The Impact of Algorithm Automated Recruitment on Gender Disparity

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Declaration:

We declare that this BBA Project (Final Year Project), submitted in partial fulfillment of the graduation requirements for UIC's Bachelor of Business Administration (Honours) degree, is our original work. No portion of the project report has been submitted to any other university or institute of learning for any other degree or qualification. All original sources of materials consulted have been properly cited and acknowledged.

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Abstract

With the wide application of artificial intelligence technology in many fields, algorithmic automated decision making has begun to play an increasingly important role in recruitment. This paper is dedicated to studying whether this development will have an impact on the gender gap between men and women. We investigated the impact of gender differences on the AI automated recruitment market by sending 480 fictitious matching resumes. Independent sample T test, ordinary least square method, binomial logistic regression, and other analytical methods were used for comprehensive evaluation. In particular, the interactive term analysis is introduced to explore the combined influence of gender, age and expected salary on the recruitment results.

The study found that the expected salary difference has a significant impact on the job recognition rate, and the results of this study suggest that automated recruitment algorithms may exacerbate the gender gap in some cases, and there are significant differences in the success rates of different genders in the recruitment process. Algorithmic automated recruitment still faces challenges in promoting gender equality, and we need to delve deeper into the design and application of algorithms to reduce the gender bias they may introduce. At the same time, policy makers and enterprises should also pay attention to this issue and ensure the fairness and transparency of the recruitment process by formulating corresponding policies and norms.

Keywords: AI algorithm recruitment, Field experiment, Labor market, Employment, Gender, Expected salary, Age

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1. Introduction

In the modern era of technological advancements, the integration of Artificial Intelligence (AI) with all aspects of society is becoming more and more prominent, and algorithms have increasingly penetrated all walks of life. The rise of algorithm-based automated recruiting systems has transformed the traditional recruiting process, promising to improve efficiency, objectivity, and scalability. Investigating the practical application of AI algorithms in recruitment, global Internet giant Tencent Technologies uses AI algorithms to efficiently screen resumes for skills and experience to match the most suitable positions. Meanwhile, Alibaba Group and Huawei also apply AI to talent identification, integrating and analyzing candidates' resume information, interview performance and social media online behavior to comprehensively assess candidates' potential and match with the company.

However, the gender gap in hiring, pay and promotion opportunities in recruitment practices, i.e., unequal representation and treatment of men and women in the labor market, is a persistent problem. Nearly half of China's female workforce report experiencing gender inequality in the workplace on a regular basis, and the average salary for women in urban China is only 67 percent of that of men. Although the Chinese government has clearly stipulated through the Labor Contract Law and the Law on the Protection of Rights and Interests of Women that workers should enjoy equal employment opportunities regardless of their status and age, automated algorithm-based recruitment systems may still embed or inadvertently perpetuate existing subjective assessments and unconscious biases, and even contribute to workplace stereotypes by inflexibly screening resumes for keywords, exacerbating some positions and increasing gender discrimination. disproportionality, serve as a cover for sexism, and produce subtle but significant gender imbalance results.

Statement of Research Problem

This research aims to identify possible hidden discrimination and embedded unconscious bias in algorithmic automated recruitment in the Chinese workplace, and to explore differential responses to gender, age, and expected salary. We hope to not only provide empirical evidence for the impact of algorithmic recruitment on gender differences, but also try to identify the key factors affecting representation in recruitment algorithms by examining the underlying mechanisms behind recruitment differences. In addition, from a societal perspective, it is necessary for firms to take proactive management measures to promote hiring equality and gender inclusion in order to improve the efficiency and productivity of the labor market as a whole. We will continue to discuss some relevant findings that provide insights into solutions regarding ethical considerations in AI and machine learning applications, helping to explore the important role of algorithms in the employment labor market in the digital economy.

2. Literature Review

2.1 Gender Bias in Recruitment

In many underdeveloped countries and developing economies, gender discrimination against women exists, and occupational gender segregation is more serious especially in economies with high unemployment rates (Pirpour, 2022). By convention, gender discrimination in the hiring process may manifest itself as a bias against women (Pirpour, 2022). For example, some employers may perceive women as less engaged in their jobs or more inclined to leave their jobs to take care of their families. This bias can lead employers to hold unfair perceptions of female candidates in the recruitment process, which affects their employment chances.

Research has shown that gender differences can significantly impact the resume screening process in the labor market. Eriksson (2012) found that women's more restrictive job search areas led to fewer firm contacts, while Tanguay (2012) highlighted the potential for gender bias in resume inferences, particularly for college athletes. Chen (2018) further investigated gender-based inequalities in resume search engines, revealing potential indirect discrimination. Zhou (2013) provided evidence of gender discrimination in hiring in China, with state-owned firms favoring male applicants and foreign and private firms favoring female applicants. These studies collectively underscore the need for further research and action to address gender biases in resume screening.

Research on the influence of gender differences in the job-seeking process reveals several key findings. Xin (2010) identifies gender, urban-rural differences, and family background as significant factors in job seeking, with male students more influenced by urban-rural differences and specializations, and female students by family backgrounds. Arhana (2015) further explores the impact of gender on job selection criteria and cognitive behavior, highlighting differences in priorities between married and unmarried women. Eriksson (2012) adds that women tend to be more restrictive in their job search, leading to fewer firm contacts, and suggests that these differences may be important in understanding gender disparities in labor market outcomes. However, Castilla (2023) challenges the effectiveness of gender-neutral job postings in addressing these disparities, finding negligible effects on job seekers' interest in applying.

The current artificial intelligence algorithm recruitment has some impact on gender differences, but whether there is a positive impact or negative correlation needs to be further studied. Leavy (2018) and Mujtaba (2019) both highlight the potential for gender bias in AI algorithms, particularly in the context of machine learning and HR applications. This bias is further exacerbated by the failure to account for sex and gender differences in biomedical AI technologies (Cirillo, 2020). Kay (2015) underscores the role of information environments in shaping perceptions and behaviors, emphasizing the need to address gender stereotypes in image search results for occupations. These studies collectively underscore the urgent need for diversity and gender theory in AI design, as well as the ethical considerations and tools to mitigate biases in AI-based recruitment.

By analyzing cases of algorithmic sex discrimination in the workplace at home and abroad, Zhang (2022) stated that algorithmic automated decision-making may embed established gender biases, serve as a means of allocation that hides sex discrimination, and result in imperceptible sex discriminatory consequences. Combined with behavioral economics, analyzing specific hiring cases in the software engineer labor market, recruiters were 6.47% less likely to express interest in female candidates than male candidates with similar observable qualifications (Murciano-Goroff, 2022). In the information technology sector, women are 15 percentage points less likely to receive a callback than men (Jumana et al., 2020).

Moreover, in employment decisions, other forms of discrimination also exist. For example, certain employers may discriminate against certain groups of people based on race, religion, age, or otherworker traits, which may have a negative impact on the recruitment process, leading to unfair treatment of certain groups of people in terms of employment opportunities.

Research on algorithmic recruitment and gender differences presents a complex picture. Foley (2018) found that anonymizing job applications, a common practice in algorithmic recruitment, may not be sufficient to reduce bias, as managers can still infer gender from implicit signals. Chen (2018) investigated resume search engines and found no evidence of explicit gender-based discrimination in their algorithms. However, Krishnan (2020) highlighted the potential for bias in gender classification algorithms, particularly in the accuracy rates for different gender-race groups. Yarger (2019) emphasized the need for algorithmic equity in the hiring process, particularly in the IT industry, where underrepresented groups face significant challenges. These studies suggest that while algorithmic recruitment has the potential to reduce the impact of gender differences, it must be carefully designed and monitored to ensure fairness and equity.

2.2 Age Preference of Employment

Research consistently shows that age discrimination is a significant factor in resume screening, with both explicit and implicit age stereotypes negatively impacting the evaluation of older applicants (Zaniboni, 2019). This discrimination is further exacerbated by factors such as inactivity or employment in an out-of-field job during additional post-educational years (Baert, 2016). However, the impact of age on hiring decisions varies by country, with Swedish employers showing a preference for younger candidates (Carlsson, 2019).

Research on age discrimination in recruitment and its impact on the labor market reveals several key findings. Bellmann (2017) highlights the low application rate of older job seekers and the varying recruitment behavior of firms. Wilson (2017) underscores the preference for younger workers, particularly in industries with talent shortages. Allen (2014) explores the impact of interviewer age on job candidate perceptions, with younger candidates feeling disadvantaged when interviewed by older recruiters. These studies collectively suggest that age discrimination in recruitment can perpetuate age differences in the labor market, particularly in terms of job suitability, short-listing, and candidate perceptions.

By collecting data from four field experiments in England, Drydakis et al. (2023), showed that the employment opportunities of older individuals, especially older women, were more negatively impacted compared to younger job seekers. Also, Carlsson and Eriksson (2019) conducted a field study of age discrimination, especially in the job recruiting process, by randomly assigning age information (35-70 years old) and sending more than 6,000 fictitious resumes to Swedish employers with open positions that mainly involve low and medium skills. In almost all types of jobs, employers showed strong discrimination against workers over the age of 40.

David et al. (2019) designed and implemented a large-scale CV communication study by submitting more than 40,000 job applications and found that during the hiring process, some employers would explicitly state that they would only hire employees under the age of 35 or prefer to hire younger employees. This age restriction may result in some older employees being excluded from employment opportunities and suffering from restricted employment opportunities.

Obviously, age difference can significantly impact the results of AI algorithm recruitment. Harris (2022) and Wu (2021) both highlight the prevalence of age bias in hiring decisions, with Harris specifically noting the challenges this bias poses for job candidate search algorithms. Wu's work further underscores the impact of age discrimination in the labor market, particularly for middle-aged and elderly individuals. These findings are supported by Persson (2004) and Touron (2009), who demonstrate age-related differences in cognitive performance and strategic behavior. These differences can influence the effectiveness of AI algorithms in accurately assessing and selecting candidates, potentially leading to biased outcomes.

2.3 Effects of Expected Salary on Job Seeking

At present, there are very few studies on the impact of salary expectation on resume selection during job hunting, Orazem (2020) explores the role of market expectations and job search in gender differences in starting pay, finding that women's lower pay expectations can lead to lower pay outcomes.

Higher salary expectations can attract better applicants, but may also result in fewer applications (Marinescu, 2018). However, the gender of the applicant can also play a role, with women who have moderate salary expectations being offered more money and being more likely to be hired (Major, 2015). In the context of Chinese college graduates, a reduction in salary expectations can significantly increase the probability of finding a job (Po, 2021).

Porter (2016) further emphasized the role of salary negotiations in recruitment outcomes, with salary levels, company responsiveness, and representative behavior all playing a significant role. Lastly, Poweu (2019) underscored the influence of recruiters' pre-interview impressions and applicants' qualifications on post-interview evaluations. These studies collectively suggest that while expected salary may play a role in resume selection, it is just one of many factors that can influence the recruitment process.

In earlier studies, job search behavior, including the writing of resumes with different salary expectations, significantly influences employment outcomes (Kanfer, 2010). Recruitment practices, including the signaling value of experiences and the impact of delays, also play a crucial role in job seeker decisions (Rynes, 2010). Furthermore, demographic, human capital, motivational, and organizational variables are key predictors of career success, with educational level and quality being particularly important for financial success (Judge, 2017). Pay preferences, including high pay levels and flexible benefits, can significantly influence job search decisions and the attractiveness of organizations (Cable, 2018).

2.4 Field experiments method used for personnel recruitment

Field experiments in the hiring process offer several advantages. They can directly observe disparity, providing estimates of its prevalence and revealing its subtlety (Pager, 2015). Algorithmic labor market recommendations can increase hiring rates without crowding out non-recommended candidates (Horton, 2015). Realistic job previews and expectation-lowering procedures can enhance employee socialization, with a combination of the two being particularly effective (Buckley, 2018). These experiments have also been instrumental in measuring hiring disparity, with a focus on ethnic and racial disparity (Zschirnt, 2016).

Compared with questionnaires, it can be closer to the facts. Questionnaires often interrupt the subjects' ongoing activities, such as watching TV at home or rushing to a certain place on the street. In addition, due to distrust of complete strangers, it is likely that data will deviate from the facts. Field experiments, as opposed to non-field experiments, are conducted in naturalistic settings and involve real-world subjects, goods, and contexts (Harrison, 2018). They are particularly useful in evaluating policies and programs, and are increasingly being used in legal studies (Green, 2019). The key factors that distinguish field experiments from non-field experiments include the subject pool, information, commodity, task or trading rules, stakes, and environment. In the field of fluvial geomorphology, field experiments are conducted at different scales, with varying levels of control over variables (Wohl, 2017).

Field experiments in the labor market recruitment have shown significant impacts on hiring and applicant behavior. Some scholars found that algorithmic recommendations to employers can increase hiring rates by 20%, particularly for job openings with smaller applicant pools. Barber (2020) further demonstrated that interview focus, with a combined recruitment-selection approach, can lead to increased persistence in pursuing a job. These studies highlight the potential of field experiments in improving recruitment strategies and outcomes.

In the recruitment process, field experiments can help researchers understand how recruiters assess the qualifications and suitability of candidates and how candidates perform and influence the outcome of the recruitment process.

Zhang et al. (2021) analyzed the data of job seekers sending resumes and obtaining interviews and found that the rate of women obtaining interviews was lower than that of men, indicating that employers may have gender discrimination in the recruitment process. And González et al. (2019) designed two sets of resumes, one of each only have gender differences and the other involves family composition and personal qualifications, submitting to job opportunities. The experimental results showed that gender differences affect female employment, and employers may discriminate against female applicants. These biases and discrimination may lead to unfair treatment of women in the job market. In addition, when considering whether to hire parents with children, employers prefer to hire men because they believe that men are better able to balance work and family.

A range of studies have explored gender differences in field experiments. Gangadharan (2021) emphasizes the unique insights provided by lab-in-the-field experiments, particularly in understanding gender disparities in decision-making. Sousa (2015) uncovers a systematic disadvantage for women in chess tournaments, highlighting the impact of psychological factors. Ergun (2012) reviews gender differences in field experiments, attributing them to sex-role stereotypes and hormonal differences. These studies collectively underscore the complexity of gender differences in field experiments, influenced by a range of factors.

3. Methodology

We plan explore the impact of algorithms on gender differences by sending a large number of fictitious resumes to be advertised positions in major companies known to use AI algorithms for resume screening.

To make the results of the study more comparable, it was necessary to create a standardized CV template with all the necessary information but without a photo, avoiding the introduction of information on irrelevant personal characteristics that influence the hiring decision, such as a possible beauty premium. The subsequent assessment of employers' response behavior to these fictitious resumes varied only on our key variables provides a realistic picture of what happens in the labor market and provides insights into gender inequality issues and other potential hiring preferences.

By using the field experiment methodology, we derive results with high external validity. In resume delivery, we not only study the effect of gender on algorithmic hiring practices. But we will also examine two more variables: how the desired level of salary and the age of applicants affect hiring outcomes.

To summarize, the main hypotheses of this paper are as follows:

H1: Gender has no significant impact on algorithm automated recruitment all else equal,

H2: Age differences have no significant impact on algorithm automated recruitment all else equal,

H3: Expected level of salaries has no significant effects on algorithm automated recruitment all else equal,

3.1 Resume Design

We conduct a 2x2x2 between-subject treatment design, with three treatment variables: gender, expected salary and age of applicants as indicated in the fictitious resumes. The specific treatment variables values selected are male and female, age 30 and 40, and expected monthly salary of 10,000 and 15,000, respectively, segmented into a total of 8possible groups. Please also note that both 10000 and 15000 fall within the advertised salary range of all the positions applied to.

We use our resume template to develop a total of eight standard resumes. Although they are not representative of every applicant segment in our society, we attempt to maintain all resumes at a normal level by the avoidance of any possibility of over-qualification or under-qualification for the advertised employment positions. For example, the eight standard resumes are all key 211 graduates with bachelor's degree, they have all held similar positions in similar companies, and have similar work experience and skills.

On this basis, to create exogenous variation between the applicant's experiences and their gender/expected salary/age, we replicate the eight resumes by the 2x2x2 combination so that each combination of three variables has eight resumes with similar personal experiences, for a total of 64 resumes.

3.2 Delivery of Resume

We choose three major Internet employment boards as our platform for the submission of resumes (51job(www.51job.com), Chinahr(www.chinahr.com), and Zhaopin(www.zhaopin.com)), on which we identify companies that use AI to screen resumes or conduct initial assessments.

Because of the large economic differences between Chinese cities that may have an impact on the screening of resumes in the recruitment process, we selected six cities as our targets, which include Beijing, Shanghai, Guangzhou, Shenzhen, Wuhan, and Chengdu. All resumes are submitted to the employers via these three platforms in February 2024. We allow a 30-day response window for all positions, so we collect employer responses ending in March 2024. For each position, we randomly select one out of the 2x2x2 variable combination for each of the 8 standard resumes. In total, we submitted 480 resumes for 60 different positions from 28 companies.

3.3 Empirical Analysis

We recorded several key outcome variables: whether during the 30-day time window each fictitious applicant/CV has received any response at all (“response”), any positive offer of a prospective interview (“approval”). We also record the length of time before they received the first reply (“first reply”) and the final reply (“last reply”). We then conducted a visual analysis on the resume delivery results, and then studied the impact of different algorithm parameters on the gender of recruitment candidates, as well as the possible impact of candidates' age and expected salary on resume screening.

In order to reveal the impact of gender differences, different age groups, and different salary expectations on resume selection, we will first obtain the approval rate and response rate and average response time through descriptive statistics to get a preliminary framework of the results. Then, independent sample t-test was conducted for each variable to obtain its significance results. Then, OLS regression was used to establish the relationship between the three treatment variables and the delivery results. Logit regression was used to analyze the observed data to explore the impact of each variable on the resume screening by AI machine.

During the experiment, due to the uncontrollable response time and the long experiment period, in order to avoid the interaction between different response times and some data may be ignored, we will discuss the actual response samples and the total samples respectively.

4. Result

4.1 Descriptive Statistics

Variable Type	Variable Name	Variable Meaning	Unit of Measurement
Independent Variable	Gender	Candidate's biological gender	Male/Female
	Age	Candidate's actual age	30/40 years old
	Expected Salary	Candidate's expected wage (within the given range of positions selected)	10/15K (￥)
Dependent Variable	Reply	Whether or not you received a reply after submitting your resume	Yes/No
	Pass	Whether the resume passed the screening process	Yes/No
	Time of First Response	When the first response to the submission was received	Day(s)
	Time of Final Reply	When the final result of the submission was received	Day(s)
Control Variable	CV Version	The version of the resume submitted	1/2/3/4/5/6/7/8
	Industry	Industry of the company where the job is posted	Consulting/ E-Business/FMCG/ Fashion or Sports/ Life Services/ Manufacturing/ Technology Industry

Table 1: Description of Variables

The independent variables ***Gender, Age, Expected Salary*** and the dependent variables ***Reply*** and ***Pass*** are all dichotomous variables. The sample size totaled 480 applications, covering 28 companies across 7 industries, and 60 specific positions.

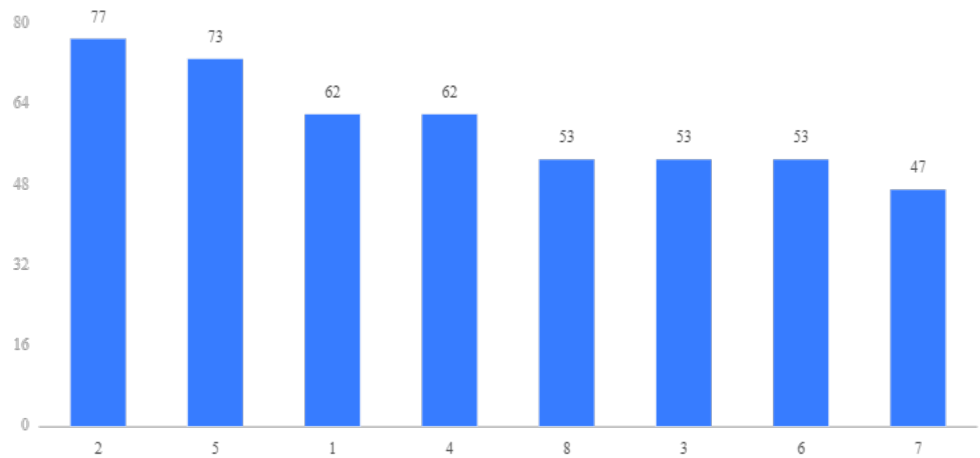

Figure 1: CV Version Delivery Status

The above figure shows the delivery of *CV Version*s 1-8 (see Methodology for the exact delivery mechanism), with little difference in distribution due to random sampling. Observing statistics on response rate, adoption rate and average response in relation to the number of decisions made, the total response rate is shown to be 20.00%, which indicates that about one-fifth of all CVs receive a response from the employers. Secondly, the total adoption rate reached 4.58%, which is about a quarter of the total number of responses.

The statistics on the response time are divided into nominal (ANR) and real values (ARR), with the Average Nominal Response days being 24.10 days, which reflects the average time of collecting all responses, includes those has no actual react and thus be recorded as 30 days. While the average nominal final response days is 24.20 days, which is slightly longer. In addition, the average actual response days and the Average Real Final Response days were 0.1 and 0.14, respectively, which reflect the average time that are actually took to receive the relevant messages as an initial communication and the ultimate decision.

Data disaggregated by gender, age, and expected salary are also tallied. Firstly, among all the responses received for our applicants, the response to males is 54.17% while the response to females is 45.83%. Males receive almost 9% more responses than their female counterparts with identical credentials. Secondly, the passes for interviews are divided equally among males and females: 50.00% for both male and female groups showing no obvious difference between genders for the possibility of pass.

Further, the average nominal response days (ANR) for first time and final as well as the average real response days (ARR) are also slightly different between genders. In terms of first time ANR, males averaged 23.49 days while females averaged 24.72 days and in terms of final ANR, males averaged 23.65 days while females averaged 24.75 days. This suggests that in terms of nominal response time, the female group may be slightly longer.

However, in terms of average true response days (ARR), the difference is smaller but still present. For the first ARR, the average was 0.11 days for males and 0.10 days for females, and for the final ARR, the average was 0.15 days for males and 0.13 days for females. These small differences may reflect subtle differences in true response times by gender.

Below is a statistical table of the above relevant data on the other two independent variables, along with a description of the highlights.

By Age	Reply Rate: 30	47.92%
	Reply Rate: 40	52.08%
	Pass Rate: 30	45.45%
	Pass Rate: 40	54.55%
	ANR (First): 30	24.21
	ANR (First): 40	23.99
	ANR (Final): 30	24.36
	ANR (Final): 40	24.04
	ARR (First): 30	0.09
	ARR (Final): 40	0.12
	ARR (Final): 30	0.11
	ARR (Final): 40	0.17

Figure 2: Possibilities & Mean, By Age

According to *Graph 2*, job seekers in their 40s had slightly higher response and pass rates than those in their 30s and took slightly longer to respond, but the difference was not significant.

By Salary	Reply Rate: Lower	45.83%
	Reply Rate: Higher	54.17%
	Pass Rate: Lower	22.73%
	Pass Rate: Higher	77.27%
	ANR (First): Lower	24.49
	ANR (First): Higher	23.72
	ANR (Final): Lower	24.64
	ANR (Final): Higher	23.77
	ARR (First): Lower	0.11
	ARR (First): Higher	0.10
	ARR (Final): Lower	0.14
	ARR (Final): Higher	0.14

Figure 3: Possibilities & Mean, By Expected Salary

As seen in *Graph 3*, job seekers with higher salary expectations have a higher reply rate and an obviously higher pass rate (77.27%), which is about 3.34 times higher than the pass rate for lower salary expectations (22.73%).

Analyzing *Reply* as a quantitative variable taking values of 0 or 1 yields a mean of 0.2 and a standard deviation of 0.4, which implies an overall probability of receiving a reply of 20%. Similarly, the *Pass* variable has a mean of 0.046 and a standard deviation of 0.209, with a probability of the resume passing the screening process of 4.6%. It is worth noting that the distributions of the *Reply* and *Pass* variables do not satisfy the normal distribution, which will be discussed in Section V. The mean of the *Response* variable is 0.046, with a standard deviation of 0.209. Instead, the *Time of First Response* and *Time of Final Reply* variables both represent time intervals in days. These two variables take values ranging from 0 to 30 days, with mean values of 24.104 days and 24.203 days, and standard deviations of 11.806 days and 11.685 days, respectively.

Through the descriptive statistical analysis of the dataset, we understand the basic characteristics, range of values and distribution of each variable. These data provide important reference information for subsequent statistical analysis and help us to better understand the content and characteristics of the data set.

4.2 Independent Sample T-test

4.2.1 Full Sample, n = 480

	P-Value		
	X= Gender	**X= Age**	**X= Expected Salary**
Reply	0.068*	0.649	0.172
Pass	1.000	0.384	0.000***
Time of First Response	0.021**	0.944	0.331
Time of Final Reply	0.039**	0.918	0.243

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 1: P-value of Variance Chi-square Test, n=480

According to *Table 1*, the significance P-value of *Time of First Response* and *Time of Final Reply* with *X= Gender*, as well as *Pass* with *X= Expected Salary* are 0.021**, 0.039** and 0.000***, respectively, which means all the three present significance at the level (p<0.05), therefore the data does not satisfy variance chi-square, and needs to be verify by Welch's T-test.

	P-Value					
	X= Gender		**X= Age**		**X= Expected Salary**	
	T-test	Welch's T-test	T-test	Welch's T-test	T-test	Welch's T-test
Reply	0.362	-	0.820	-	0.495	-
Pass	1.000	-	0.663	-	-	0.009***
Time of First Response	-	0.251	0.979	-	0.633	-
Time of Final Reply	-	0.303	0.947	-	0.561	-

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 2: P-value of Independent Samples T-test Analysis, n=480

According to the table above (*Table 2*), the P-value of *Expected Salary* on *Pass* is 0.009*** (P<0.05), which means that the factor *Expected Salary* in the resume of the job application has a significant role in the final result of the pass. While other variables are not significant.

4.2.2 Real Sample, n = 96 (Actual Responses Received)

	P-Value		
	X= Gender	**X= Age**	**X= Expected Salary**
Pass	0.380	0.459	0.000***
Time of First Response	0.057*	0.078*	0.303
Time of Final Reply	0.072*	0.061*	0.257

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 3: P-value of Variance Chi-square Test, n = 96

According to *Table 3*, the significance P-value of *Pass* with *X= Expected Salary* is 0.000***, which presents significance at the level ($p<0.05$), therefore the data does not satisfy variance chi-square, and needs to be verify by Welch's T-test.

	P-Value					
	X= Gender		**X= Age**		**X= Expected Salary**	
	T-test	Welch's T-test	T-test	Welch's T-test	T-test	Welch's T-test
Pass	0.659	-	0.712	-	-	0.009***
Time of First Response	0.263	-	0.243	-	0.482	-
Time of Final Reply	0.288	-	0.177	-	0.410	-

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 4: Results of Independent Samples T-test Analysis, n=96

Same as 4.2.1, the P-value of *Expected Salary* on *Pass* is 0.009*** ($P<0.05$), which means that the factor *Expected Salary* presents a significance in the result of pass, while other variables are not significant.

4.3 Ordinary Least Square Analysis

4.3.1 X= Gender, Age, Expected Salary

	OLS Model Analysis Results, n=480					
	X= Gender_Male		**X= Age_40**		**X= Expected Salary (￥)_15000**	
	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value
Reply	0.91	0.363	0.228	0.820	0.683	0.495
Pass	0	1.000	0.438	0.662	2.628	0.009***
Time of First Response	-1.146	0.252	0.026	0.979	-0.478	0.633
Time of Final Reply	-1.029	0.304	-0.067	0.947	-0.581	0.562

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 5: Results of Linear Regression Analysis, X= Gender, Age, Expected Salary

As can be seen in *Table 5*, since the P-value is 0.009*** (P<0.05), the null hypothesis is rejected, and it can be concluded that *Expected Salary (¥)_15000* is significant for *Pass*. Rejecting the null hypothesis, the age variable is also not significant in the model. *Gender* and *Age* do not contribute significantly to the explanatory power of the model. In addition, for the covariate covariance performance, the VIF is all less than 10, thus the model has no multicollinearity problem and the model is well constructed. The following table shows the equations of above four models:

Reply= 0.167 + 0.033*Gender_Male + 0.008*Age_40.0 + 0.025*Expected Salary (￥)_15000.0

Pass= 0.017 - 0.0*Gender_Male + 0.008*Age_40.0 + 0.05*Expected Salary (￥)_15000.0

Time of First Response = 24.967 - 1.237*Gender_Male + 0.028*Age_40.0 - 0.516*Expected Salary (￥)_15000.0

Time of Final Reply = 25.1 - 1.1*Gender_Male - 0.072*Age_40.0 - 0.621*Expected Salary (￥)_15000.0

Table 6: The Equation Set, X= Gender, Age, Expected Salary

4.3.2 X= Gender, Age, Expected Salary, CV Version

	OLS Model Analysis Results, n=480					
	X= Gender_Male		X= Age_40		X= Expected Salary (￥)_15000	
	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value
Reply	0.881	0.379	0.21	0.834	0.667	0.505
Pass	-0.103	0.918	0.524	0.601	2.543	0.011**
Time of First Response	-1.115	0.265	0.054	0.957	-0.436	0.663
Time of Final Reply	-1	0.318	-0.046	0.963	-0.532	0.595

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 7: Results of Linear Regression Analysis, X= Gender, Age Expected Salary, CV Version

After adding the control variable ***CV Version***, the results of the analysis are presented in Table 7, which still shows the correlation values of the three independent variables and four dependent variables for convenience. The P-value obtained shows that *Expected Salary* (¥)_15000 is significant for *Pass*, and the rest of the variables do not show significance, the conclusion is consistent with section 4.3.1.

CV Version only has a P-value slightly less than the commonly used significance level (0.05) for *Time of First Response*, and *CV Versions* 4 and 5 are 0.048** and 0.046**, respectively, which are slightly less than the commonly used significance level (0.05) and contribute slightly to the *Time of First Response*'s explanatory power with a marginally significant contribution.

Reply= 0.226 + 0.032*Gender_Male + 0.008*Age_40.0 + 0.025*Expected Salary (￥)_15000.0 - 0.015*CV Version_2.0 - 0.012*CV Version_3.0 - 0.11*CV Version Version_4.0 - 0.125*CV Version_5.0 - 0.068*CV Version_6.0 - 0.069*CV Version_7.0 - 0.067*CV Version_8.0

Pass= 0.005 - 0.002*Gender_Male + 0.01*Age_40.0 + 0.049*Expected Salary (￥)_15000.0 + 0.055*CV Version_2.0 + 0.04*CV Version_3.0 - 0.011*CV Version_4.0 - 0.026*CV Version_3.0 - 0.011*CV Version_3.0 4.0 - 0.026*CV Version_5.0 + 0.003*CV Version_6.0 + 0.031*CV Version_7.0

+ 0.01*CV Version_8.0

Time of First Response = 22.725 - 1.208*Gender_Male + 0.059*Age_40.0 - 0.477*Expected Salary (￥)_15000.0 + 0.888*CV Version_2.0 + 0.843*CV Version_3.0 + 4.218*CV Version_4.0 + 4.096*CV Version_5.0 + 2.425*CV Version_6.0 + 2.565*CV Version_7.0 + 2.453*CV Version_8.0

Time of Final Reply = 23.303 - 1.074*Gender_Male - 0.05*Age_40.0 - 0.576*Expected Salary (￥)_15000.0 + 0.394*CV Version_2.0 + 0.353*CV Version_3.0 + 3.669*CV Version_4.0 + 3.569*CV Version_5.0 + 1.902*CV Version_6.0 + 2.129*CV Version_7.0 + 1.93*CV Version_8.0

Table 8: The Equation Set, X= Gender, Age, Expected Salary, CV Version

4.3.3 X= Gender, Age, Expected Salary, Industry

	OLS Model Analysis Results, n=480					
	X= Gender_Male		**X= Age_40**		**X= Expected Salary (￥)_15000**	
	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value
Reply	0.952	0.342	0.238	0.812	0.714	0.476
Pass	0	1.000	0.453	0.651	2.715	0.007***
Time of First Response	-1.195	0.233	0.027	0.978	-0.499	0.618
Time of Final Reply	-1.073	0.284	-0.07	0.944	-0.606	0.545

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 9: Results of Linear Regression Analysis, X= Gender, Age Expected Salary, Industry

When the control variable ***Industry*** is added to the analysis, for *Reply, Time of First Response* and *Time of Final Reply*, the *Consulting* industry (P-values are 0.016**, 0.024**, 0.024**, respectively) and the *Life Service* industry (P-values are all 0.000***) are significant (p-value < 0.05). For *Pass,* the *Life Service* industry (p=0.022**) is significant with *Expected Salary*, while others are not.

In Addition，all P-values of the F-test is 0.000***, which presents significance at the level and rejects the original hypothesis that the regression coefficient is 0. Therefore, the models basically meet the requirements and are well constructed with no multicollinearity problems, for the covariate covariance performance (VIF <10). The following table shows the equations of above four models:

Reply= 0.029 + 0.033*Gender_Male + 0.008*Age_40.0 + 0.025*Expected Salary (￥)_15000.0 + 0.257*Industry_Consulting + 0.208*Industry_E-Business + 0.125*Industry_FMCG + 0.162*Industry_Fashion/Sports + 0.437*Industry_Life Service + 0.062*Industry_Manufacturing + 0.028*Industry_Technology Industry_Manufacturing + 0.028*Industry_Technology
Pass= 0.033 - 0.0*Gender_Male + 0.008*Age_40.0 + 0.05*Expected Salary (￥)_15000.0 - 0.035*Industry_Consulting + 0.062*Industry_E-Business - 0.021 *Industry_FMCG - 0.038*Industry_Fashion/Sports + 0.137*Industry_Life Service - 0.038*Industry_Manufacturing - 0.057*Industry_Technology
Time of First Response = 8.987 - 1.237*Gender_Male + 0.028*Age_40.0 - 0.516*Expected Salary (￥)_15000.0 - 7.089*Industry_Consulting - 6.109*Industry_E-Business - 4.311*Industry_FMCG - 4.745*Industry_Fashion/Sports - 12.812*Industry_Life Service - 1.787*Industry_Manufacturing - 0.827*Industry_Technology Industry_Manufacturing - 0.827*Industry_Technology
Time of Final Reply = 29.023 - 1.1*Gender_Male - 0.072*Age_40.0 - 0.621*Expected Salary (￥)_15000.0 - 7.07*Industry_Consulting - 5.942*Industry_E-Business - 3.665*Industry_FMCG - 4.734*Industry_Fashion/Sports - 12.676*Industry_Life Service - 1.788*Industry_Manufacturing - 0.825*Industry_Technology Industry_Manufacturing - 0.825*Industry_Technology

Table 10: The Equation Set, X= Gender, Age, Expected Salary, Industry

4.3.4 X= Gender, Age, Expected Salary, CV Version, Industry

OLS Model Analysis Results, n=480			
	X= Gender_Male	**X= Age_40**	**X= Expected Salary (￥)_15000**

	T-statistic	P-value	T-statistic	P-value	T-statistic	P-value
Reply	0.912	0.362	0.238	0.812	0.684	0.494
Pass	-0.094	0.925	0.56	0.576	2.616	0.009***
Time of First Response	-1.152	0.250	0.034	0.973	-0.447	0.655
Time of Final Reply	-1.034	0.302	-0.069	0.945	-0.544	0.587

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 11: Results of Linear Regression Analysis, X= Gender, Age Expected Salary, CV Version, Industry

When the two control variables (***CV Version*** and ***Industry)*** are added to the analysis at the same time, for *Reply, Time of First Response* and *Time of Final Reply*, the *Consulting* industry (P-values are 0.015**, 0.023**, 0.021**, respectively) and the *Life Service* industry (P-values are all 0.000***) are significant (p-value < 0.05). For *Pass,* the *Life Service* industry (p=0.014**) is significant with *Expected Salary*, while others are not.

In Addition， all P-values of the F-test is 0.000***, which presents significance at the level and rejects the original hypothesis that the regression coefficient is 0. Therefore, the models basically meet the requirements and are well constructed with no multicollinearity problems, for the covariate covariance performance (VIF <10). The following table shows the equations of above four models:

Reply= 0.041 + 0.032*Gender_Male + 0.008*Age_40.0 + 0.024*Expected Salary (￥)_15000.0 + 0.021*CV Version_2.0 + 0.006*CV Version_3.0 - 0.047*CV Version_4.0 - 0.059*CV Version_5.0 - 0.015*CV Version_6.0 - 0.013*CV Version_7.0 - 0.022*CV Version_8.0 + 0.262*Industry_Consulting + 0.21* Industry_E-Business + 0.129*Industry_FMCG + 0.169*Industry_Fashion/Sports + 0.431*Industry_Life Service + 0.06*Industry_Manufacturing + 0.039 *Industry_Technology

Pass= -0.009 - 0.002*Gender_Male + 0.01*Age_40.0 + 0.049*Expected Salary (￥)_15000.0 + 0.066*CV Version_2.0 + 0.049*CV Version_3.0 + 0.017*CV Version_4.0 + 0.006*CV Version_5.0 + 0.029*CV Version_6.0 + 0.056*CV Version_7.0 + 0.032*CV Version_8.0 - 0.024*Industry_Consulting + 0.071* Industry_E-Business - 0.005*Industry_FMCG - 0.025*Industry_Fashion/Sports +

0.149*Industry_Life Service - 0.03*Industry_Manufacturing - 0.044 *Industry_Technology

Time of First Response = 28.128 - 1.203*Gender_Male + 0.036*Age_40.0 - 0.47*Expected Salary (Ұ)_15000.0 - 0.187*CV Version_2.0 + 0.269*CV Version_3.0 + 2.354*CV Version_4.0 + 2.182*CV Version_5.0 + 0.856*CV Version_6.0 + 0.873*CV Version_7.0 + 1.102*CV Version_8.0 - 7.209*Industry_Consulting - 6.136* 1.159*Industry_Technology

Time of Final Reply = 28.618 - 1.069*Gender_Male - 0.071*Age_40.0 - 0.567*Expected Salary (Ұ)_15000.0 - 0.632*CV Version_2.0 - 0.203*CV Version_3.0 + 1.867*CV Version_4.0 + 1.681*CV Version_5.0 + 0.369*CV Version_6.0 + 0.493*CV Version_7.0 + 0.645*CV Version_8.0 - 7.238*Industry_Consulting - 6.022* 1.182*Industry_Technology

Table 12: Results of Linear Regression Analysis, X= Gender, Age Expected Salary, CV Version, Industry

4.4 Binomial Logistic Regression

4.4.1 X= Gender, Age, Expected Salary

	Binomial Logistic Regression P-Value		
	X= Gender_Male	**X=Age_40.0**	**X= Expected Salary (￥)_15000.0**
Reply	0.362	0.819	0.493
Pass	1.000	0.661	0.014**

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 13: Results of Binomial Logistic Regression, X= Gender, Age Expected Salary

According to *Table 13*, Since the field *Expected Salary (¥)_15000.0* has a significance P-value of 0.014**, which presents significance at the level and rejects the original hypothesis, *Expected Salary (¥)_15000.0* has a significant effect on *Pass*, meaning that for every unit increase in *Expected Salary (¥)_15000.0*, *Pass* is 1. increases by one unit, the probability of *Pass* being 1.0 is 258.463% higher than the probability of 0.0. And the original hypothesis cannot be rejected because the P-values of significance for the rests do not present significance at the level, and therefore have no significant effect on *Reply*.

4.4.2 X= Gender, Age, Expected Salary, CV Version

	Binomial Logistic Regression P-Value		
	X= Gender_Male	**X=Age_40.0**	**X= Expected Salary (￥)_15000.0**
Reply	0.372	0.832	0.499
Pass	0.939	0.609	0.016**

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 14: Results of Binomial Logistic Regression, X= Gender, Age Expected Salary, CV Version

Since the *Expected Salary (¥)_15000.0* has a significance P-value of 0.016**, which presents significance at the level and rejects the original hypothesis, *Expected Salary (¥)_15000.0* has a significant effect on *Pass*, meaning that for every unit increase in *Expected Salary (¥)_15000.0*, *Pass* is 1. increases by one unit, the probability of *Pass* being 1.0 is 251.35% higher than the probability of 0.0.

Observing the P-value of *CV Version* category, the levels of significance do not present and the original hypothesis cannot be rejected, therefore *CV Version* will not have a significant effect on both *Reply* and *Pass*.

4.4.3 X= Gender, Age, Expected Salary, Industry

	Binomial Logistic Regression P-Value		
	X= Gender_Male	**X=Age_40.0**	**X= Expected Salary (￥)_15000.0**
Reply	0.337	0.810	0.471
Pass	1.000	0.644	0.010**

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 15: Results of Binomial Logistic Regression, X= Gender, Age Expected Salary, Industry

According to *Table 15*, *Gender*, *Age*, and *Expected Salary* do not have a significant effect on the *Reply*. Comparing the data shown in *Table 14*, the P-values for all three variables have decreased in this row. And for *Pass*, since the field Expected Salary (¥)_15000.0 has a significance P-value of 0.010**, which presents significance at the level and rejects the original hypothesis, *Expected Salary (¥)_15000.0* has a significant effect, meaning that for every unit increase in *Expected Salary (¥)_15000.0, Pass* is 1. increases by one unit, the probability of *Pass* being 1.0 is 296.323% higher than the probability of 0.0, while the other two independent variables are not significant.

Additionally, the significant P-values of *Industry_Life Service* shows the significance at the level with a 0.012** P-value, which can reject the original hypothesis. Therefore, the Industry_Life Service do have a significant effect on Reply, implying that for every unit increase in Industry_Life Service, the probability of Reply being 1.0 is higher than the probability of it being 0.0 by 1414.367%.

4.4.4 X= Gender, Age, Expected Salary, CV Version, Industry

	Binomial Logistic Regression P-Value		
	X= Gender_Male	**X=Age_40.0**	**X= Expected Salary (￥)_15000.0**
Reply	0.366	0.787	0.463
Pass	0.924	0.587	0.007***

Note: ***, **, * represent 1%, 5%, and 10% significance levels, respectively.

Table 16: Results of Binomial Logistic Regression, X= Gender, Age Expected Salary, CV Version, Industry

After adding both two control variables (*CV Version* and *Industry*), as the same, only the

Expected Salary (￥)_15000.0 is significant on the *Reply*.

In addition, the *Industry_Life Service* shows the significance at the level with a 0.013** P-value, which can reject the original hypothesis. Therefore, the *Industry_Life Service* do have a significant effect on *Reply*, implying that for every unit increase in *Industry_Life Service*, the probability of *Reply* being 1.0 is higher than the probability of it being 0.0 by 1379.093%. And the significant P-values for *CV Version* do not present significance at the level and do not allow for the rejection of the original hypothesis, having no significant effects on both *Reply* and *Pass*.

4.5 Interaction Term (X= Gender, Age Expected Salary)

Interaction Term	F-test P-value			
	Reply	Pass	Time of First Response	Time of Final Reply
Intercept	0.000***	0.000***	0.000***	0.000***
Gender	0.362	1.000	0.251	0.304
Age	0.820	0.662	0.979	0.947
Expected Salary	0.494	0.009***	0.632	0.561
Gender * Age	0.494	0.382	0.520	0.607
Gender * Expected Salary	0.041**	0.190	0.035**	0.047**
Age * Expected Salary	0.362	0.382	0.346	0.422
Gender * Age * Expected Salary	1.000	0.662	0.827	0.906
Errors	NaN	NaN	NaN	NaN

Table 17: Results of Interaction Effects Analysis

Analyzing the results of F-test, the P-value of the interaction terms *Gender * Age, Age * Expected Salary, Gender * Age * Expected Salary* do not show significance at the level of significance, and there is neither significant effect on *Reply, Pass, Time of First Response*, and *Time of Final Reply* nor interaction exists.

However, the interaction term ***Gender * Expected Salary*** is significant at the level of significance, and has a significant effect on *Reply, Time of First Response*, and *Time of Final Reply*. Therefore, there is an interaction effect of *Gender * Expected Salary* on the dependent variable other than *Pass*.

5. Discussion

5.1 Limitation

As this study aims to explore the application of AI in corporate recruitment scenarios, the industries involved are based on firm-specific lock-in. In this particular condition, AI algorithms are widely used in technology enterprises, so the differences visible by the figure appear.

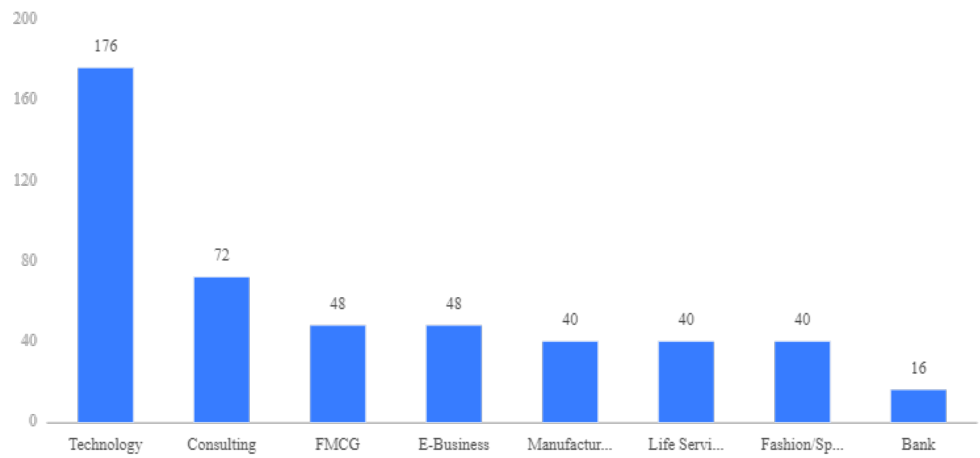

Figure 4: Industries Recovered

Due to the timeliness of job recruitment, this study cannot cover all AI platforms, and the job demand is constantly changing due to changes in the natural market at any time. We only collected data for one month, which may cause certain errors. In the natural labor market, we only have eight basic resumes to modify and send, and we have to minimize the differences between their direct educational background and work experience, so they are limited in choosing their personal field, and the undergraduate colleges and work experience they represent are not representative of everyone in the whole job market.

The overall CV pass rate was 4.58%, which means that only a small percentage of all responses met the predefined criteria or requirements. This may imply that further analysis is needed on what factors are affecting the pass rate and measures should be taken to improve it accordingly.

The relatively low total response rate and total pass rate, despite the short average real response time, may mean that in most cases requests are not responded to effectively or satisfactorily. This suggests that while the system is performing well in terms of response speed, improvements may be needed in terms of improving response and adoption rates to ensure that more requests are responded to in a timely and satisfactory manner.

5.2 Other findings

After we combusted 480 data from all resume delivery results, we found something special. In the descriptive statistics, for a lot of companies, no matter the time of the applicant's delivery is at any time within three days, the target company's HR will process and respond to the message at a specific point in time, and the language used in the reply is the same. For example, the recruiter of Beike Housing replied the following contents at the same time to the resumes submitted by our eight candidates. We have just entered into in-depth communication with other candidates, and we are sorry that we cannot provide positions. Also, since we sent eight resumes for each position, we found that the response rate for many specific target positions was very similar, with up to 90% of all responses received or all rejected. With the uniform point-in-time responses generated and the response rates, we can further confirm that AI screening resumes exists and that there may be uniform automated responses.

In the case of repeated company experience, HR chose to communicate with 30-year-old women, indicating that recruiters prefer to communicate with 30-year-old women under the same experience. In addition, It can also be seen that the average time of women's first reply is generally shorter than that of men, but the passing rate of women in the same position is not higher than that of men. It can be concluded that HR is more inclined to communicate with women in time, and there is an invisible difference in the treatment of men and women in the AI algorithm recruitment when screening resumes.

At the same time, we found that according to the specific time line of communication for each position, the time interval of reply from recruiters for some positions was fixed, and the response frequency of women was higher than that of men. As a result, the passing rate of women is also higher, so we reasonably guess that the response frequency affects the judgment of recruitment screening. In addition, the uniform post has a fixed reply interval for multiple applicants, which further confirms the existence of AI and that AI algorithms may affect different results caused by gender differences in recruitment.

Also, in the statistical analysis, we find that the distribution of Reply variables does not satisfy the normal distribution, which may be caused by the non-normal nature of the data or the insufficient sample size.

5.3 Combined with the thinking of existing research

It is not difficult to find that according to previous studies, gender differences and age differences may affect recruitment results to a certain extent in the recruitment process of AI algorithm, while the difference in expected salary has not been studied maturely. We want to be clear that the AI algorithm itself is not gender biased, its behavior is entirely based on the input data and training model. However, AI algorithms may inadvertently exacerbate gender disparities in the hiring process due to possible biases in the data itself, as well as potential problems in the algorithm design and training process.

On the one hand, AI algorithms are often trained on large amounts of historical data, which may imply patterns of gender inequality. For example, if one gender dominates a position in historical data, the algorithm may tend to recommend more candidates of that gender, limiting the opportunities for the other gender.

On the other hand, imperfections in the algorithm may also affect its treatment of gender differences during training.

However, the previous AI algorithm is mainly used for the preliminary screening of resumes and keyword matching. By setting specific keywords and conditions, AI algorithm can automatically filter out resumes that do not meet the requirements, with the purpose of reducing the workload of HR.

With the continuous progress of technology, the application of AI algorithm in recruitment screening is gradually deepened and constantly improved. The introduction of natural language processing and machine learning technology allows algorithms to parse resume content more deeply, extracting key information such as education, work experience, age and expected salary. At the same time, the algorithm can also make a preliminary assessment of the matching degree of candidates based on historical data and algorithm model, providing HR with more accurate screening results.

In short, the development process of AI algorithm recruitment and screening resumes is a process of continuous progress and optimization. With the continuous development of technology, AI algorithms will play an increasingly important role in the recruitment field, providing enterprises with more efficient and accurate recruitment solutions.

5.4 Implications for governments and enterprises

The use of AI algorithms in recruitment has significant implications for society. The first is that algorithm design and presentation are extremely important in shaping perceptions of fairness and trust, but the potential for AI to replace HR jobs may have negative consequences.

First, AI algorithms are often trained on large amounts of data, which can be biased in some way. If an algorithm fails to adequately correct for these biases, it can lead to unfair screening of certain groups, such as race, gender, or age. Such discriminatory behavior may not only violate employment discrimination laws, but also damage the reputation and image of the enterprise.

In addition, while AI algorithms can process large amounts of data quickly, they have limitations in assessing candidates' soft skills, personality, character, and work ethic. These aspects usually require in-depth communication and understanding by human interviewers, which is difficult for AI algorithms to completely replace. In addition, AI is also unable to identify the candidate's emotions and attitudes, which are a very important part of the interview.

But on the whole, the application of AI algorithm in recruitment screening has a significant impact and benefit on both the government and enterprises.

Governments and enterprises can use AI algorithm recruitment to improve recruitment efficiency and fairness. With the help of AI algorithm, governments can quickly identify the most suitable candidates among the massive number of applicants, greatly shortening the screening time.

At the same time, AI algorithms screen based on data and algorithmic models, reducing bias and discrimination caused by human factors and improving the fairness of recruitment itself.

More importantly, AI algorithm recruitment optimizes talent allocation. Enterprises can use AI algorithm to conduct in-depth analysis of candidates' skills, experience and background, and more accurately match job needs. This helps to optimize the talent allocation of social resources and improve the operation efficiency and service level of enterprises and government agencies. Finally,AI algorithms are conducive to data-driven policy making across institutions and enterprises: Through the analysis of recruitment data, the government and enterprises can understand the current talent market conditions, industry trends and other information, and provide data support for policy formulation.

In general, the application of AI algorithms in recruitment screening has brought more efficient and fair recruitment methods for governments and enterprises, helping to optimize talent allocation and enhance overall competitiveness. However, in the application process, attention should also be paid to solving relevant challenges and problems, ensuring the accuracy and fairness of the algorithm, and protecting the security and privacy of personal data.

6. Conclusion

In conclusion, our comprehensive analysis of gender, age, and expected salary variables in AI recruitment reveals robust evidence of gender disparity. Algorithms, despite their power, inherit human biases and can amplify them. Therefore, a multifaceted approach is required, including improving algorithm design, enhancing recruiter training, and establishing regulatory frameworks. In the "Introduction" to this study, we outlined our goal of delving into the complex dynamics that influence recruiter decision-making and ultimately the hiring process. Now, at the conclusion of our study, we can confidently assert that our research does shed new light on these complex interactions.

This study found that Expected Salary showed a significant effect on job search pass rate, implying that a candidate's expected salary level is one of the important factors in determining whether or not to get a job offer. In addition, there was a significant interaction between the combination of gender and expected salary (Gender * Expected Salary) in the job search process. This interaction had an impact on recruiters' willingness to respond, time to first response, and time to final response. This finding suggests that gender and expected salary are not variables that independently affect recruitment outcomes, but rather work together in all aspects of the recruitment process. Therefore, in order to promote the fairness and efficiency of recruitment, enterprises should consider the interaction effect of gender and salary expectation more carefully and optimize their recruitment strategies and processes accordingly.

Our findings help to resolve preconceived puzzles, collect primary data in an interesting way, summarize the conditional significance of expected salary for passing the resume screen versus the non-significance of other variables, and make clear the important influence of personal factors on AI hiring decisions. Second, the intricate interactions between variables reveal dynamics that impact hiring outcomes, not only challenging traditional hiring paradigms, but also providing valuable insights for optimizing hiring strategies. Finally, we do value the process of field experiments and have gained some interesting findings and insights, which further enhance our understanding of the domestic job market and new recruitment models from the perspective of economics and labor and management while addressing the research questions.

As we embrace digitalization, it is crucial to ensure that technological advancements do not undermine equity and inclusivity. Specifically, we advocate for stronger gender equality awareness in AI recruitment, optimized algorithm design, and careful consideration of variable impacts to minimize algorithmic bias and inequality, particularly regarding gender. By doing so, we can strive for a fairer and more inclusive recruitment process.

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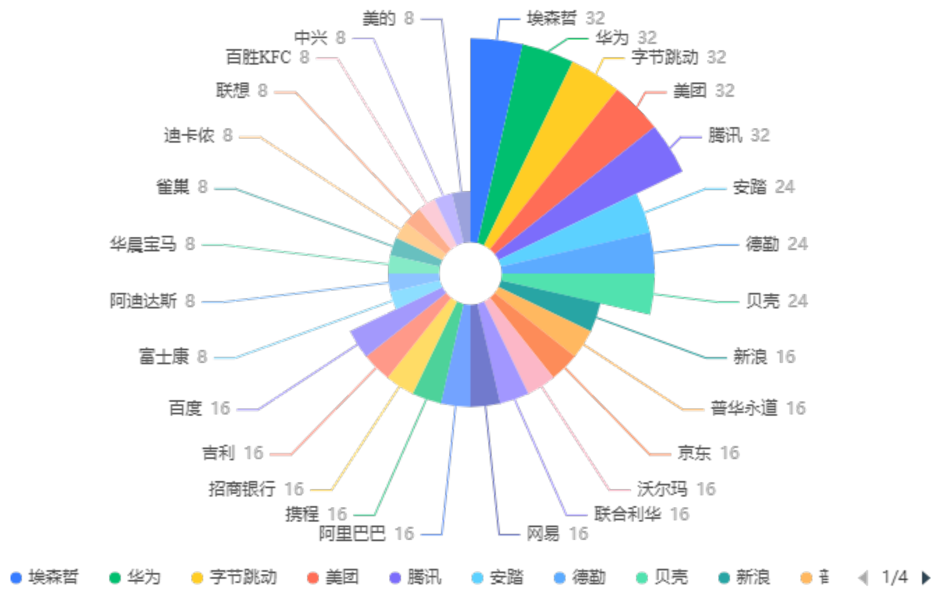
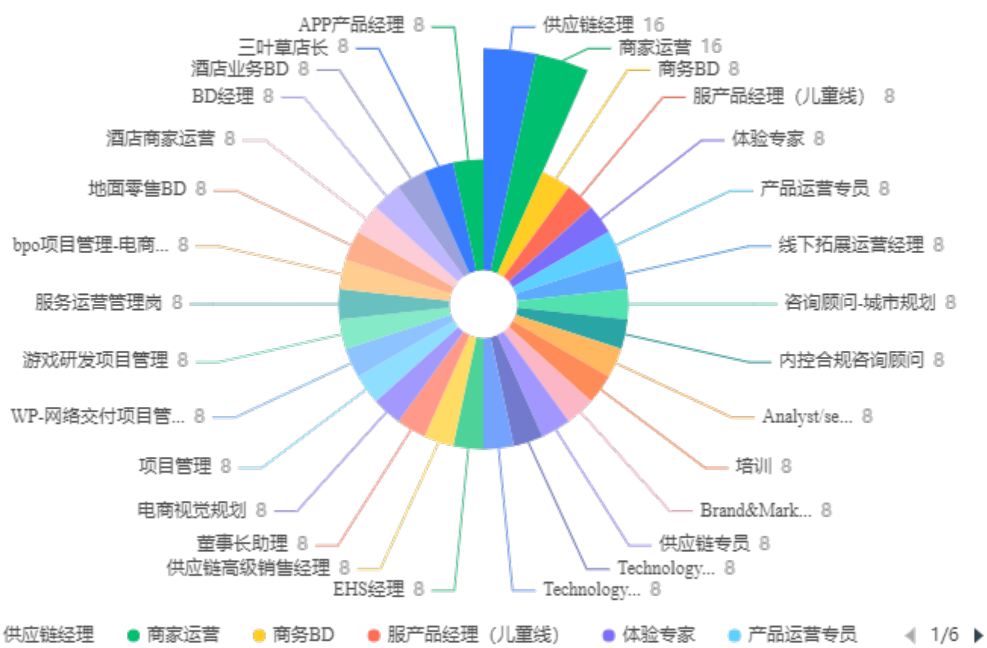
Appendix



Appendix Graph 1: Companies Selected



Appendix Graph 2: Specific Positions Recovered

Mary Chen

陈楠

性别：女　 现居地：广东深圳　出生年月：1982 年 11 月　工资预期：15k
联系电话：18096110015　电子邮箱：2848571506@qq.com

教育背景：

西南财经大学

- 人力资源管理 本科　　09/2000-06/2004
- 团支部书记，在校先进党员

工作经历：

仲量联行（深圳） 租赁经理

- 负责客户接待、咨询工作，提供销售咨询及房地产业租赁咨询服务；　　08/2019-01/2024
- 对接渠道客户，沟通和跟进新客户的拓展工作，负责交易中的房源商务谈判；
- 了解深圳房地产市场动态，追踪市场趋势，通过目标市场分析与营销定位，撰写针对具体需求的调研报告。

TCL通讯 公共传播专员

- 支持产品落地与公关发展工作，协助项目核收交付宣发工作；　　02/2014-06/2019
- 对接销售平台日常报告产出，协助活动发布及促销企划；
- 协助新产品发布会举办，负责公司内部文化建设；
- 负责媒体联络与官网新闻文案撰写，联系合作方洽谈与会议场地预定；
- 协助其他部门按时完成工作任务安排及企业形象、品牌建设。

中海物业　人资调度HR

- 协助开展人才规划、管理与能力发展培训，协助绩效考核与激励的实施；　　07/2004-10/2013
- 整理、归档员工个人信息，规范管理员工档案，汇总分析相关数据统计工作；
- 协助公司员工关系管理，负责协助招聘事务，包括职位发布、电话沟通，跟进调动全流程；
- 协助完成日常投诉、建议处理，维护业主与物业的有效沟通与和睦关系。

相关技能：

- 工具：熟练掌握 Word、Excel、PPT 等办公软件；
- 语言：普通话、粤语、简单英语、日语会话；
- 爱好：羽毛球、长跑、摄影

徐腾 Alex

性别：男 | 电话：13985478211 | 现居城市：上海 | 期望薪资：1w | 出生年月：1992 年 2 月

教育背景

上海大学 2010 年 9 月- 2014 年 6 月

金融学 本科 经济学院 上海市

工作经历

长江证券 投行股权线负责人 2019 年 10 月- 2023 年 12 月

- 带领项目团队进行承揽企业的尽职调查和数据收集与项目计划书的编写，涵盖化学制品制造业、医疗设备制造业、电力设备制造业。企业盈利数据的收集主要源自巨潮资讯、荣大二郎神等数据库中的年度报告等公开资料；
- 通过 DCF、PE 模型等调配部门进行智能机器人行业上市公司的估值和财务建模工作，组织部门路演、推介会等投资者关系活动并制作行业内公司的项目推介材料和 PPT 进行展示；
- 对热点行业的发展形势、监管部门及行业内政策情况进行整理，带领团队完成 IPO 招股书行业研究部分及业务与技术部分内容、行业深度研究报告，内容涵盖生物医药、半导体和智能机器人行业；
- 对特定食品饮料、化工制造、机械设备等领域内的企业进行网络核查，对拟 IPO 企业进行包括法律合规性检验，包括股权穿透、法律诉讼等，分析同业竞争及关联交易的核查程序。

远望达创业投资集团 市场部 2014 年 8 月- 2019 年 6 月

- 研究新能源汽车公司私募融资的可行性，融资规模 11 亿人民币。协助对拟投资项目进行公司所在行业的行业研究并撰写新能源汽车行业研究报告，内容包括但不限于产业链、供求关系、PEST 与竞争关系（波特五力）分析等；
- 进行特种船舶及海工装备制造企业关于行业背景、发展前景、业务与技术、财务状况与预测等情况的尽职调查，撰写内部尽调报告与投资建议书；
- 收集和分析上述企业各季度、半年度和年度财务报表并参与对拟投企业经营和财务状况等的内部调研，撰写项目计划书，通过构建 DCF、LBO、行业可比 PE、PS 等财务估值模型进行项目收益率的测算与敏感性分析。

项目经历

药明生物股权投资项目 | 研究员 2013 年 3 月- 2013 年 7 月

- 项目描述：药明生物 C 轮股权投资项目
- 项目职责：1）对项目进行行业分析、财务分析、估值测算、风险分析，并撰写项目尽职调查报告；2）协助维护项目和公司团队关系，掌握项目进度、协助谈判、促成项目成交；3）实地考察、与公司负责人进行访谈。
- 项目成果：最终协调公司成功参与药明生物的 C 轮融资。

相关技能

- **软件工具：** MS Office，熟悉彭博、Wind、CSMAR、企查查、巨潮咨询、荣达二郎神等金融数据库用法
- **证书/执照：** 证券从业资格证、基金从业资格证
- **语言：** 普通话，英语（CET-6）

张名成

- 年龄：31 岁
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教育经历

2011.09~2015.06　　东华大学（本科）　　信息管理与信息系统

工作经历

2015.09~2018.09　　深信服科技股份有限公司　　产品助理

实习概述：在 SASE 产品线实习，主要参与了云计算/云安全中 DLP 数据防泄漏产品研发、深信服 ALL IN ONE 项目，完成了用户调研、分析、产品功能定位等工作。撰写 CASB 产品评价国家标准。

需求分析：分别进行对名创优品、招商银行等大客户的用户调研，MCAfee、微软、腾讯云竞友商产品的分析；各个产品线用户的调研，McAfee、Zscaler 的对比分析等，为原型图设计、输出解决方案奠定基础。

功能设计：负责功能设计，撰写详细的产品需求和原型设计文档，全程跟进功能输出。

2018.11~2023.10　　快手　　产品运营

竞品&用户调研：回收内部 549 名用户调查问卷，分析用户痛点及需求，得出 HR 智能客服存在答案生硬、匹配不准问题不全等问题；从数据指标/使用体验/学习价值等维度对比淘宝、美团等商业智能客服产品，提出产品功能迭代建议。

系统知识库搭建：从 0-1 搭建 HR 智能客服系统知识库，独立配置 10+业务场景知识库流程 300+条（占总流程的 25%+）。浮窗功能上线后，独立配置 2 个浮窗按钮的业务咨询模块，包括多轮交互设计、语料梳理、知识质量测试及原始场景迭代等。

数据监控：监控多个业务咨询模块数据维度，评估匹配不精准等原因后迭代原始场景，完全匹配率 98%。

项目经历

DLP 数据防泄露产品研发项目　负责人

项目描述：该项目可增强 SASE 产品的 DLP 数据防泄漏功能，解决影子 IT、BYOD 以及云上安全问题

项目职责：担任产品经理，独立完成了名创优品、招商银行等大客户的用户调研；MCAfee、微软、腾讯云竞友商产品分析；设计云服务消费者和云服务提供商之间的安全策略执行点，增加用户分析内部泄密情况以及邮件外发情况的新功能；设计原型图、撰写用户手册等内容

项目业绩：该成果作为公司下半年主打产品，整体未识别率降低 0.4%，规则库更新率 91.5%，速度提升 0.6%

技能奖项

技能证书：大学英语四级（CET-4）、大学英语六级（CET-6）、全国计算机二级

个 人 简 历

赵君雅

Mia

个人信息

出生年月：**1994.10**

性别：女

民族： **汉族**

籍贯： **湖南长沙**

电话： **15185125077**

学历： **本科**

邮箱：junya1@yeah.net

期望薪资：15k

兴趣爱好

阅读：已阅读 200+经典书籍

舞蹈：中国舞 10 级

跑步：已坚持夜跑 3 年

教育背景

2012.09-2016.06　　河海大学　　市场营销（本科）

- GPA：3.8/4.0 （专业排名**前 5%**）

工作经历

2019.11-2023.11　　工银理财　　证券投资研究员

- **客户销售**：公司提供客户资源，通过网络沟通了解客户需求，以客户需求为导向进行服务，讲解产品服务，促成合作，定期与合作客户沟通，形成长期合作关系；
- **凭证审核**：兼职出纳，负责公司的各类成本费用的付款流程及单据的审核，审核无误及时支付，并协助成本会计完成 ERP 系统出纳模块的制单、台账的建设及维护运行；
- **报表编制**：负责登记现金、银行日记账，编制会计凭证，做到日清月结，保证账实相符。

2016.07-2019.09　　北京蓝色光标　　品牌经理

- **品牌推广**：负责公司品牌定位及建设工作，并根据公司主营项目进行针对性推广工作；其中包括篮球俱乐部项目的市场推广工作；
- **渠道推广**：负责公司篮球俱乐部的商业运作，包括前期的市场推广和商业性尝试，与校园、企业、事业单位等机构合作，在媒体宣传、票务资源、品牌联动等方面开展工作，培养项目前期的基础粉丝和群众基础；
- **产品开发**：跟进公司项目（食品类）需求，挖掘客户需求，提成相关产品定位方式，如商品包装、名称、品牌故事、定价、渠道市场等，并指定相关的产品推广计划和营销计划；
- **直播活动**：策划并组织各类线上、线下直播、营销活动、开展门店及商品的市场营销及推广工作。运营期间，组织了网红直播活动，并进行多平台多媒体宣传转发。

技能专长

- **语言技能：**大学英语六级、能简单英语交流、德语略懂
- **专业技能：**精通品牌管理知识，具备系统的品牌规划和管理能力，能熟练的运用品牌推广的工具及手段
- **办公技能：**熟练操作 office 办公软件

求职优势

- 具备较好的文案撰写及项目策划能力，能独立完成相关市场策划、营销方案的编写；
- 较强的学习应变能力与良好的团队精神，能快速适应新环境；
- 性格开朗、抗压能力强，工作积极主动，执行力强