Fetch Bias Evaluation

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This bias evaluation, including Workday's testing approach, observations, and analysis shared in this document are intended to assist customers in evaluating products and capabilities for their use and adoption planning. Workday conducts this bias testing as part of our efforts to improve and continue to develop our AI products and in line with our commitments to responsible AI. Information shared in this document is not intended, and shall not be used, to satisfy customers' legal obligations on their behalf. Customers remain responsible for complying with any legal obligations arising from the implementation and use of the product, including any required assessments, testing, or documentation under applicable laws and should consult with their own legal counsel about those obligations..

Data from multiple customers has been aggregated for the bias evaluation analysis described in this document. While Workday considers this method suitable for its own testing as a developer of responsible AI tools, it should not be misunderstood to imply that Fetch generates uniform or static outputs across different jobs or customers. Fetch is not an assessment; its outputs rely heavily on the specific job requisition requirements set by the customer and the qualifications provided by the lead, which means results will vary across and between customers, based on these inputs. Workday does not have insight, influence, or control over the quality or accuracy of these inputs.

Executive Summary

HiredScore's Fetch is an AI-powered feature that highlights existing talent within an organization's talent pool by identifying workers that are facially qualified for open jobs and surfacing relevant job opportunities to workers who might be interested. Workday enables customers to build talent pools during the application process by obtaining candidate consent to be considered for future roles. These candidates are then added to the organization's talent pool as potential leads. When a new job requisition opens, Fetch analyzes the requisition against the profiles of potential leads —considering qualifications and prior application activity—to provide recruiters with a list of leads the recruiter may want to invite to apply.

As part of our commitment to responsible AI development, we conduct annual bias evaluations of aggregate Fetch AI outputs. Our evaluation methodology reflects our effort to isolate the Fetch AI models by holding constant aspects of the overall selection system that are not within our control as a developer, such as job requirements that are determined by the customer and qualifications that are reported by the lead on their previous application. This approach is designed to assess whether the Fetch AI models themselves introduce bias.

We conducted a bias evaluation on a random sample of hundreds of thousands of leads across 47 US customers. The outcome variable for this evaluation was 'Basic Qualification Rate', which was defined as the proportion (percentage) of potential leads in a given demographic group who meet the minimum requirements for the target job as specified by the customer's requisition. Basic qualification rate was analyzed by gender and race/ethnicity. The results of this initial analysis revealed higher basic qualification rates for men and Asian leads in our sample.

In order to understand what was causing this result, we engaged in further analysis. Descriptive analysis revealed that men and Asian leads were more likely to have advanced educational degrees or to have previous experience in more senior leadership positions. Men also were likely to have more work experience compared to women. For these reasons, we find[1] that men and Asian leads were proportionately more likely to meet the basic qualifications for the job positions included in our analysis.

We reason that this set of findings does not indicate bias in the product or the AI. As an illustrative example of this reasoning, consider a role requiring a master's or doctoral degree. If 50 men and 50 women are present in the talent pool, and 25 of these men and 15 of the women have a master's degree or higher, Fetch will identify 50% of men and 30% of women in the pool as promising leads for the opportunity. While this result initially seems to favor men, when the dataset is adjusted to compare only the leads with similar educational backgrounds, then all relevant workers would be highlighted as promising leads by Fetch regardless of gender.

After adjusting the dataset to compare leads with similar qualifications in the context of requirements for target roles, no statistically significant differences in Fetch basic qualification rates were observed across gender and race groups ($p > 0.05$). This indicates that the Fetch AI models do not introduce or amplify bias. The findings emphasize the importance of accounting for job-relevant attributes in bias testing to accurately assess AI model fairness.

After adjusting the dataset to compare leads with similar qualifications in the context of requirement for target roles, no statistically significant differences in Fetch basic qualification rates were observed across gender and race groups ($p > 0.05$). This indicates that the Fetch AI models do not introduce or amplify bias when evaluated on a level playing field. The findings emphasize the importance of accounting for job-relevant attributes in bias testing to accurately assess AI model fairness.

Table 1. Summary of Fetch Basic Qualification Rate Differences by Gender

	Unadjusted Fetch Basic Qualification Rate (Full Population)	Adjusted Fetch Basic Qualification Rate (Stratified Random Sample)	
Men[1]	7.3%	5.7%	0.24
Women	6.5%	5.9%	

Table 2. Summary of Fetch Basic Qualification Rate Differences by Gender

	Unadjusted Fetch Basic Qualification Rate[1] (Full Population)	Adjusted Fetch Basic Qualification Rate (Stratified Random Sample)	
Asian[2]	8.7%	6.5%	p=0.83
Black or African American	6.4%	6.4%	
Asian	8.7%	4.5%	p=0.49
Hispanic or Latino	6.1%	4.1%	
Asian	8.7%	6.7%	p=0.38
White	6.4%	6.4%	

[1] We conducted additional statistical testing on the unadjusted dataset and found statistically significant differences in basic qualification rates by race and gender. These differences go away when you adjust for job-relevant factors (e.g., required years of experience).
[2] Men and Asian leads are the Control Groups because they had the highest Fetch Basic Qualification Rates. All other groups are defined as Test groups for each pairwise comparison presented in Tables 1-2.

Introduction

Overview of Fetch

HiredScore's Fetch is an AI-powered feature designed to enhance the efficiency of the sourcing process. Workday provides customers the ability to configure consent when candidates apply to a role to be considered for future job opportunities and will be added to a talent pool. Going forward in this document, we will refer to these candidates in the talent pool as leads. When a new job requisition is opened, Fetch analyzes both the job requirements articulated in the job requisition and included on the leads' profile based on their previous application (e.g., the educational attainment or years of experience they reported in their previous application to a prior job requisition). The Fetch AI models specifically determine whether the leads meet the basic qualifications listed on the new job requisition to initially identify which leads to highlight to recruiters. The recruiters can then review these profiles and decide whether to invite these individuals to apply to the role.

It's important to note that Fetch conveys information and adds a layer of insights on leads in an actionable form, but does not make any decisions about whether to invite any individual to apply to a particular role. Fetch also does not consider or reject any individuals for a position. Fetch is not intended to be used as an employment test or selection procedure, nor is it intended to assess the accuracy of lead-provided information or the job-relatedness of client-defined criteria. It simply provides data-driven insights to complement human judgment in the recruiting process.

Bias Evaluation Background & Objectives

As part of our commitment to fairness and transparency, we conduct annual bias evaluations of Fetch. To assess the Fetch AI model's potential for bias in its initial identification of leads within the talent pool who meet the basic qualifications listed on the job requisition, we have developed a targeted analytical approach.

The evaluation described in this report focuses specifically on isolating Fetch's impact by controlling for job-relevant factors, allowing us to assess whether the Fetch AI models contribute to any significant differences in basic qualification rates across demographic groups.

Methodology

Evaluation Cadence

We conduct this testing on an annual basis. This approach is designed to ensure that Workday understands the impact of any updates or improvements to the model, and is positioned to address any unintended consequences that might arise. This regular evaluation helps us maintain consistent performance of our AI-driven matching services.

Evaluation Criteria

Our primary evaluation metric is the Fetch Basic Qualification Rate. This is the proportion (expressed as percentage) of leads identified by the Fetch AI models that meet at least the basic qualifications listed on the target job requisition. This Basic Qualification Rate is analyzed by demographic groups in our approach. As described earlier, Fetch performs this analysis on leads within a talent pool (candidates who previously applied and consented to be considered for future roles). We focus on this metric because it represents an initial crucial step where Fetch identifies which leads to highlight to recruiters, enabling them to invite suitable leads to apply for the new job requisition.

Data used for Testing

Worker Demographics Included. The dataset utilized for the analysis reported here includes 491,695 leads with associated gender data and 466,662 with race and ethnicity data. The data was aggregated from 47 US customers. Table 4 shows a breakdown of the number of leads included in our testing for both the unadjusted and adjusted results reported(incorporating lead- and job-specific attributes). To construct this testing dataset, which simulates Fetch's analysis of a customer's talent pool, we employed a specific data curation process. For each job requisition sampled from these customers, we created a proxy talent pool by taking a random sample of applicants who had previously applied to similar roles. For example, for a Software Engineer requisition, our sample of leads consisted of individuals who had previously applied to various IT-related positions. This method of creating targeted applicant samples allowed us to construct a robust testing dataset, enabling us to evaluate Fetch's performance under conditions that closely resemble its intended use. Accordingly, while our analysis provides valuable high-level insights, customers should conduct their own testing on their specific requisitions and talent pools to fully understand Fetch's behavior within their unique hiring context.

Table 3. Total leads included in analysis in unadjusted and adjusted tests

	Demographic Group	# Leads (Unadjusted)	# Leads (Adjusted)
Race			
Control Group[3]	Asian	104,505	*Randomly sampled to match each of the test group counts below*
Test Group(s)	Black or African American	85,190	4,523
	Hispanic or Latino	43,700	2,596
	White	233,267	10,211
Gender			
Control Group[3]	Men	199,820	25,447
Test Group(s)	Women	291,875	25,447

Job-relevant attributes for adjusted testing. Below we provide examples of the job-relevant attributes we analyzed and adjusted for in our bias evaluation. While Workday assumes these job-relevant attributes are important and necessary to consider in recruiting decisions, we are aware that they could potentially lead to differences in lead pools in our sample. External or societal factors such as time in the workforce, career breaks, or available opportunities to pursue higher education or certain professions may differ by demographic indicators. Failing to account for these attributes could confound our results, as differences in lead demographic representation might be misinterpreted as bias in the Fetch product. Yet these differences are better explained by societal variation in the pools for different types of job requisitions. Adjusting for these job-relevant attributes during testing enables us to analyze a sample of leads who are similarly qualified for target job requisitions to assess Fetch basic qualification rates for any potential demographic disparities.

Note that the demographic distributions of these job-relevant attributes, as well as additional details on job professions, required experience and seniority level, and education and certification requirements, are available within the Appendices of this report.

[3] The control group is determined for each demographic variable (race, gender) based on which group had the highest proportion of leads who met basic qualifications. For instance, because 7.3% of men met basic qualifications compared to 6.5% of women, men are the control group for gender tests.

- **Job Profession:** The job requisitions we sampled across HiredScore customers included a variety of roles across nine categories. Professions include roles in medicine, customer support, IT & software development, marketing, and engineering, accounting and finance, etc.

- **Required Experience and Seniority Level**

  - **Years of experience:** Professional job requisitions generally specify the expected number of years of work experience and the minimum years of experience for a role. Leads typically specify their years of relevant experience on their profile. Adjusting for these three metrics allows us to assess the alignment between the job's experience requirements and the applicant's relevant professional background.

  - **Seniority Level:** Seniority level on a job requisition indicates the required level of experience and responsibility as identified by the customer. Leads also tend to list the seniority level of their previous work experience. HiredScore extracts the seniority level of the leads' previous work experiences. Our sample of job requisitions included 8 seniority levels: (1) Student; (2) Intern; (3) Entry Level; (4) Junior; (5) Senior; (6) Manager; (7) VP; (8) C-Level.

- **Educational and Certification Requirements**

  - **Educational Degrees:** Professional jobs typically require some kind of educational degree and indicate the minimum formal education needed for the role as identified by the customer. Leads tend to list all of the educational degrees they attained on their profile. HiredScore extracts all degrees and determines the highest educational degree from the lead's profile. In our analysis these are both measured using the same five categories: (1) No degree required, (2) High School or Equivalent, (3) Associates, (4) Master's, and (5) Doctorate.

  - **Certifications:** This indicates whether the job requisition required a specific certification as identified by the customer. We created a binary flag to determine whether a job requisition required at least one certification in order to adjust for this factor.

Adjustment Downsampling Process

We first converted all attributes to categorical variables (e.g., binning continuous variables like years of experience or creating binary flags). We then identified the demographic group with the highest representation within each attribute category. For example, 38% of women previously worked in senior-level roles, compared to 45% of men. To adjust for differences in demographic representation among leads with different seniority levels, we take a stratified random sample of the men who previously worked in senior roles to match the relevant number of women. In the adjusted dataset they were equally represented within each job seniority level. After this adjustment process, 33% of both groups were represented in our sample, having worked in senior-level roles.

Statistical Testing

To evaluate potential disparities in basic qualification rates across demographic groups within the Fetch AI model outputs, we utilized the Binomial-Z two proportion test to determine if there is a statistically significant difference between the proportions of two independent groups[4]. All statistical tests were pairwise comparisons (e.g., Black/African American vs. Asian, Black/African American vs. White). For each pair we designate a test and control group.

Defining Test and Control Groups. We determined which demographic group had the highest Fetch basic qualification rates and assigned them as the "Control" group while all others were assigned as "Test" groups. For instance, since 7.3% of men met basic qualifications compared to 6.5% of women, men represent the control group for gender tests.

Statistical Test and Interpretation. We calculated p-values for each comparison. If all adjusted p-values exceeded 0.05, we concluded that there was no statistically significant evidence of disparity in basic qualification rates between the tested groups, suggesting the observed differences were likely due to random chance. Conversely, if we had observed statistically significant differences post-adjustment, indicated by p-values below 0.05, further investigation into potential model biases would be warranted.

[4] https://www.itl.nist.gov/div898/software/dataplot/refman1/auxillar/binotest.htm

Results & Discussion

Tables 4-5 show a summary of *Fetch Basic Qualification Rate* differences before and after adjusting datasets as described in this report. Below we detail the differences we observed in *Fetch Basic Qualification Rates* by demographic groups, differences in job-relevant factors by demographics that could influence Fetch AI models, and the interpretation of statistical testing results before and after adjustment for these job-relevant factors.

Table 4. Summary of Fetch Basic Qualification Rate Differences by Gender

	Unadjusted Fetch Basic Qualification Rate (Full Population)	Adjusted Fetch Basic Qualification Rate (Stratified Random Sample)	
Men[6]	7.3%	5.7%	p=0.24
Women	6.5%	5.9%	

Table 5. Summary of Fetch Basic Qualification Rate Differences by Gender

	Unadjusted Fetch Basic Qualification Rate[5] (Full Population)	Adjusted Fetch Basic Qualification Rate (Stratified Random Sample)	
Asian[6]	8.7%	6.5%	p=0.83
Black or African American	6.4%	6.4%	
Asian	8.7%	4.5%	p=0.49
Hispanic or Latino	6.1%	4.1%	
Asian	8.7%	6.7%	p=0.38
White	6.4%	6.4%	

Differences in Fetch Basic Qualification Rate by demographics.

Table 5 above shows a breakdown of the Fetch basic qualification rates by race and gender. In our sample, we observed Asians as the highest proportion of leads who met basic qualifications on the job requisitions (8.7%), followed by Black/African American and White leads (6.4% each), and Hispanic or Latino (6.1%). Men also had a higher Fetch basic qualification rate compared to women (7.3% and 6.5% respectively).

[5] We conducted additional statistical testing on the unadjusted dataset and found statistically significant differences in basic qualification rates by race and gender. These differences go away when you adjust for job-relevant factors (e.g., required years of experience).

[6] Men and Asian groups are the Control Groups because they had the highest Fetch Basic Qualification Rates. All other groups are defined as Test groups for each pairwise comparison presented in Tables 4-5..

Differences in Job-relevant Factors

Leads' experience and seniority level. In our sample, on average men had 10.3 years of relevant experience compared to women who on average had 8.7 years of relevant experience. Men were also more likely to have previously worked in more senior-level roles compared to women. Our analysis revealed that 38% of women previously worked in senior-level roles or above (senior, manager, director, VP, and C-level positions), compared to 45% of men.

Asian leads on average had 9.1 years of relevant experience compared to 10.6 years for White leads, 8.9 years for Hispanic leads, and 8.4 years for Black/African American leads. Approximately half of Asian leads and White leads previously worked in senior-level roles compared to only 46% of Hispanic leads and 38% of Black/African American leads.

Educational and Certification Requirements. Asian leads were more likely to have attained an advanced degree, with nearly 95% of Asian leads achieving over a high school or equivalent degree. In fact over half of Asian leads reported attaining a graduate level degree on their profile. Whereas only 23% of White leads, 21% of Hispanic leads, and 23% of Black or African American leads reported a graduate level degree on their profile. Men and women had more comparable educational attainment, with 72% of women and 75% of men attaining an advanced degree.

Job-relevant attributes demonstrate differences in Fetch. Men and Asian leads were both more likely to have reported previous experience in more senior-level roles and attained more advanced degrees. Men in particular were more likely to have relevant work experience compared to women in our sample. These are all factors that could lead to differences in the make up of the lead pool for Fetch and whether they met basic qualifications on the job requisitions.

These findings highlight distinct patterns in how different demographic groups navigate the job market, potentially influenced by a combination of factors such as historical access to education and employment opportunities, societal biases and stereotypes shaping career choices, and industry-specific trends in valuing formal education versus certifications. Understanding these nuances is crucial for interpreting the results of our bias testing and ensuring we accurately assess Fetch's impact on equitable recruiting outcomes.

Statistical Test Results. After adjusting for these influential factors, the disparities in Fetch basic qualification rates largely disappeared. Notably, the differences across all racial groups and between genders became statistically non-significant, with p-values ranging from 0.24 to 0.82. This indicates that the initial disparities observed were largely attributable to differences in lead qualifications and the types of target jobs included in this analysis.

Discussion

Initial observations indicated differences in Fetch's basic qualification rates across various demographic groups, with workers from some demographic groups being highlighted as promising leads more often than others. These initial disparities appeared to correlate with differences in job-relevant attributes present within the lead pool.

Our analysis of these job-relevant factors revealed notable demographic variations in experience levels, seniority in previous roles, and educational attainment. For instance, some demographic groups, on average, possessed more years of relevant experience and were more likely to have held senior-level positions. Similarly, significant differences were observed in the proportion of leads holding advanced degrees across different racial and ethnic groups, while gender differences in educational attainment were less pronounced. These findings suggest that the initial differences in Fetch's basic qualification rates could be explained by pre-existing variations in these key job-related qualifications among different demographic groups.

After statistically accounting for these job-relevant factors, the initial disparities observed in Fetch's basic qualification rates largely vanished. The differences in qualification rates across racial and ethnic groups, as well as between genders, became statistically non-significant. This strongly suggests that the initially observed demographic differences were primarily driven by underlying variations in lead qualifications, rather than bias introduced or amplified by Fetch's evaluation process. This highlights the necessity of conducting thorough and nuanced bias testing that considers the complex interplay of lead and job-specific attributes to accurately assess the fairness of AI-powered features like Fetch.

Appendix

Job Profession

Appendix Table 1a. Distribution of the 8 Most Common Job Professions[7] by Gender

Job Profession	Overall Population (n = 491,695)	Female (n = 199,820)	Male (n = 291,875)
IT & Software Development	21%	18%	23%
Medical	13%	25%	5%
Engineering	13%	6%	17%
Sales	9%	10%	9%
Maintenance & Repair	8%	3%	11%
Marketing	6%	7%	5%
Manufacturing	6%	4%	7%
Other	24%	26%	22%

Appendix Table 1b. Distribution of the 8 Most Common Job Professions by Race

Job Profession	Overall Population (n = 466,662)	Asian (n = 104,505)	Black / African American (n = 85,190)	Hispanic / Latino (n = 43,700)	White (n = 233,267)
IT & Software Development	20%	38%	15%	14%	16%
Medical	13%	6%	24%	7%	13%
Engineering	12%	13%	9%	13%	13%
Sales	10%	9%	8%	13%	12%
Maintenance & Repair	8%	5%	6%	11%	8%
Marketing	6%	7%	4%	6%	7%
Customer Support	6%	3%	10%	7%	6%
Manufacturing	6%	3%	5%	7%	7%
Other	19%	17%	19%	22%	19%

[7] Most common professions are determined by the top job professions per race and gender demographic group overlapped across all groups.

Experience and Seniority Level

Required Years of Experience

Appendix Table 2a. Distribution of Required Years of Experience (number of years) by Gender

Gender	N	Mean	Standard Deviation	Median	Min	25th percentile	75th percentile	Max	Missing Count
Female	35,800	3.61	3.53	3	0	0	5	20	164,020
Male	62,575	3.52	3.72	3	0	0	5	20	229,300

Appendix Table 2b. Distribution of Required Years of Experience (number of years) by Race

Race	N	Mean	Standard Deviation	Min	25th percentile	Median	75th percentile	Max	Missing Count
Asian	27,883	3.42	4.06	0	0	2	6	20	76,622
Black or African American	13,915	3.33	3.28	0	0	3	5	20	71,275
White	42,874	3.75	3.55	0	0	4	6	20	190,393
Hispanic or Latino	7,911	3.54	3.62	0	0	3	5	20	35,789

Required Minimum Years of Experience

Appendix Table 3a. Distribution of Required Years of Experience (number of years) by Gender

Gender	N	Mean	Standard Deviation	Median	Min	25th percentile	75th percentile	Max	Missing Count
Female	135,818	4.80	3.23	1	2	5	7	20	64,002
Male	227,461	5.19	3.27	1	3	5	7	20	64,414

Appendix Table 3b. Distribution of Required Years of Experience (number of years) by Race

Race	N	Mean	Standard Deviation	Min	25th percentile	Median	75th percentile	Max	Missing Count
Asian	84,834	5.62	3.45	1	3	5	8	20	19,671

Black or African American	53,829	4.44	3.04	1	2	4	6	20	31,361
White	175,131	5.00	3.22	1	2	5	7	20	58,136
Hispanic or Latino	31,020	4.83	3.16	1	2	5	6	20	12,680

Lead Relevant Years of Experience

Appendix Table 4a. Distribution of Required Years of Experience (number of years) by Gender

Gender	N	Mean	Standard Deviation	Median	Min	25th percentile	75th percentile	Missing Count
Female	141,021	8.66	11.67	6.92	0	3.39	12.00	58,799
Male	227,461	10.30	12.94	8.09	0	3.97	14.74	84,600

Appendix Table 4b. Distribution of Required Years of Experience (number of years) by Race

Race	N	Mean	Standard Deviation	Min	25th percentile	Median	75th percentile	Missing Count
Asian	72,924	9.12	27.86	0	3.38	7.00	12.72	31,581
Black or African American	60,239	8.45	7.00	0	3.42	6.84	11.62	24,951
White	168,228	10.65	17.02	0	4.00	8.26	15.01	65,039
Hispanic or Latino	29,774	8.89	7.24	0	3.33	7.01	12.42	13,926

Required Seniority Level

Table 5a. Distribution of Seniority Level on Job Requisition by Gender

Seniority Level	**Overall Population** (n = 491,695)	**Female** (n = 199,820)	**Male** (n = 291,875)
Student	0.3%	0.3%	0.3%
Intern	0.2%	0.2%	0.2%
Entry Level	12%	15%	9%

Junior	38%	40%	36%
Senior	37%	31%	41%
Manager	6%	6%	7%
Director	6%	6%	5%
VP	0.5%	0.6%	0.5%
C-level	0.4%	0.5%	0.4%

Table 5b. Distribution of Seniority Level on Job Requisition by Race

Seniority Level	Overall Population (n = 466,662)	Asian (n = 104,505)	Black / African American (n = 85,190)	Hispanic / Latino (n = 43,700)	White (n = 233,267)
Student	0.3%	0.2%	0.2%	0.4%	0.4%
Intern	0.2%	0.1%	0.3%	0.3%	0.2%
Entry Level	11.3%	6.7%	18.2%	11.0%	10.9%
Junior	38.6%	32.2%	43.4%	41.9%	39.1%
Senior	36.4%	44.8%	27.5%	33.1%	36.5%
Manager	6.4%	7.3%	5.5%	7.3%	6.2%
Director	5.8%	7.8%	3.9%	5.0%	5.7%
VP	0.5%	0.8%	0.4%	0.5%	0.5%
C-level	0.4%	0.3%	0.5%	0.5%	0.4%

Lead Seniority Level

Table 6a. Distribution of Leads' Seniority Level by Gender

Seniority Level	Overall Population (n = 491,695)	Female (n = 199,820)	Male (n = 291,875)
Student	0.4%	0.4%	0.3%
Intern	3%	3%	3%

Entry Level	4%	5%	3%
Junior	45%	47%	44%
Senior	14%	12%	15%
Manager	20%	19%	21%
Director	6%	6%	7%
VP	1%	1%	1%
C-level	2%	1%	2%
Missing	5%	5%	5%

Table 6b. Distribution of Leads' Seniority Level by Race

Seniority Level	Overall Population (n = 466,662)	Asian (n = 104,505)	Black / African American (n = 85,190)	Hispanic / Latino (n = 43,700)	White (n = 233,267)
Student	0.4%	0.7%	0.3%	0.2%	0.3%
Intern	3%	6%	2%	2%	2%
Entry Level	4%	3%	6%	4%	4%
Junior	45%	40%	54%	48%	43%
Senior	14%	19%	10%	11%	13%
Manager	20%	18%	16%	21%	22%
Director	6%	6%	4%	5%	8%
VP	1%	1%	1%	1%	2%
C-level	2%	1%	1%	2%	2%

Missing	5%	4%	7%	6%	5%

Educational and Certification Requirement

Lead Highest Educational Degrees

Appendix Table 7a. Distribution of Lead Highest Educational Degrees by Gender

Educational Degree Required	Overall Population (n = 491,695)	Female (n = 199,820)	Male (n = 291,875)
None Required	7%	7%	7%
High School	10%	11%	10%
Associates	9%	10%	8%
Bachelors	44%	43%	44%
Masters	26%	26%	27%
Doctorate	4%	4%	4%

Appendix Table 7b. Distribution of Lead Highest Educational Degrees by Race

Educational Degree	Overall Population (n = 466,662)	Asian (n = 104,505)	Black / African American (n = 85,190)	Hispanic / Latino (n = 43,700)	White (n = 233,267)
None Required	6.9%	3.2%	8.2%	9.7%	7.5%
High School	10.2%	2.2%	18.1%	15.1%	10.0%
Associates	8.5%	1.6%	12.4%	11.4%	9.5%
Bachelors	43.6%	35.7%	38.4%	43.1%	49.2%
Masters	26.6%	49.3%	20.3%	18.8%	20.3%
Doctorate	4.1%	8.0%	2.5%	1.7%	3.4%

Required Educational Degrees

Appendix Table 8a. Distribution of Educational Degrees on Job Requisition by Gender

Educational Degree Required	Overall Population (n = 491,695)	Female (n = 199,820)	Male (n = 291,875)
None Required	33%	36%	31%
High School	17%	19%	16%
Associates	7%	6%	7%
Bachelors	38%	34%	41%
Masters	5%	4%	5%
Doctorate	0.3%	0.3%	0.3%

Appendix Table 8b. Distribution of Educational Degrees on Job Requisition by Race

Educational Degree	Overall Population (n = 466,662)	Asian (n = 104,505)	Black / African American (n = 85,190)	Hispanic / Latino (n = 43,700)	White (n = 233,267)
None Required	34%	30%	37%	36%	35%
High School	16%	10%	23%	16%	17%
Associates	6%	4%	8%	6%	7%
Bachelors	38%	49%	30%	37%	37%
Masters	5%	7%	4%	5%	5%
Doctorate	0.3%	0.5%	0.1%	0.2%	0.2%

Certifications

Appendix Table 9a. Distribution of Certification Requirements on Job Requisitions by Gender

Certification	Overall Population (n = 491,695)	Female (n = 199,820)	Male (n = 291,875)
Yes, required	27%	31%	25%
No, not required	73%	69%	75%

Appendix Table 9b. Distribution of Certification Requirements on Job Requisitions by Race

Certification	Overall	Asian	Black / African	Hispanic /	White

	Population (n = 466,662)	(n = 104,505)	**American** (n = 85,190)	**Latino** (n = 43,700)	(n = 233,267)
Yes, required	28%	20%	36%	25%	29%
No, not required	72%	80%	64%	75%	71%