)	419 (54.6%)
African American	86 (11.2%)	27 (3.5%)	35 (4.6%)	15 (2.0%)	27 (3.5%)	43 (5.6%)	40 (5.2%)	63 (8.2%)	29 (3.8%)	29 (43.8%)	53 (6.9%)
Hispanic	49 (6.4%)	19 (2.5%)	33 (4.3%)	11 (1.4%)	18 (2.3%)	18 (2.3%)	11 (1.4%)	30 (3.9%)	7 (0.9%)	11 (1.4%)	26 (3.4%)
Asian	50 (6.5%)	21 (2.7%)	27 (3.5%)	11 (1.4%)	12 (1.6%)	30 (3.9%)	20 (2.6%)	29 (3.8%)	18 (2.3%)	14 (1.8%)	37 (4.8%)
American Indian	7 (0.9%)	2 (0.3%)	3 (0.4%)	1 (0.1%)	1 (0.1%)	3 (0.4%)	0 (0.0%)	4 (0.5%)	0 (0.0%)	1 (0.1%)	4 (0.5%)
Multi-racial	42 (5.6%)	9 (1.2%)	17 (2.2%)	6 (0.8%)	11 (1.4%)	26 (3.4%)	20 (2.6%)	36 (4.7%)	12 (1.6%)	7 (0.9%)	32 (4.2%)
High school or less	247 (32.2%)	88 (11.5%)	143 (18.6%)	30 (3.9%)	56 (7.3%)	68 (8.9%)	69 (9.0%)	168 (21.9%)	53 (6.9%)	61 (7.9%)	154 (20.1%)
Some college	189 (24.6%)	69 (9.0%)	94 (12.2%)	23 (3.0%)	32 (4.2%)	74 (9.6%)	75 (9.8%)	138 (18.0%)	53 (6.9%)	34 (4.4%)	139 (18.1%)
College graduate and higher	332 (43.2%)	176 (22.9%)	216 (28.1%)	133 (17.3%)	131 (17.1%)	258 (33.6%)	193 (25.1%)	235 (30.6%)	155 (20.2%)	113 (14.7%)	278 (36.2%)
Unemployed	503 (65.5%)	179 (23.3%)	263 (34.2%)	77 (10.0%)	101 (13.2%)	239 (31.1%)	204 (26.6%)	371 (48.3%)	159 (20.7%)	100 (13.0%)	367 (47.8%)
Self-employed	126 (16.4%)	84 (10.9%)	92 (12.0%)	65 (8.5%)	74 (9.6%)	71 (9.2%)	63 (8.2%)	72 (9.4%)	49 (6.4%)	66 (8.6%)	93 (12.1%)
Underemployed	91 (11.8%)	48 (6.3%)	66 (8.6%)	26 (3.4%)	24 (3.1%)	59 (7.7%)	56 (7.3%)	72 (9.4%)	40 (5.2%)	19 (2.5%)	79 (10.3%)
Homemaker.	39 (5.1%)	15 (2.0%)	24 (3.1%)	8 (1.0%)	11 (1.4%)	12 (1.6%)	10 (1.3%)	26 (3.4%)	10 (1.3%)	9 (1.2%)	27 (3.5%)
Retired, Military, Unable to work or Other specific statuses[2]	94 (12.2%)	40 (5.2%)	61 (7.9%)	31 (4.0%)	33 (4.3%)	48 (6.3%)	36 (4.7%)	59 (7.7%)	25 (3.3%)	38 (4.8%)	69 (9.0%)
Ages 18-30	180 (23.4%)	58 (7.6%)	91 (11.8%)	40 (5.2%)	55 (7.2%)	88 (11.5%)	49 (6.4%)	138 (18.0%)	56 (7.3%)	51 (6.6%)	120 (15.6%)
31-50	412 (53.6%)	225 (29.3%)	280 (36.5%)	131 (17.1%)	148 (19.3%)	218 (28.4%)	207 (27.0%)	276 (35.9%)	162 (21.1%)	131 (17.1%)	327 (42.4%)
51-78	176 (22.9%)	50 (6.5%)	82 (10.7%)	15 (2.0%)	16 (2.1%)	94 (12.2%)	81 (10.5%)	127 (16.5%)	43 (5.6%)	26 (3.4%)	125 (16.3%)
Income < $30K	377 (49.1%)	137 (17.8%)	208 (27.1%)	44 (5.7%)	69 (9.0%)	141 (18.4%)	117 (15.2%)	266 (34.6%)	84 (10.9%)	76 (9.9%)	256 (33.3%)
$30K-$75K	194 (25.3%)	84 (10.9%)	116 (15.1%)	56 (7.3%)	64 (8.3%)	115 (15.0%)	106 (13.8%)	147 (19.1%)	79 (10.3%)	55 (7.2%)	148 (19.3%)
> $75K	182 (23.7%)	106 (13.8%)	121 (15.8%)	84 (10.9%)	84 (10.9%)	137 (17.8%)	109 (14.2%)	119 (15.5%)	93 (12.1%)	74 (9.6%)	156 (20.3%)
Prefer not to disclose	15 (2.0%)	6 (0.8%)	8 (1.0%)	2 (0.3%)	2 (0.3%)	7 (0.9%)	5 (0.7%)	9 (1.2%)	5 (0.7%)	3 (0.4%)	11 (1.4%)

Table 6: Number (percentage) of people using different online platforms by demographic factors. For demographic comparison, according to the 2019 US Census Bureau Report, there were roughly 60.1% White, 13.4% Black, 5.9% Asian, 18.5% Hispanic, 1.3% Native American, and 2.8% multi-racial [9]. Our population consisted of slightly more White people and fewer Hispanic people. Platforms: FB Grp=Facebook Group, FB=Facebook, TW=Twitter, IG=Instagram, LI=LinkedIn, CB=Career Builder, ID=Indeed, YT=YouTube

1: The percentage sum here may exceed 100% as people can have multiple races.

2: The percentage sum here may exceed 100% as people can have multiple employment status.

	7a. Base Model		7b. Interaction Model with income		7c. Interaction Model with education	
	β	*CI*	β	*CI*	β	*CI*
(Intercept)	1.350***	[0.749, 1.955]	1.307***	[0.703, 1.917]	1.330***	[0.735, 1.930]
Income	0.050**	[0.016, 0.084]	−0.086	[-0.234, 0.061]	0.039*	[0.006, 0.072]
Education	−0.010	[-0.055, 0.034]	−0.016	[-0.060, 0.028]	−0.333**	[-0.527, -0.140]
Man	0.421***	[0.225, 0.617]	0.372***	[0.173, 0.571]	0.346***	[0.151, 0.542]
Asian	0.063	[-0.312, 0.454]	0.013	[-0.365, 0.407]	−0.017	[-0.387, 0.367]
African American	−0.100	[-0.410, 0.219]	−0.078	[-0.390, 0.242]	−0.031	[-0.346, 0.291]
American Indian	−0.857	[-2.367, 0.727]	−0.781	[-2.288, 0.791]	−0.816	[-2.321, 0.742]
Hispanic	−0.197	[-0.587, 0.204]	−0.195	[-0.583, 0.203]	−0.270	[-0.659, 0.128]
Multiracial	−0.069	[-0.473, 0.350]	−0.018	[-0.426, 0.405]	0.056	[-0.350, 0.476]
Age	−0.004	[-0.013, 0.005]	−0.003	[-0.012, 0.006]	−0.003	[-0.012, 0.006]
Northeast	0.056	[-0.264, 0.373]	0.039	[-0.281, 0.357]	0.046	[-0.269, 0.359]
South	0.050	[-0.235, 0.331]	0.035	[-0.250, 0.317]	0.055	[-0.226, 0.332]
West	0.294·	[-0.027, 0.613]	0.282·	[-0.037, 0.599]	0.264·	[-0.052, 0.578]
Strategies						
Strategy_haphazard	0.009	[-0.089, 0.106]	0.013	[-0.089, 0.116]	0.007	[-0.100, 0.113]
Strategy_exploratory	−0.051	[-0.192, 0.089]	−0.039	[-0.179, 0.100]	−0.067	[-0.206, 0.072]
Strategy_focused	−0.007	[-0.156, 0.141]	−0.014	[-0.164, 0.136]	0.009	[-0.145, 0.162]
Interaction with income						
Income:Strategy_haphazard			−0.012	[-0.037, 0.013]		
Income:Strategy_exploratory			0.027	[-0.008, 0.063]		
Income:Strategy_focused			0.019	[-0.020, 0.057]		
Interaction with education						
Education:Strategy_haphazard					−0.005	[-0.039, 0.029]
Education:Strategy_exploratory					0.089***	[0.039, 0.139]
Education:Strategy_focused					0.002	[-0.050, 0.052]

*** $p < .001$; ** $p < .01$; * $p < .05$; . $p < .1$

Table 7: Negative binomial regression results for changes in number of received call-backs associated with strategies and demographic variables.

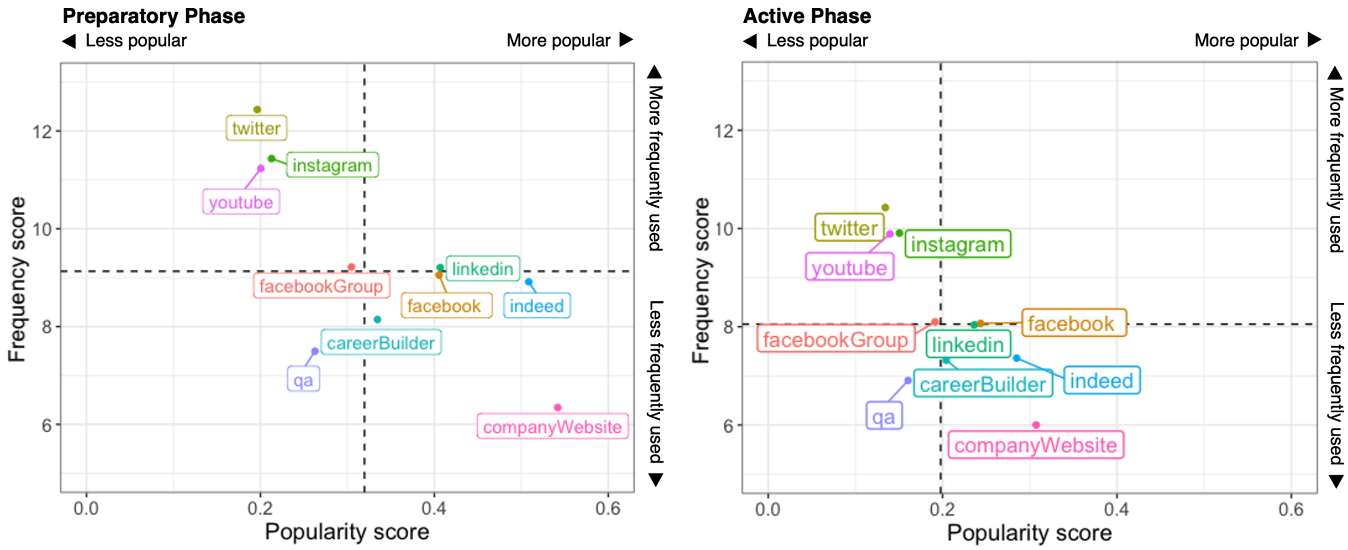

Figure 5: Of all the platforms, which were the most "popular" and most intensely used for preparatory versus active phases?

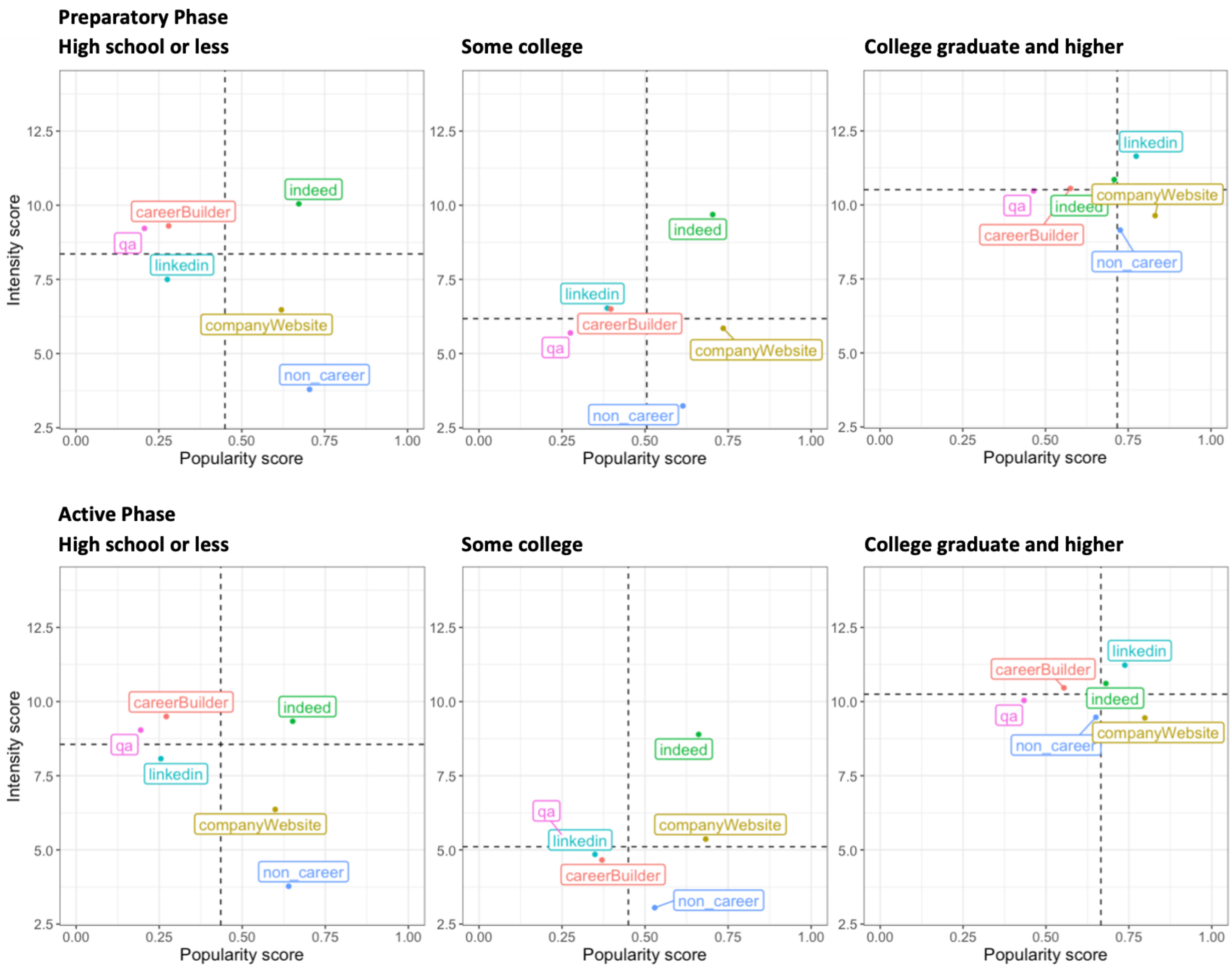

Figure 6: Popularity score vs. frequency score for platform use by education level when people are in preparatory and active phases of searching for a job.

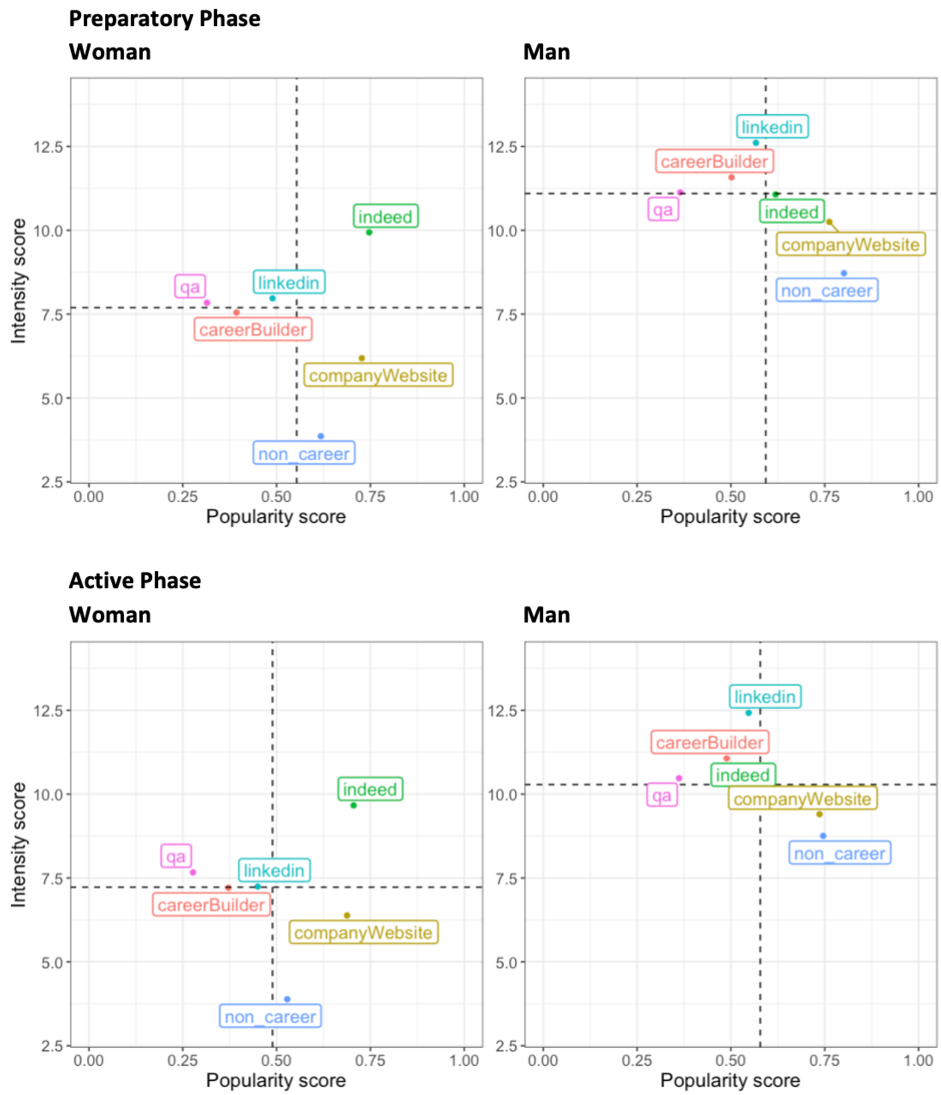

Figure 7: Popularity score vs. frequency score for platform use by gender when people are in preparatory and active phases of searching for a job.

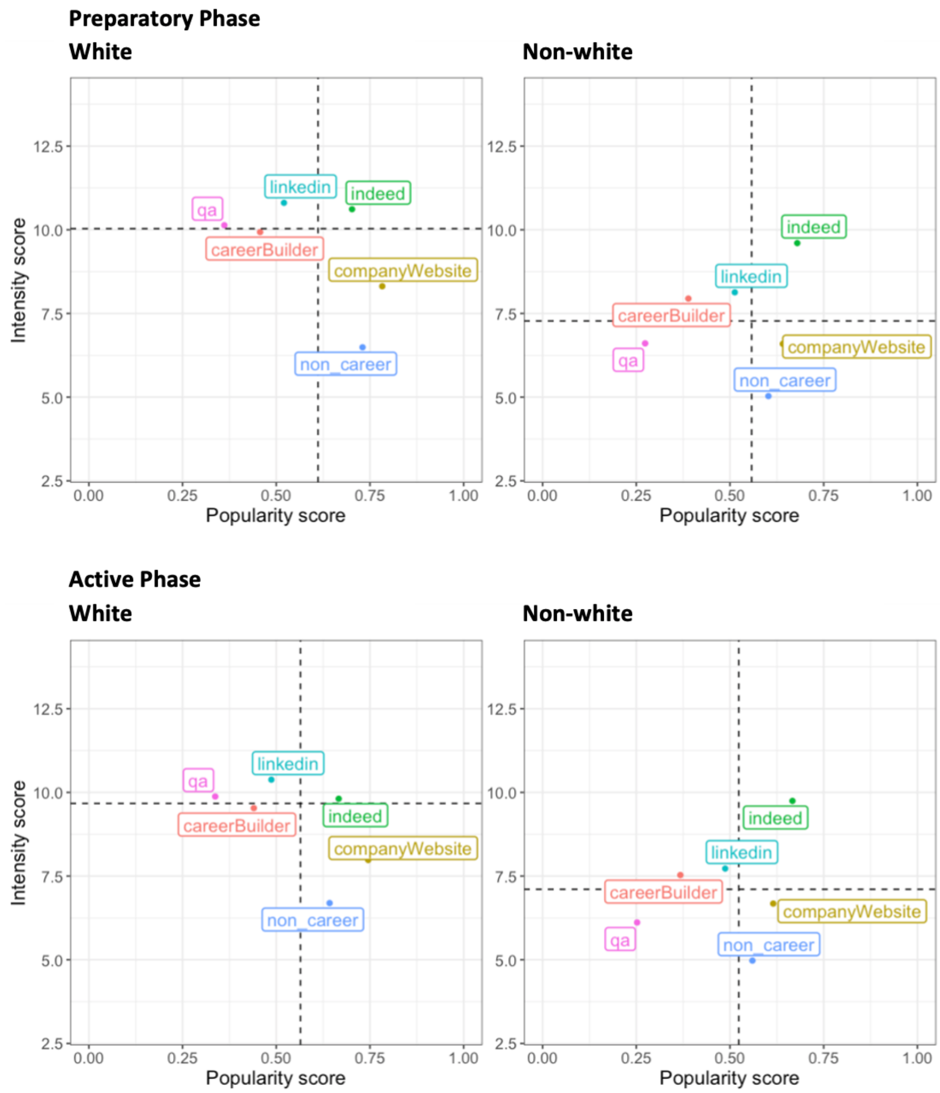

Figure 8: Popularity score vs. frequency score for platform use by race (white vs. non-white) when people are in preparatory and active phases of searching for a job.