

Ensuring Human Intelligence in
Artificial Intelligence (AI) Hiring Tools:

A Mixed-Methods Exploration of Current Impacts and Challenges in Algorithmic Hiring



December 10, 2023



Algorithmic hiring is the usage of tools based on Artificial intelligence (AI) for finding and selecting job candidates. As with other applications of AI, it is vulnerable to perpetuating discrimination. Considering technological, legal, and ethical aspects, the EU-funded FINDHR project will facilitate the prevention, detection, and management of discrimination in algorithmic hiring and closely related areas involving human recommendation. FINDHR aims to create new ways to ascertain discrimination risk, produce less biased outcomes, and meaningfully incorporate human expertise. Moreover, it aims to create procedures for software development, monitoring, and training. On completion, the project's publications, software, courseware and datasets will be made freely available to the public under free and open licenses.”¹



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<https://cordis.europa.eu/project/id/101070212>*

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¹ FINDHR, November, 2023. Accessed via <https://findhr.eu>

² Fairness and Intersectional Non-Discrimination in Human Recommendation, November 2023. Accessed via <https://cordis.europa.eu/project/id/101070212>

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Executive Summary

As Artificial Intelligence (AI) tools increasingly shape the hiring landscape, a critical question arises: do these tools contribute to the widening labor gap between open positions and qualified, yet non-traditional, applicants?

The current EU labor market is dealing with a significant imbalance of job vacancies and skilled job seekers. Especially, females and migrants find themselves over-represented in surplus occupations involving clerical, design, and hospitality jobs. Jobs involving tech professionals, construction workers, and medical specialists are short staffed. Moreover, widespread hiring practices including algorithmic hiring tools screen out many qualified candidates and artificially constrain the talent pool that companies consider, essentially “hiding” prospective workers. Researchers estimate that the U.S. accounts for more than 27 million hidden workers and conclude similar proportions of hidden workers across the U.K. and Germany.³

³ Fuller, Joseph B., Manjari Raman, Eva Sage-Gavin, and Kristen Hines (September 2021). “Hidden Workers: Untapped Talent.” Harvard Business School Project on Managing the Future of Work and Accenture, <https://www.hbs.edu/managing-the-future-of-work/Documents/research/hiddenworkers09032021.pdf>

System and Human Biases

One challenge is the inherent bias built into the current hiring practices. A mostly traditional, native workforce leads hiring processes. Hiring managers reinforce job profiles and searches based on characteristics of the current workforce. Existing research coupled with this Project's Interviews and Experiments demonstrate how educated and experienced female migrants are effectively excluded from opportunities due to their ethnic-sounding name or international work experience.

Computational Biases

Algorithmic hiring tools exacerbate the “hidden” workforce by rigid systems that match exact keywords and outcomes based on primarily biased historical data sets in black (opaque) boxes. “...these black box models are created directly from data by an algorithm, meaning that humans, even those who design them, cannot understand how variables are being combined to make predictions.”⁴

This Project unearthed how algorithmic hiring tools such as Applicant Tracking Systems (ATS) are not matching a “hidden” workforce of skilled women and migrants into opportunities. Unmanaged, these systems can amplify bias and effectively reduce the pool of workers that are considered for a growing roster of unfilled roles.

Key Perspectives and Experiences

In this Project, **college-educated, experienced, and motivated job applicants detailed significant hurdles to securing initial interviews, often receiving quick rejections after submitting resumes.**

⁴ Cynthia Rudin and Joanna Radin (November 2019). “Why Are We Using Black Box Models in AI When We Don't Need To? A Lesson From an Explainable AI Competition.” Harvard Data Science Review, <https://hdr.mitpress.mit.edu/pub/f9kuryi8/release/8...>

Recruiters and talent acquisition personnel are dealing with little time to search and select candidates, and this drives the desire to use algorithmic hiring tools that can create process efficiencies. A global market review found that an estimated 35% to 45% of companies have adopted AI in recruitment, and more than 73% of companies are planning to invest in recruitment automation in 2023.⁵ **Even when diverse candidates make it into the selection process, hiring managers with traditional skills and characteristics drive the decision making process based on their own predispositions.**

AI recruitment technology companies prioritize data security and privacy compliance. The Project's interviews with work tech firms reveal proactive measures, such as external bias testing, aimed at addressing hiring bias. However these happen too infrequently, often annually. These tech companies aspire to become "co-pilots" in talent intelligence, expanding the worker pool to encompass the "hidden" workforce. Skill-based hiring and sophisticated AI solutions are emerging in the talent tech space to tackle this pervasive issue.

Stakeholders' Input and how we can address biases in algorithmic hiring tools

We must unite all stakeholders — job seekers, talent acquisition teams, hiring managers, and talent tech companies — to collaboratively establish the most effective and ethical approaches for sourcing, screening, and selecting co-workers. Within the Report, we offer recommendations for each stakeholder, outlining strategies to mitigate bias and broaden outreach to the often-overlooked "hidden" workforce. Furthermore, the Report highlights instances where AI is employed as a catalyst for diversity, bringing forth the untapped potential of the "hidden" workforce.

Ultimately, AI bias is not a technology problem, it is a people problem. We can only begin by addressing systemic biases, human biases, and computational biases if we create a union where diverse communities have access to participate in forming our society.

⁵ Intelion Systems. "AI Recruitment Statistics." Byte-Sized Brainfood, July 1, 2023. Accessed via LinkedIn, <https://www.linkedin.com/pulse/ai-recruitment-statistics-intelion-systems/>

Firsthand Experts' Knowledge

In compiling this report, we garnered insights from a diverse pool of a total of **110 stakeholders**. The data collection process included the collecting of 88 resumes, leading to in-depth, one hour long, 1:1 interviews with three (3) job applicants. Additionally, we facilitated three (3) online focus groups, engaging a total of 15 participants in discussions. We distributed an email questionnaire to five (5) respondents who were unable to partake in the focus groups. Complementing this, we conducted 1:1 interviews with 22 industry experts.

This comprehensive approach to stakeholder engagement allowed us to draw from a wide spectrum of perspectives. These findings were tested with our own experiments in order to create a more robust foundation for our recommendations.

6 Talent Aquisition Leaders

16 AI experts

88 Job Applicants

Key Findings Experiments

Experiment I (A) - Manual scoring of resumes.

Experiment I (B) - Automated scoring of resumes with use of an Applicant Tracking System (ATS).

Experiment II - Automated scoring of resumes with use of an Artificial Intelligence (AI) system.

Differences between manual versus automated scoring of candidates could be due to resume readability issues

In Experiment I (A) and I (B), we sought to understand how manual- and automatic testing of applicants might vary. For the manual test arm, a professional recruiter was asked to review and select the candidates for the job of Project Manager (See Appendix A). For the automated test arm, an open source ATS system was used to identify viable candidates for the same position. **We observed that numerous resumes that were graded as “A-Candidates” in the manual testing arm received lower scores than other applicants despite possessing relevant experience and closely aligning with the job description’s requirements.** We believe this outcome was due in part to a resume’s parsability – the system’s ability to effectively read and extract the pertinent keywords and information. In essence, the accuracy and efficiency of this parsing process emerged as a pivotal factor influencing the scoring outcomes. While our findings were not statistically significant, it’s worth noting that we did not detect any discernible bias within the application of a system like [resume-matcher](https://www.resumematcher.fyi/) (<https://www.resumematcher.fyi/>).

Automated scoring of candidates with use of AI indicates high likelihood of bias against migrants

The final Experiment (II) that compared the treatment of British (considered local in this Experiment) and international resumes in an U.K. based ATS found that it consistently assigned higher scores to local (British) resumes.

International resumes that incorporate a subtle attribute denoting migrant status show on average a decline of 2-3 points (out of a 100) in their score, as opposed to local resumes (such as highlighting that the applicant is a British native), which experience an approximate 1-point decrease.

Of the subtle attributes studied, **International Education exerts the most pronounced negative impact on resumes scores, with a notable 80% of international resumes receiving lower rankings.**

Comparing resumes scores based on Nationality, English/British- and Indian resumes ranked the highest and resumes from Japanese applicants the lowest. This suggests potential preference to ethnic groups that have a higher representation in the U.K.

One of the Project's advisors clarified that this phenomenon arises from how the hiring system has been trained. **The ranking of identical job applicants can yield distinct outcomes, influenced by the machine learning derived from various historical datasets.**

Further ATS experiments should be conducted testing local versus international resumes in the various European countries.

Introduction & Context

Across the European Union (EU), there is a pressing labor market imbalance. This is shared across sectors and industries. In recent years, most European countries have seen a consistent widespread shortage of, especially “...software engineers, health professionals, and building trades.”¹ In contrast, Europe has a surplus occupation of clerical professionals such as secretaries and office clerks, unskilled laborers, and workers from the humanities and creative arts.

While females accounted for 46% of all workers in the EU countries in 2021, they represented only 34% of the 38.82 million working in the most widespread shortage occupations (such as software engineers). **Female workers, however, account for 62% of 39.88 million who were employed in the most widespread surplus occupations (such as office clerks).** If healthcare occupations were removed from the list of widespread shortages, the female representation would further decline by 10 million or 14%. **Migrant workers find themselves in delicate positions where a 12% find themselves in a shortage occupation.**²

A Stark Divide Between Employers and Job-Seekers

The mismatch between the needs of the labor market and workers with other skills and talents does not only affect the livability of society, but is detrimental to economic growth. More than 75% of EU companies struggle to fill positions.³ A survey by the ifo institute (Leibniz Institute for Economic Research at the University of Munich) found that 87% of family businesses in Germany were suffering from the impact of shortages of workers. At the same time, millions of skilled, educated, and motivated workers find themselves left out of the job market.⁴ **Germany alone faces a shortage of almost 2 million workers, yet 2.5 million people in the country are in search of employment.**⁵

¹ Fondazione Giacomo Brodolini Srl SB, EURES Report on labour shortages and surpluses 2022. Publications Office of the European Union, 2023, <https://www.ela.europa.eu/sites/default/files/2023-03/eures-labour-shortages-report-2022.pdf...>

² Fondazione Giacomo Brodolini Srl SB.

³ Jiménez, Ivan. “Europe is facing a shortage of skilled workers,” Euronews, July 2023, <https://www.euronews.com/2023/07/18/europe-is-facing-a-shortage-of-workers-the-basque-experience-could-be-the-answer#:~:text=EU%20member%20states%20are%20struggling,fill%20jobs%2C%20hampering%20economic%20growth...>

⁴ Baniya, Sudesh. “Europe’s labour problem: More than 27 million unemployed or underemployed in the EU in 2022,” Euronews, May 2023, <https://www.euronews.com/next/2023/05/24/europes-labour-problem-more-than-27-million-unemployed-or-underemployed-in-the-eu-in-2022...>

⁵ Kaufman, Dirk. “What skilled workers does Germany really need,” Deutsche Welle, April 2023. <https://www.dw.com/en/what-skilled-workers-does-germany-really-need/a-65223664#:~:text=In%20Germany%2C%20more%20than%202.5,almost%20%20million%20skilled%20workers...>

Beyond a mismatch of qualifications and skills between job vacancies and job seekers, another reason for this unfulfilled potential could be that employers are simply not seeing the candidates in front of them. **A report conducted by the Harvard Business School found that widespread management practices and tools screen out many qualified candidates and artificially constrain the talent pool that companies consider, essentially “hiding” prospective workers.** The researchers estimate that the U.S. accounts for more than 27 million hidden workers and conclude similar proportions of hidden workers across the UK and Germany.⁶

AI Exacerbates the Hidden Workforce Challenge

One category of tools heavily impacting the “hiding” workers phenomenon are automated recruiting systems known as Applicant Tracking Systems (ATS). ATS may or may not use Artificial Intelligence (AI) to source and select job candidates. The majority of large companies use ATS recruitment software to process, sort, and rank the incoming resumes; in Germany, more than half (54%) of companies use automated recruitment software systems.⁷

These systems are meant to improve the efficiency of the hiring process, and as such they use rigid screening parameters such as excluding anyone with an employment gap, or proxies for desirable but subjective attributes like a college degree. This excludes candidates who are high performing but not an exact match for system criteria.⁸ Applicants with resumes that are optimized for ATS review may be screened as a better match for a position than a candidate with more relevant skills and motivation.⁹

⁶ Fuller, Joseph B., Manjari Raman, Eva Sage-Gavin, and Kristen Hines (September 2021). Hidden Workers: Untapped Talent. Harvard Business School Project on Managing the Future of Work and Accenture. <https://www.hbs.edu/managing-the-future-of-work/Documents/research/hiddenworkers09032021.pdf> ...

⁷ Fuller et al.

⁸ Fuller et al.

⁹ Henderson, Robert. “What Is An ATS? 8 Things You Need to Know About Applicant Tracking Systems,” Jobscan (May 2023). <https://www.jobscan.co/blog/8-things-you-need-to-know-about-applicant-tracking-systems/>...

A Worrying New Variable for Hiring Systems

The widespread use of ATS raises serious concerns that candidates may be screened out because of characteristics in their applications that relate to their identities rather than to the needs of the job – for example, women are more likely than men to take a career gap to engage in care giving for family members.¹⁰

A Brookings Institution report on algorithmic bias found that “Bias in algorithms can emanate from unrepresentative or incomplete training data or the reliance on flawed information that reflects historical inequalities. If left unchecked, biased algorithms can lead to decisions which can have a collective, disparate impact on certain groups of people even without the programmer’s intention to discriminate.”¹¹

The existence of bias in hiring has been well documented long before the advent of automated recruiting systems, particularly for women and members of minority groups. There is extensive research demonstrating that applications with foreign-sounding names are less likely to progress through the hiring process, regardless of the associated level of education and experience.^{12, 12a, 12b}

Equally Qualified but with Female and Foreign Name = Fewer Interviews

Researchers have found that when women apply for jobs, they receive fewer interview invitations than equally qualified men – an effect that is compounded for older women, women with children, and women from certain ethnic or racial groups.¹³ This compounded effect for women is what Kimberlé Crenshaw called **intersectional discrimination**.¹⁴

¹⁰ Parker, Kim. “Women more than men adjust their careers for family life,” Pew Research Center, October 2015, <https://www.pewresearch.org/short-reads/2015/10/01/women-more-than-men-adjust-their-careers-for-family-life/>

¹¹ Lee, Nicol Turner, Paul Resnick, and Genie Barton, “Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms,” Brookings Institute, May 2019. <https://www.brookings.edu/articles/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/>

¹² Kline, Patrick, Evan K. Rose, and Christopher R. Walters, “Systemic Discrimination Among Large U.S. Employers,” *The Quarterly Journal of Economics* (2022), 1–74. <https://eml.berkeley.edu/~crwalters/papers/randres.pdf>

^{12a} Immen, Wallace. “How an Ethnic-Sounding Name May Affect the Job-Hunt,” *The Globe and Mail*, November 2011. <https://oreopoulos.faculty.economics.utoronto.ca/wp-content/uploads/2014/03/How-An-Ethnic-sounding-Name-May-Affect-The-Job-Hunt.pdf>

^{12b} Adamovic, Mladen and Andreas Leibbrandt, “Is there a glass ceiling for ethnic minorities to enter leadership positions? Evidence from a field experiment with over 12,000 job applications,” *The Leadership Quarterly* (2023). <https://www.sciencedirect.com/science/article/pii/S1048984322000583?via%3Dihub>

The motivating concern for this Report is that an increase in the use of automated recruiting software that systematically exclude applicants with certain characteristics is combining with existing biases in society to create a new and detrimental blind spot that disproportionately affects those with membership in two marginalized groups – migrant women.

Intersectional discrimination manifests in online hiring practices, yet there is a notable scarcity of information regarding the intricacies of these interrelations and their consequential impacts. This deficiency extends to our understanding of how intersectional discrimination influences the career paths and experiences of affected groups. A much more comprehensive research and analysis are essential to unveil the nuanced dynamics at play and to develop informed strategies for fostering inclusive and equitable online hiring practices. In this Report, we set out to experiment ourselves to better understand how AI hiring systems behave with qualified yet non-traditional resumes. We sought to understand the women migrants self-reported experiences prior- and post experiments with algorithmic hiring systems.

Furthermore, we approached this investigation from the vantage point of technology industry leaders, and talent acquisition professionals within some of Germany's largest companies. Our focus was on gauging their awareness of the intersectionality inherent in candidates and assessing their comprehension of the ramifications associated with current hiring practices. By delving into these aspects, we aimed to shed light on the critical interplay between diversity, inclusion, and effective talent acquisition.

¹³ Foley, M; Cooper, R; and Mosseri S (2019). Gender equitable recruitment and promotion: Leading practice guide, WGEA Commissioned Research Paper, The Australian Women's Working Futures (AWWF) Project, University of Sydney, Sydney, Australia. https://www.wgea.gov.au/sites/default/files/documents/Recruitment_and_Promotion_0.pdf ...

¹⁴ Coaston, Jane , "The intersectionality wars," Vox, May, 2019. <https://www.vox.com/the-highlight/2019/5/20/18542843/intersectionality-conservatism-law-race-gender-discrimination...>

Challenging Public Sentiment: Navigating Contrary Perspectives

The study “Applicants' perception of artificial intelligence in the recruitment process” with 552 respondents found a favorable perception of the AI's usefulness, ease of use, satisfaction, and perceived attractiveness of companies. The study did not examine differences between demographic profiles such as gender, nationalities, industries, or age of respondents.¹⁵ It may explain the contrast to what we found in this much smaller sample set of migrant job seekers.

In the report, Does Artificial Intelligence Help or Hurt Gender Diversity? Evidence from Two Field Experiments on Recruitment in Tech “...we observe that the use of AI reduces the gender gap in application completion rates...female job seekers believe that there is less bias in recruitment when assessed by AI instead of human evaluators.”

The sentiment, however, could be misguided, Harvard Business Review discussed in All the Ways Hiring Algorithms Can Introduce Bias: “...we found that most hiring algorithms will drift toward bias by default.”¹⁶ Perceiving bias and actual bias are distinct.

A talent technology expert we interviewed for this Report pointed out that many people assume machines, lacking emotions, deliver fair judgments. Unfortunately, machines are basing their recommendations to the existing data set in the system and learnings from the past. If a company tended to hire a majority of men, the system learns to favor men applicants.

¹⁵ Horodyski, Piotr. “Applicants' perception of artificial intelligence in the recruitment process,” Computers in Human Behavior Reports Volume, August 2023. <https://www.sciencedirect.com/science/article/pii/S2451958823000362#bib3...>

¹⁶ Bogen, Miranda. “All the Ways Hiring Algorithms Can Introduce Bias,” May 2019, Harvard Business Review. <https://hbr.org/2019/05/all-the-ways-hiring-algorithms-can-introduce-bias>

AI Bias

Historical training data bias

When a corporation consistently hires male candidates for a specific role and these hires are deemed the most successful, machine learning models may infer that men are better suited for the job. This inference aligns with previous research and Experiment II, which indicated that female workers with names that sound ethnically diverse face a reduced likelihood of consideration.

Algorithmic bias

Programming errors can cause flawed data which will repeat, reinforce, and amplify data errors. Computer scientist Joy Buolamwini evaluated the accuracy of AI image recognition software from three different companies (Microsoft, Face, and IBM). **All three companies' products "...performed better on male than female faces; and on lighter subjects than those with darker skin color.** The worst recognition was on darker females, failing on over 1 in 3 women of color. **A key factor in the accuracy differences is the lack of diversity in training images and benchmark data sets."**¹⁷

Confirmation bias

We all unconsciously process data in ways that affirm our preexisting beliefs and hypotheses. An AI system can interpret the pre-existing data and trends that support bias. "Confirmation Bias: A Ubiquitous Phenomenon in Many Guises" by Sage Journals explains how confirmation bias can affect decision-making and lead to discriminatory outcomes.¹⁸

Application bias

Recruitment experts within the Project have emphasized that bias often originates in the job profiles themselves. For instance, a simple change in job title, such as from 'Software Coder' to 'Technical Writer,' can have a significant impact on attracting more female applicants. Additionally, biases in online advertisements and search engine results have resulted in presenting high-paying positions to males rather than females."¹⁹

¹⁷ Photopoulos, Julianna, "Fighting algorithmic bias in artificial intelligence," May 2021, Physics World. <https://physicsworld.com/a/fighting-algorithmic-bias-in-artificial-intelligence/>

¹⁸ Nickerson, Raymond S. "Confirmation Bias: A Ubiquitous Phenomenon in Many Guises," Review of General Psychology (June 1998) Volume 2, Issue 2. <https://journals.sagepub.com/doi/10.1037/1089-2680.2.2.175>

¹⁹ IBM Data and AI Team. "Shedding light on AI bias with real world examples," October 2023. IBM. <https://www.ibm.com/blog/shedding-light-on-ai-bias-with-real-world-examples/>

Intersectional bias

"AI biases pose particular challenges for migrant women, who are confronted with bias and discrimination across dimensions, including ethnicity and gender, as well as age, socioeconomic status, and potentially disability." ²⁰

It's a well-established fact that the majority of big data sets, generated by Machine Learning (ML) / AI models, exhibit bias.²¹ **Many recruitment platforms utilizing AI in their talent intelligence software rely on these same biased data sets, which can lead to decision-making based on flawed data and perpetuate inaccurate outcomes within the datasets.**

In the U.S. most people (roughly eight-in-ten people) find bias and unfair treatment based on an applicant's race or ethnicity a problem. "Among those who say racial and ethnic bias in hiring is a problem, 53% think bias and unfair treatment based on race and ethnicity will improve with increased use of AI by employers in the hiring process." ²²

Minimizing AI hiring bias cannot be covered as a merely technology problem.

Algorithmic hiring is informed through systemic biases, human biases, and computational biases. Due to these multiple sources of biases, the U.S. National Institute of Standards and Technology (NIST) makes the case in a 2022 report for a "socio technical" approach to mitigating bias in AI.²³

Therefore, the EU-wide initiative led development of this Report in order to:

- Gain a better understanding of the current use of AI in hiring practices.
- Test migrant women's resumes in AI hiring systems.
- Investigate migrant women's experiences dealing with AI hiring tools.

This report will contribute to the larger body of findings generated by the Fairness and Intersectional Non-Discrimination in Human Recommendation (FINDHR) project. FINDHR was funded by the European Union to facilitate the prevention, detection, and management of discrimination in algorithmic hiring and closely related areas involving human recommendation.

²⁰ "Gender & intersectional bias in artificial intelligence," Publications Office of the European Union, September 2020. <https://op.europa.eu/en/publication-detail/-/publication/286e1432-021a-11eb-836a-01aa75ed71a1>

²¹ Krishnamurthy, Prabhakar. "Understanding Data Bias." Towards Data Science, September 2019. <https://towardsdatascience.com/survey-d4f168791e57>

²² Lee Rainie, Monica Anderson, Colleen Anderson, Colleen McClain, Emily A. Vogels, and Risa Gelles-Watnick, 2023. "AI in Hiring and Evaluating Workers: What Americans Think," Pew Research Center. <https://www.pewresearch.org/internet/2023/04/20/ai-in-hiring-and-evaluating-workers-what-americans-think/>

²³ "There's More to AI Bias Than Biased Data, NIST Report Highlights," US National Institute of Standards and Technology (NIST), March 2022. <https://www.nist.gov/news-events/news/2022/03/theres-more-ai-bias-biased-data-nist-report-highlights>

1 Project Overview

Over the course of four months, August - November 2023, we sought both to understand functionally how algorithmic hiring tools are being deployed and how they are impacting peoples' lived experience of looking for a job. The Project's goal was to understand a broad spectrum of possible intervention points in order to make recommendations on minimizing and mitigating bias and discrimination in algorithmic hiring.

We used qualitative methods to uncover learnings directly from stakeholders as well as quantitative methods to provide a more in-depth comparison of

...how resumes are processed when the selection is led solely by human intelligence (recruiter) in experiment I (A) versus processed by an automated hiring tool such as an Applicant Tracking System (ATS) in experiment I (B).

In experiment II, we use an AI hiring tool to test potential "hidden" bias in resumes.

The experiments conducted several tests on the impact of name, gender, and school location on resumes.

1.1 Engaging with Stakeholders

We engaged directly with a wide range of stakeholders, including job applicants, recruiters who both utilize and abstain from automated tools for sourcing, screening, and selecting candidates, and experts of AI-based recruitment platforms. Our approach encompassed 1:1 interviews, three focus group discussions, and an email survey, which collectively involved 23 participants representing diverse backgrounds and genders in Germany. Furthermore, we received unsolicited comments from individuals who shared their personal experiences.

1.2 Uncovering the Application Selection Process

For this Report, we solely focused on the first step in the hiring journey – the processing of incoming resumes. We posted a mid-level Project Manager position (Appendix A) and invited members of our community networks on- and off [LinkedIn](#) to participate in data collection and submit their resumes for review as if applying for a position. While this limited the people being sourced for the job to those who are active on LinkedIn, willing to engage in research, and belonging to certain networks, it did attract a broad array of personal and professional backgrounds.

The participants were well-informed that they were applying for a research-oriented job profile. The application and upload function were exclusively available on a landing page, which comprehensively detailed the Project. Additionally, participants were requested to actively opt-in for General Data Protection Regulation (GDPR) compliance (<https://www.impactmania.com/im/gdpr/>). Following this, informational emails were sent to brief the participants about the Project. All participants who uploaded their resume were invited to the November 2, 2023 video meeting, where the initial findings of the Project were shared.

The upload function was available on <https://www.impactmania.com/im/ai-hiring-eu/> between August 22 - September 13, 2023. A total of 88 people submitted their resume.

1.3 Human Intelligence

To understand how human intelligence might approach an application review, we worked with a Vice President of Diversity and Human Resources (HR) Director from a German public company to process the 88 resumes in the same manner as she would process resumes received in a company that does not use algorithmic hiring systems. She documented her process and criteria for selecting 12 candidates that would be invited to a first interview.

1.4 Machine Intelligence

To understand the impact of automated- and artificial intelligence hiring tools, we worked with a co-founder and CEO of an AI company in Germany who opted to use an open source ATS system to conduct some basic testing. There are hundreds of platforms available on the market that cover the sourcing, screening, and selecting of job applicants. These platforms offering talent intelligence tools range widely from basic pattern matching to predefined algorithms. A few talent intelligence systems offer generative artificial intelligence where new data is generated prior to OpenAI ChatGPT's launch in November 2022. Today, many more recruitment products, especially point solutions such as video interviews recording and processing, embed this AI-powered Large Language Model (LLM) making most systems basing their output through the same dataset.

Algorithmic hiring systems are challenging to test in any form, details on their functioning – from the exact database they are run on to how the machine learns is all proprietary. Despite a half dozen meetings with recruitment platforms using AI, no company would allow us to test resumes on their platform in the manner we wanted.

We therefore consulted with a privacy & data governance technology company in the U.K. for Experiment II that set out to explore bias in a range of algorithmic software systems.

2 Interviews - Job Applicants

2.1 . Methodology

A Mixed-Methods Exploration of Current Impacts and Challenges in Algorithmic Hiring

Introduction: This Project's qualitative experiment consists of resume collection, interviews, and Experiment I (A). We aimed to explore the subjective experiences of **college-graduated German job seekers, especially the experiences of female migrants with non-European sounding names**. The focus was placed on understanding how they experienced **online job application processes and their awareness of algorithmic hiring tools**. By employing in-depth interviews, focus groups, and a questionnaire of a total sample size of 88 job applicants (Appendix B), the Program provided initial insights into the multifaceted challenges of job search in today's German labor market.

Experiment Design: The four (4) months study adopted a qualitative approach selecting 88 participants with diverse backgrounds, ages, and socioeconomic statuses. **This deliberate diverse selection allowed for a more comprehensive exploration of the job search experiences, capturing a broad range of perspectives. Only then were we able to tease out similar and dissimilar experiences between the varied groups of job seekers.**

Data Collection: Semi-structured online interviews served as one of the methods of data collection. **The Program offered participants the opportunity to share their stories and perceptions in their own words.** The participants in 1:1 interview and focus groups agreed to video recording beforehand. Each interview was conducted via a video meeting by two Project leaders, one of which was either the Program Executive or the Program Director.

Data Analysis: Thematic analysis was applied to the transcribed interview data. **This involves identifying patterns, themes, and connections across all participants.** The coding process by the Program's Director reviewed and refined emerging themes, ensuring a systematic analysis. A **second verification** was conducted by the Program Executive.

Ethical Considerations: Ethical principles, including verbal and electronic consent, confidentiality, and participant anonymity, were adhered throughout the research process. Participants were **continuously informed** about the study's purpose, their rights, and the **voluntary nature** of their participation through the Project's landing page and direct communications with the Program Director. GDPR and recording consent were obtained before each interview, and efforts were made to protect the confidentiality of participants' identities. Participants quoted in the Report were requested for approval for use of quote and verification of comment.

Trustworthiness and Rigor: To strengthen the trustworthiness of the study, the Program combined multiple data sources: existing research, interviews with AI- and hiring experts, and the results of the Project's own quantitative experiments. The 88 job applicants were invited to an online video meeting where the Program Executive and team shared the Project's findings. **This allowed participants to respond, refine, and validate the accuracy of the interpretations.**

Conclusion: This qualitative research, with its emphasis on a diverse sample of 88 job seekers contributed initial insights into the current job search experience of college educated and skilled migrant workers. **By adopting a mixed-method research design, the Project offered a broader understanding of what contributes to especially the experiences of migrant female talent. Migrant female workers shared candid experiences of navigating the opacity of the job search process and selection. Moreover, it provided a glimpse to how algorithmic hiring tools can hinder or aid migrant female talent inclusion into the workforce and society-at-large.**

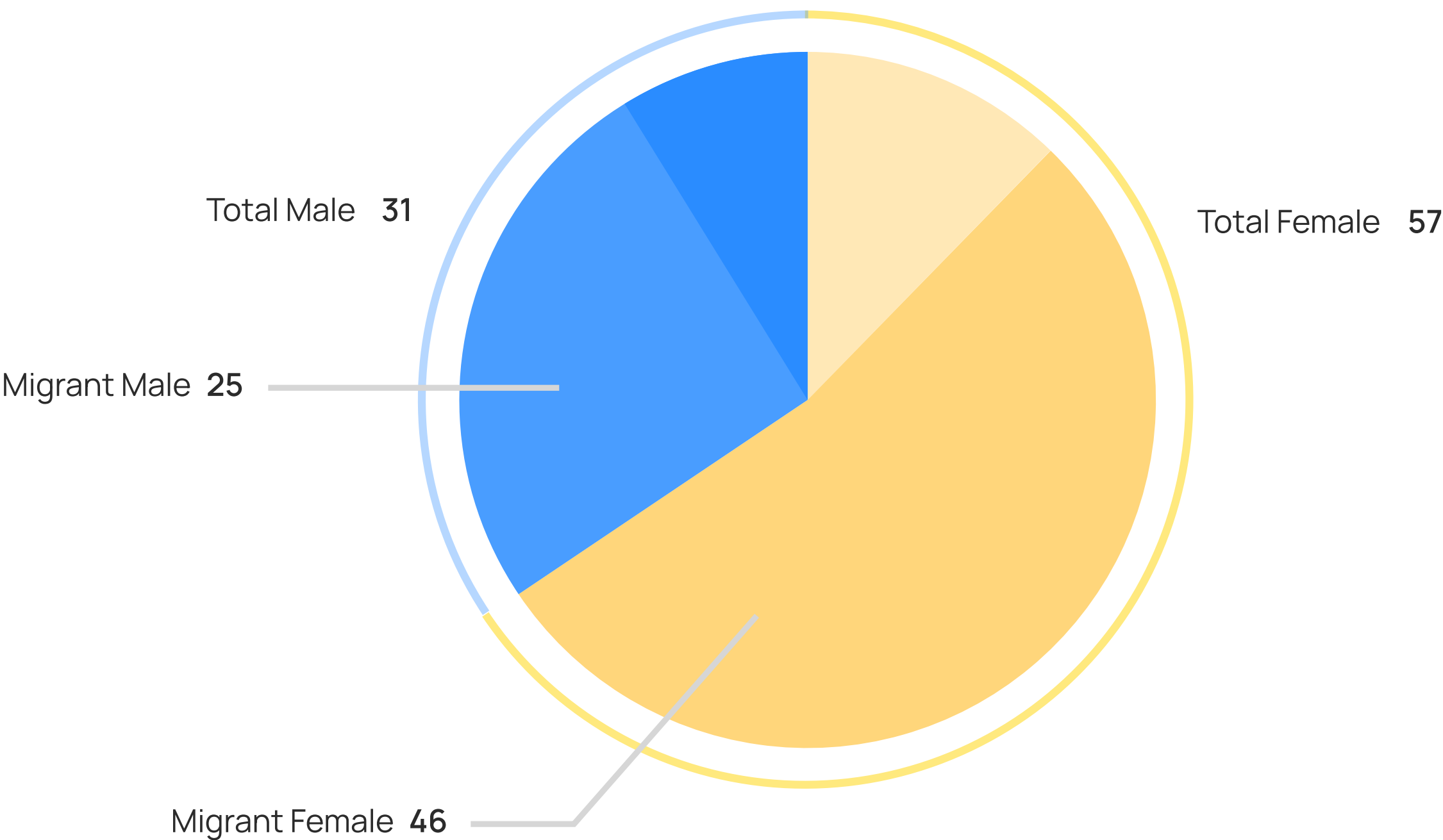
2.2 Approach

The participants in the Project voluntarily submitted their resumes through a dedicated landing page at <https://www.impactmania.com/im/ai-hiring-eu/>. The upload function was available from August 22 until September 13, 2023. The page provided a clear indication that this submission was for research purposes. Subsequent follow-up emails were sent to confirm Project details, and an opt-in agreement for GDPR compliance was obtained.

A total of 88 resumes were collected for testing (see Experiments) and 23 of the participants engaged in further interviews. We employed a combination of methods to facilitate focused group interactions and deeper conversations. This included three (3) 1:1 meetings of one (1) hour each with migrant women of different ethnic backgrounds. In addition, we held three (3) focus groups of 1.5-2 hours hours with a total of 15 participants, professionals (all gender) of diverse ethnic and native German backgrounds. Including German professionals in the discussions enabled us to explore general reactions to AI hiring tools and potential variations in experiences among the respondents. For those unable to participate in the focus groups, we administered an email questionnaire with the same set of questions to five (5) individuals.

All interviews were conducted by two members of the Project's team, recorded with explicit participant consent, and subsequently anonymized for inclusion in the Report. **Following this, on November 2, 2023, all 88 participants were invited to an online meeting where we presented the Project's initial findings and for further discussions. The meeting was attended by 27 participants.**

Classification of 88 resumes by Gender and Ethnicity



Total 57 Female and 31 Male.

46 Migrant Female and 25 Migrant Male.
11 Non-Migrant Female and 6 Non-Migrant Male.

Do migrant women experience the algorithmic hiring application process differently than other applicants?

2.3 Profile of Interviewees

The Project's participants resided in Germany and represented a mix of genders, backgrounds, and ethnicities, including native German job applicants. **We focused on migrant women, and those we spoke with were college-educated and had a range of skills and experiences – from technical (computer science and engineering) to non-technical (management and sales).**

2.4 Questions Asked – JOB APPLICANTS

- 1) Please describe one of your recent job search experiences.
- 2) Were you aware during the process that AI tools were used in sourcing and selecting candidates for interviews?
- 3) How do you know AI tools were involved? How did you experience this?
- 4) Have you done anything differently because of this experience? What?
- 5) Recommendations on how to go about finding jobs that are a fit?

The section is a summarized compilation of the 23 responses. All personal interviews and focus group meetings were asked the above questions. The answers have been recorded with the consent of participants. The quoted statements are verbatim comments, recorded, transcribed, and then submitted to the respective interviewees for additional verification via email. These excerpts were acquired with explicit consent. All names of participant names have been changed for anonymity but known to the Project's researchers. For the demographic details of the participants, please see Appendix B.

1) Please describe one of your recent job search experiences.

Job search and applying for jobs is challenging. Participants in the Project feel frustrated with their job search experience due to the many rejections and the lack of feedback. **Common themes were: rarely being invited to interviews, not being able to speak directly to a human about their application, or frequently receiving no response to applications.** A number of interviewees mentioned that they feel their confidence is affected during the job search process.

I sent probably around 50 applications, I've had some interviews, I even got to the second stage. The typical response is that I have great skills but there are little things that made them choose another person. Maybe I am looking in the wrong direction, but I am a bit confused and decided that I am feeling a little burned out after a couple of long months of looking for a job.

— **Agnieszka**

I did video interviews (micro videos, answering questions) for 3 roles. The hiring companies give you up to a week to respond to questions so you can film them. I was not sure how they were being used and I did not even hear back: no rejection, no follow-up interviews. There are no insights to the hiring process, no criteria communicated. Of course, the job description is being used but that is all. To be honest, the takeaways and learnings are still not clear to me from the job search / sending out so many resumes so far.

— **Aisha**

I had my own business back in Kenya as an entrepreneur and decided to come to Germany for an MBA program. It was through this MBA program that I got a working student position with a company in the energy sector. I've applied to large corporations, and initially, I was able to get through the next round and received fast responses, but it appeared like I was a diversity hire. In the end, they decided to go with someone else, even though I have a lot of experience in the relevant sectors. I spoke to some recruiters asking them what the problem could be, and I also showed them the interview recordings. It was so heartbreaking for me because they told me, "It is in your name; it is difficult to get hired for a managerial position." They tell me the best thing for you to do is just get an entry-level job or start your own business. They cannot hire me for a high-level management role.

— **Layla**

2 and 3) Were you aware during the job application process that AI tools were used; how did you experience this?

Candidates frequently could not say for sure whether AI tools were used to process their applications, but they suspected that they were, or that at a minimum, there was some degree of automated sorting involved. Contributing factors to this belief were receiving responses to applications in a time frame that seemed unrealistic for a human (within 24 hours or on a weekend) or being asked to submit applications via a third-party website. Furthermore, **candidates who were exceptionally well positioned in their field did not find their low interview rate credible without there being some additional factor involved beyond their control.**

I applied for a product manager role at a tech company in Berlin. I submitted my application in the afternoon, and the next day I received a rejection email around midnight. This made me think an AI tool was likely used to screen applications, as no human resources team would assess candidates' CVs at such a late hour.

— Ming

I sent out 100 resumes in 1 month but did not get any interview call-back. The only few interviews I managed to get were through referrals.

— Ju

I sent out 200+ job applications before receiving only one interview in Berlin which resulted in my current job. Despite adapting my CV to clearly highlight my work visa, immediate availability, as well as my Masters obtained in Europe, I still heard back from less than 10% of the companies I applied to. It was a challenging period as it led me to think if I should switch my career or study something else, but I'm glad I didn't give up.

— Monisha

I have applied to 500+ companies in the EU from 2018 until now. I was invited to 2 interviews in total. There is something really problematic with the current HR software. There is no way someone with my profile has such few hits (0.4%)?

— Arjun

I've spoken to classmates who've had similar experiences receiving quick rejections late at night or on weekends from companies known to use AI screening tools. Many job seekers now tailor their CVs, adjusting keywords and experience descriptions to better match criteria that AI tools assess, in hopes of passing the initial automated screening. However, this risks optimizing applications for algorithms rather than clearly communicating qualifications to potential employers.

— Ling

I've noticed that it is becoming much more common for the big companies to have career sites. You're not sending an email with your attachments and everything to an actual person. But you have to log into some kind of new site, set up an account, and you put up all your information in there. You keep copy-pasting from your actual CV hoping that everything fits and then basically you send it out to the Internet. I'm not even sure if an actual human being will read it. I assume that companies have an algorithm that goes through it and sorts it out according to whatever their job criteria are.

— Emilia

4) Have you done anything differently because of this experience? What?

Job applicants spend a lot of effort navigating and familiarizing themselves with local hiring practices. One specific concern was discussed at length during the first focus group: **photos on resumes**.

Including a candidate photo on a resume is preferred in Germany (versus in the U.S where your resume will be dismissed because of potential legal repercussions for the hirer, i.e. the possibility of being accused of discriminatory practices). This stands in stark contrast to how resumes are treated in Germany, where we learned from hiring managers that a resume without a photo is often ignored. One interviewee informed us that a local German university they attended even encouraged students to include nationality, date-of-birth, and photos on their resumes.

Other changes were even more dramatic, such as **(legally) changing names so that they appeared less foreign or removing any mention of nationality from an application**. These were explicit attempts to avoid bias on the part of hirers.

Migrant applicants tend to apply to job postings published in English and avoid applying to job profiles published in German because of the perception that the hirer will be less open to someone of their background. **This was the case even if they have intermediate German language skills and the positions require both German and English language proficiency**. Even when the job posting language is in English, they feel there is a barrier to get selected.

Other changes to the application process after unsuccessfully job hunting included:

- Going from mass applications to being **more selective and targeted**.
- **Avoiding machines** by going through referrals or direct contact.

Throughout my professional journey, I strategically chose to use my middle name on my resume to enhance my career prospects. Operating under the name Melissa., I achieved a remarkable 50% increase in job interview invitations compared to when I used my official name. Fortunately, I was able to gain the work experience which has led me to my current position in a multinational company where my name no longer slows down my career.

— Melissa

I had a picture in my CV, but I decided to make some tweaks and remove my picture after getting feedback from a friend's friend that this will help remove the bias...that people won't see that you are a woman applying for a developer position. I also removed the mention that I was from Colombia. And after that, it seems to really change and I got more successful from hearing back to move on to the next round.

— Tala

I'm German and a native German speaker. My CV is actually in English without a picture, without my birth date, or location, and without my nationality. I decided to translate everything into German, because I believe it reduces the bias, especially as I'm a German speaker. I also put a picture, I'm still not sure if I should leave it or not.

— Lina

I finished my masters this last year in Germany. I have previous work experience from India and was actively looking for full-time opportunities. It was easier to get an internship, student jobs, or part time jobs though, I did two of them and then also found two full time opportunities. Whereas for full-time opportunities, I haven't got that good of a response. I'm still figuring out and tweaking the resume. At the university, we were very much encouraged to put our pictures on the resume, as in, it was part of the template that they advised us to use for job hunting in general. In fact, there was a session altogether for photography so we could get professional pictures. So it's quite an interesting intake for me that the picture of the candidate is also taken into consideration. could also be taken, not so positively.

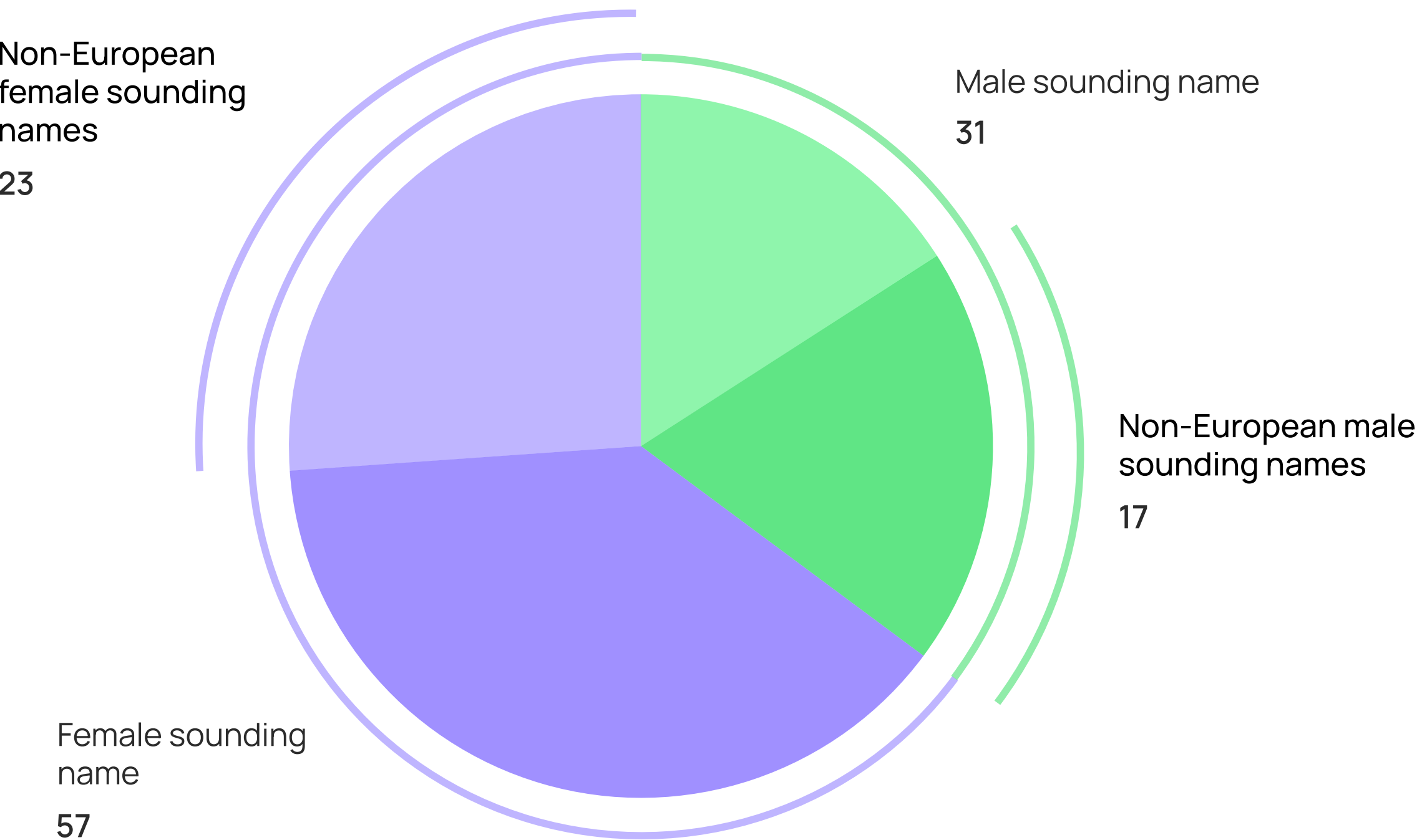
— Anvi

I have 8+ years of working experience including overseeing operations and growth in companies, but even for a working student position, I applied to around 40 different companies but did not hear back from any. I noticed that when I took my picture off my resume, and with my name which is quite a European sounding name, I definitely got a lot more replies. It was an eye-opening experience for me, and disheartening when I saw other peers, with a less fulfilling career trajectory receive call-backs for interviews. I am leaving Europe at this point.

— Peter

For more details on participants’ breakdown, please see Appendix B.

Classification of 88 Resumes by Names



5) Recommendations on how to go about finding jobs that are a fit?

Interviewees agreed that one of the most successful ways of securing a job is through referrals or direct contact to the hiring manager or HR/ company representative. This can be difficult for migrant professionals applying for work for the first time in a new market without an existing network. The responses are similar for both native German and migrants; native German applicants agree that sending in an application is usually not the most successful.

The migrant female participants have encountered bias and favoritism from hiring managers. They feel that their identity had to be compromised: a few changed their names, many removed photos and place-of-births from their resumes. The migrant male interviewees provided similar responses.

Referrals from personal or professional networks are often better avenues for finding roles versus broad online applications, as they allow for more interpersonal engagement and balanced impressions compared to text-based profiles. On-campus or company-hosted events provide opportunities for in-person connections that capture fit factors beyond what can be gleaned from paper qualifications alone. Initial human screening of CVs prior to any AI involvement could also strengthen the hiring process.

— Jia

I applied as a working student at a big medical technology company and got the standard reply: we will take a look and maybe come back to you. Then later on through a contact, I gave the same CV and got a job offer – working closely with the CEO on a project. There was a huge difference in applying to the online platform versus having a contact, and then the level was way up compared to the position I applied for and got a rejection initially.

— Marie

On LinkedIn, there is a button where you can just apply for jobs. It's very easy. Within seconds you can apply, I've noticed 95% rejection emails through that function. When people reach out to me for guidance, I always say: Never apply through LinkedIn, rather reach out to the company's recruiter or someone else in the organization — find a referral. Or at least apply from the company's website career page.

— Vishnu

The migrant professionals we spoke with feel more negatively affected than the German native applicants. The Project's participants did all feel that AI has not reached a point where they can be unbiased in processing resumes.

For me, I am also concerned about the data that the AI hiring tools are using. Usually these companies purchase the AI tools which are already trained on certain data sets. If the data coming from people is already biased then what happens is not 100% neutral. For example, what happens when 80% of people you are hiring have the same type of background, same location, etc. and this is built into the systems, wouldn't the AI tool also develop some type of bias?

— Isabella

2.5 Summary

Shared Experiences Between Migrant and Native Job Applicants

Many job seekers in the Project were **aware of the algorithmic tools** that scrutinize their applications. However, they often found themselves **perplexed** by the inner workings and decision-making processes of the hiring system. **This puzzlement is especially pronounced when media coverage highlights labor shortages, yet they receive no interview invitations despite holding local degrees, work experience, and relevant skills.**

Our conversations uncovered a shared struggle among job seekers, transcending their background, whether they were native German nationals or migrant women from India. Native speakers, though frustrated, grapple with challenges on a different scale. **They recount sending out numerous resumes, sometimes dozens, while migrant women embark on dispatching hundreds of applications.**

Beyond Technology

The candid discussions illuminated a more profound issue of bias and discrimination, reaching beyond the confines of an ATS or technology. We heard accounts from migrant professionals who encountered discrimination not only in the job application process but also when seeking rentals for example. **In our small experiments, while we couldn't clearly detect bias or discrimination in an open source ATS, it surfaced in the final experiment involving synthetic data on a proprietary AI system.**

As we embrace AI and comparable datasets across diverse domains such as education, employment, housing, and healthcare, we must scrutinize whether we're establishing a foundation that perpetuates the exclusion of significant segments of our society, including women, migrants, older adults, Lesbian, Gay, Bisexual, Transgender, Queer, and Intersex (LGBTQI+) people, and individuals with health conditions or impairments. **This exclusion negatively impacts our entire community.**

During the course of our Project, a comprehensive survey on discrimination in Germany was released by the German Centre for Integration and Migration Research (DeZIM). The report revealed the numbers behind the personal accounts from the Project's job applicants of African descent for example. The employment rate for individuals aged 20 to 64 of African descent (71%) closely aligns with that of the general population within the same age group (73%). However, a significant proportion (32%) of these respondents were engaged in "elementary occupations," a stark contrast to the general population's 8% average across all 27 EU member states. **Black individuals were also found to be disproportionately overqualified for their current jobs**, with 35% of university-level qualifications engaged in low or medium-skilled occupations, compared to 21% in the general population.¹ **We spoke with job applicants from African descent with local German university degrees and work experiences being considered for internship jobs only. One realized there was discrimination because of invitations to interviews after the photo on the resume was removed. Another job applicant was simply told that it would be challenges for companies to consider someone with an African name for any position beyond entry level despite her work experiences and MBA. Muslim women shared similar stories of receiving more invitations to job interviews after changing their names to a more European sounding name or adding a German last name.**

Migrant Women's Unique Strengths Become Multiple and Compounding Inequalities

The migrant women in our Project represent diverse ethnic backgrounds, including Asian, Middle Eastern, South- and North American, and European countries. They often refrain from expressing their challenges, fearing that speaking out will draw undue attention to their struggles. **No one wishes to admit their difficulties while diligently working, holding advanced degrees, possessing multilingual skills, and international work experience, especially when witnessing others seemingly thrive with less robust professional backgrounds.**

¹ Boffey, Daniel, 'Pervasive and relentless' racism on the rise in Europe, survey finds, October 2023. The Guardian., October 2023. The Guardian. <https://www.theguardian.com/world/2023/oct/25/pervasive-and-relentless-racism-on-the-rise-in-europe-survey-finds>

Some migrants are turning to **entrepreneurship** as a response to the continuous challenges in the job market. **Others are choosing to conceal their unique identities by adopting alternative names, eliminating distinctive details, or even contemplating leaving the country.** It's disheartening to witness missed opportunities for talented and motivated workers. **Despite these migrants already residing here, holding local degrees, and expressing eagerness to contribute to their community and adopted country, barriers persist.**

Migrant women tend to notice bias and discrimination most prominently in tech jobs, where the required skills are more easily comparable. For instance, one migrant woman received significantly more interview invitations after omitting her birthplace and photo from her resume. The DeZIM survey also highlights that more than a third of black and Muslim women, along with 29% of Asian women, reported occasional unfair treatment and concerns about their health being disregarded.² Notably, 26% of white women faced similar issues, **emphasizing the existence of intersectional discrimination. This underscores that migrant women encounter ongoing exclusion and harassment as part of their daily lives.**

The data from the survey is concerning, although not surprising to most female migrants in Germany. **The critical question is how we can begin to construct a foundational and equitable system for sourcing, screening, and selecting individuals, especially since AI will likely serve as the backbone of most, if not all, systems determining people's access to services and opportunities.**

² Kassam, Ashifa, "More than half of black people surveyed in Germany report racism," November 2023. The Guardian. <https://www.theguardian.com/world/2023/nov/08/more-than-half-of-black-people-surveyed-in-germany-report-racism>

3 Interviews - Talent Acquisition Leaders

How do Talent Acquisition (TA) specialists work with algorithmic recruitment tools?

3.1 Profile of Interviewees:

Chief Diversity and Inclusion and Talent Acquisition (TA) leaders.

Via our personal network, we interviewed a total of six (6) people tasked with hiring: four (4) talent acquisition executives from German headquartered global companies and two (2) TA leaders from German tech companies.

All interviewees provided consent to be interviewed. Two (2) recruitment professionals provided consent to be named, the other names are withheld for anonymity but are known to the Project's initiators.

3.2 Questions Asked – TALENT ACQUISITION LEADERS

- 1) What is your initial screening process?
- 2) What is your experience working with AI hiring tools? Please provide an example. If not working w/ AI tools, why not? If yes, how are you using AI tools to find the right candidates you are looking for?
- 3) If you work with/would like to work with AI tools, what would you ideally want from an AI tool?
- 4) How do you actively minimize bias and discrimination in the hiring process? How do you minimize bias working with AI tools?
- 5) What do you recommend to current job seekers with respect to uploading resumes?

The Talent Acquisition leaders we spoke with view general AI tools on the market as helpful but limited, and requiring human oversight. The tools are seen as productivity enhancers, able to do select volume tasks like screening 400 resumes quickly or administer proficiency tests, but still require a human to oversee and direct for quality, content, and to mitigate biases.

3.3 Talent Intelligence Technology

Hiring is time consuming and expensive; companies often deal with hundreds of applicants per job opening. This calls for the need of an automated tool to process all of the incoming resumes. **However, resume screening is just one facet of the extensive hiring journey.** In today's challenging hiring landscape, where retaining top talent is paramount, **organizations are turning to software platforms to enhance their understanding of human capital performance.**

In conversations with German talent acquisition managers, SAP's SuccessFactors came up a few times as an example of a Talent Intelligence platform, where the ATS is only one element of a suite of human capital tools. The platform aims to cover the entire scope of sourcing, selecting, training, and promoting candidates. SuccessFactors will be integrated with Microsoft's 365 Copilot and Azure OpenAI Service to access language models and generate natural language.

Most large organizations use the ATS Applicant Tracking System 'SuccessFactors' by SAP. "It is not the most agile tool, but still works the best for large-scale data in organizations.

— Ayse Semiz-Ewald, VP of Diversity, Equity, and Inclusion, Deutsche Telekom

Beyond the initial hiring process, one of the Project's advisors mentioned a concern caused by biases in the offer and promotion dimensions of Talent Intelligence tools. Despite the increasing reliance of companies on these systems to assess employees' compensation and advancement, there exists limited research on these aspects.

Generative AI holds the promise of delivering even greater benefits when it delves into more specialized learning. **The Talent Intelligence platforms are already aiding in the discovery of value and skill sets that transcend the confines of conventional resumes.** There looms a potential risk: the over-reliance on the same foundational (already bias) American datasets across these platforms. Job candidates use a wide spectrum of language- and writing skills in their submissions. However, amid this diversity, **there is a consistent method for assessing job suitability – a method grounded in the world’s prominent American-based Large Language Models (LLM), regarded as a singular and reliable source of evaluation.**

For technical positions, usually a test is given upfront even at the initial stage so we can really filter the candidates quickly.

— Talent Acquisition leader, tech company

An oft-cited example of a Talent Intelligence platform offering strategic talent development is Eightfold (founded by ex-Google computer scientists). It is a leader in the Talent Intelligence space, having built their own AI models over the years: “Eightfold has amassed a data trove of 1.5 million skill sets and 1.5 billion worker profiles, in 20 languages.”

The power of an AI powered Talent Intelligence platform? **Vodafone used Eightfold hiring 19% more women and reducing the average time to hire candidates by 58%.”¹**

While the potential of AI hiring tools is undeniable, it’s crucial to approach their design with careful consideration, as they shape the future landscape of companies and organizations in the EU. **Human oversight is imperative, and it’s essential to collaborate with experts such as diverse teams of psychologists, linguists, ethics advisors, and other specialists to craft tools and algorithms that embody inclusive and equitable values.** These tools should be engineered to attract highly skilled talent from diverse backgrounds.

¹ Lohr, Steve, “An A.I. Start-Up Boomed, but Now It Faces a Slowing Economy and New Rules,” New York Times, March 2023.
<https://www.nytimes.com/2023/03/13/business/ai-hiring-jobs.html>

Harnessing the strengths and unique attributes of a broad range of candidates within an equitable and inclusive framework is the foundational step in constructing forward-thinking, high-performance organizations. This process is essential for redefining outdated business practices, modernizing HR, and aligning the hiring process with the evolving needs of society.

3.4 Strategic Leadership and AI Integration for Organizational Values

In the current landscape, it is essential for individuals to provide leadership to their organizations and guide their HR and talent acquisition teams in aligning with the organization's hiring principles, cultural values, and bias mitigation strategies. **When developing an AI solution for the organization, these cultural and organizational principles should be integrated**, serving as a foundational framework for instructing the AI system. The objective is to leverage AI to not only identify the ideal candidates who align with the organization but also to foster the retention of valuable human resources, thus enriching the workforce.

A Head of Talent Acquisition at a global company emphasizes key considerations for fostering diversity in the recruitment process.

- *Appropriate language to ensure the pipeline of talent is diverse.*
- *How do we move talent resources internally incl. female succession planning.*
- *The company interview panel has at least representation of two other diverse groups.*
- *The company trains recruiters, line managers, or hiring managers to understand their own bias.*
- *The challenge is that measurement and accountability are typically two different positions in the company, one must be underrepresented and measuring data across the company.*

The below talent recruitment executives we interviewed for the Project shared similar viewpoints:

AI has shortcomings. It is binary; If the candidate does not have skill X, it eliminates the candidate from the shortlist. This is where I provide instructions to HR heads that before AI filters, there needs to at least be

- *Diverse candidates; gender, nationality, diversity of experience,*
- *All roles must be advertised externally or internally, and*
- *Sometimes we have an interview process where there is a diverse panel interviewing the candidate, a panel from different fields of expertise, representatives outside from the business function or function.*

— **Maria Ferraro, Chief Inclusion and Diversity Officer, Siemens Energy**

There's a huge opportunity for AI to take out some of the quantity of administrative tasks, but it is important to work with your partners and providers that you don't get that AI groupthink, it is about having AI outside the human and not instead of the human.

— **Head of Talent Recruitment, global company**

Generative AI is only as good as the data that's in it. We're just not there yet, but we're starting to dabble in it in all disciplines in my company, and what AI can do is astounding.

— **Division Executive, global company**

I use API plug-ins to look for keywords matches which will be highlighted in the CVs, this helps me to speed up the process for review. For example, if it's Project Management, I will look for words like problem-solving or analyticals skills.

— **Talent Acquisition leader, tech company**

3.5 Interview with Kadi Niggulis, birkle IT, Employer Brand Lead

Six talent acquisition leaders generously offered their time and insights for this Project. Among them, Kadi Niggulis, with over a decade of experience in recruitment. Kadi is presently employed by a German tech company operating in Europe, exemplifying the growing trend of German companies adopting algorithmic hiring tools. This, compared to the hiring leaders we interviewed from public German corporations who are already utilizing Talent Intelligence platforms.

1) What is your experience working with AI hiring tools? Please provide an example.

The ATS we are using has recently rolled out a “co-pilot” mode beta version – taking notes, summarizing meetings, and at one point will be recording videos. It is not necessarily a hiring tool, but I also use ChatGPT to create easy to read job ads/job descriptions in English – as I am not a native speaker. For example, making sure the words I use are not geared hiring a male or female, but have a neutral tone.

2) If not working with AI hiring tools, why not?

I would love to use more AI tools, but there is sensitivity around content shared during an interview and the whole application process. I haven’t had the need to shift through hundreds of CVs and therefore I have opted for reviewing each candidate's CV.

3) How do you minimize bias and discrimination in the hiring process? How do you minimize bias working w/ AI hiring tools?

Diversity and being unbiased are important in my mind. I try to keep myself updated on these topics. As I have done recruitment for more than 10 years, I have taught myself to ignore birth dates, name, gender, or other similar data and focus on the job experience we are seeking for instead. It is difficult at times, to be honest, as we all have biases, it takes constant effort, and work on myself, and helping Hiring Managers navigate this as well. I am fortunate to work in the IT sector where on a macro level only two things matter – the candidate can code at the desired level and speaks English (as we are an English-first company).

I have used anonymizing CVs – taking away name, age, and photograph (if it was provided) and leaving the work experience plus some relevant training if there were any to mention. On the ATS system, for our company, the information is taken out automatically by the system when I want to share it.

4) What do you recommend to current job seekers with respect to uploading resumes (optimize search and qualification for invitation to interview).

To be honest, I am not a fan of keyword dense CVs from where I can't really understand the expertise and tasks a person has done. Spend some time to really research about keywords that are sought after in the industry you are applying for makes a difference. If the ATS system is using an AI-powered tool to scan through the CVs, I hope the person setting it up has spent equal amounts of time to really understand the role.

I appreciate a short but free-form cover letter, intro email, where the candidate has taken a small moment to understand what the role is and how they see their experience fit the expectation. ChatGPT gives a start, but you can feel the style of the tool. I recommend you to still be you and use your personal style to communicate. Customize your resume for each job application, it takes time but yields better results.

I would start with a small intro of you as a professional, followed with job roles, skills, and then education. Please list key skills and tasks about each job and check the job ad to make sure you will highlight the expected one. If you are embellishing your CV and copy-pasting from the job ad then it will come out during the interview, in the worst-case scenario when you are on the job. Fake it 'til you make it is not a motto I endorse as I expect honesty from both parties.

Don't just list tasks you did at the jobs, emphasize your achievements whenever possible.

Also, it makes sense to have a well-written and comprehensive LinkedIn profile (or sometimes even instead) of a CV. For tech roles GitHub or other similar repositories for demonstrating skill is great. In design a portfolio.

5) Any other surprises working with AI hiring tools?

I am a bit apprehensive about teaching AI tools as the previous hiring decisions could have been biased. For example, out of 10 roles one (or none) of the hired candidates has been a female. Maybe the system then learns to avoid proposing females. The models learn but the data we put in gives them a direction already.

I prefer real (video) conversations and spending a few seconds on every candidate's profile when doing the initial CV review. It is a bit troubling for me that some excellent candidates might fall through the cracks as they don't have expected keywords.

I see it as my job to find the best candidate for the role at that point of time, also considering the potential and ability to adapt/learn which I feel can be assessed better in person. I guess AI is moving towards also being able to read facial expressions but are the tools capable to understand that culture also plays a role in how our body reacts (involuntarily). Small talk and big smiles are a norm for some countries but if a candidate is from a culture where a serious face is considered respectful then it must be taken into consideration.

If 60% of the applicants are female, but you only generated 30% female hires. How and why are the female applicants dropping out?

— Head of Talent Acquisition

4 Interviews - AI & Talent Acquisition Technology Experts

Do Talent Intelligence technology companies confirm there is bias in algorithmic recruitment platforms? And if so, how do they deal with bias in systems?

4.1 Profile of Interviewees:

AI Experts and Talent Acquisition (TA) Software Leaders.

We conducted 1:1 interviews with 16 experts from some of the world's leading Talent Intelligence companies. Additionally, we carried out our own ATS experiments using the Project's collected resumes. To maintain anonymity, we've refrained from including direct quotes in this section. Instead, we've synthesized insights from multiple interviews throughout the Report, with the selected interview on the next page providing a comprehensive representation summarizing our discussions. This approach ensures a cohesive and insightful overview while respecting the confidentiality of individual contributors.

4.2 Questions Asked – AI and TALENT ACQUISITION TECHNOLOGY EXPERTS

- 1) What is your experience working with AI hiring tools?
- 2) How do you minimize bias and discrimination in the hiring process?
- 3) How do you minimize bias working with AI hiring tools?
- 4) What do you recommend to current job seekers with respect to uploading resumes?
- 5) Any other surprises working with AI hiring tools?

4.3. Interview with Yusuf Jazakallah, CEO and co-founder, Recruitment Smart Technologies

From the 80+ recruitment tools we reviewed through AMS Verified ¹ (from general ATS to point solutions for scheduling meetings and conducting video interviews) approximately 44% do not work with AI yet. From what we gleaned in conversations with experts most recruitment platforms are focused on data protection and data security rather than tackling potential bias in hiring systems.

AI experts and talent intelligence tech companies graciously dedicated their time and insights to this Project. Notably, one expert, Yusuf Jazakallah, CEO, and co-founder of Recruitment Smart Technologies, agreed to share his perspectives on the record, providing valuable insights, based on years of research, that enhance the depth of our focus. We found that aligned with our other expert conversations.

1) What is the key finding from your upcoming report, 'Effective Strategies for Mitigating Bias in Hiring Algorithms'?

*The study reveals that while automated hiring systems (AHSs) are being used to detect and address discrimination against protected groups, **claims of 'bias mitigation' are rarely scrutinized and evaluated.** The proposed framework for reducing bias in hiring algorithms aims to ensure that decision-making is done fairly and transparently, and provides support and guidance to employees during the recruitment and hiring process. However, the study also acknowledges that bias mitigation comes at a cost of efficiency and accuracy. **The study suggests that ethical considerations should guide the development and implementation of AI-enabled recruitment practices, and that diverse groups should be represented in the development and testing of hiring algorithms.** The study also highlights the importance of research methodology, including machine learning and statistical analysis, in providing greater accuracy and precision in results.*

¹ 1,000s of talent technology solutions. Find the one that's right for you. Meet AMS Verified." AMS, accessed November, 2023. <https://www.weareams.com/digital/verified/>

2) What is your experience working with AI hiring tools? Please provide an example.

We use our own AI hiring tool, Sniper AI, for internal recruitment. I also have extensive experience building and helping customers work with AI hiring tools to streamline the recruitment process and enhance decision-making. AI hiring tools have proven to be valuable in several aspects of talent acquisition, from sourcing and screening candidates, to improving diversity and reducing bias.

SniperAI utilized natural language processing (NLP), machine learning algorithms, and deep learning to analyze resumes and job descriptions, making it easier to match candidates with job openings.

Here's how it works:

- **Resume Screening:** *The AI tool would automatically scan and categorize resumes, highlighting key skills and experiences. This greatly reduced the time HR staff spent on manual resume screening, allowing us to focus on more strategic aspects of recruitment.*
- **Candidate Ranking:** *The tool assigned a suitability score to each candidate based on their qualifications and the job requirements. This helped us prioritize the most promising candidates, improving the efficiency of our initial screening process.*
- **Bias Mitigation:** *The AI tool was designed to be neutral and unbiased, minimizing the impact of unconscious bias in the initial screening phase. This was a significant step towards improving diversity and inclusion in our hiring process.*
- **Data-Driven Decision-Making:** *Over time, the AI tool generated valuable data and insights about our recruitment process. We could track which sources were providing the best candidates, which job descriptions were attracting more applicants, and even which interview questions were most predictive of success.*
- **Improving Candidate Experience:** *By automating routine communications with candidates and providing instant feedback, the tool improved the overall candidate experience, making our company more attractive to top talent.*

*While the AI hiring tool significantly improved our efficiency and reduced bias in the early stages of recruitment, it's important to note that AI is not a panacea. It complements human decision-making but does not replace it. **We still conducted interviews and assessments to evaluate a candidate's cultural fit and soft skills. Additionally, we regularly audited the AI tool's outcomes to ensure fairness and accuracy.***

Overall, the use of AI hiring tools in our organization has resulted in faster and more efficient recruitment processes, reduced bias, and improved data-driven decision-making, making it a valuable asset in our HR toolkit.

3) How do you minimize bias and discrimination in the hiring process?

Minimizing bias and discrimination in the hiring process is a crucial aspect of creating a fair and inclusive workplace. As an expert in building and implementing AI tools for Talent Acquisition, we employ various strategies and best practices to achieve this goal for our customers. Here are some key approaches:

Structured and Consistent Interviewing

- *Implement structured interview processes with predefined questions and evaluation criteria to ensure consistency across all candidates.*
- *Train interviewers to avoid making snap judgments or relying on gut feelings, which can introduce bias.*

Blind Resume Review

Remove personally identifiable information (such as names, photos, and addresses) from resumes during the initial screening process to prevent unconscious bias based on gender, ethnicity, or other factors.

Diversity and Inclusion Training

Provide training to hiring managers, interviewers, and all involved in the hiring process on the importance of diversity and inclusion, as well as how to recognize and address bias.

Diverse Interview Panels

- *Form diverse interview panels representing different backgrounds and perspectives to minimize individual bias.*
- *Encourage open discussions among panel members to collectively assess candidates.*

Standardized Testing and Assessments

- *Use validated assessments and tests that are relevant to the job and administered consistently to all candidates.*
- *Regularly review and update these assessments to ensure they remain fair and effective.*

Job Descriptions and Requirements

- *Ensure that job descriptions are free from gender-biased or exclusionary language.*
- *Carefully consider the necessity of specific requirements to avoid unintentionally disqualifying qualified candidates.*

Unconscious Bias Training

- *Offer unconscious bias training to all employees involved in hiring to help them recognize and mitigate their own biases.*
- *Encourage ongoing discussions about unconscious bias within the organization.*

Diverse Sourcing

- *Use a variety of channels to source candidates, including platforms and organizations that cater to diverse groups.*
- *Build relationships with universities and professional organizations that have diverse memberships.*

Metrics and Accountability

- *Set diversity goals and regularly track and report on progress.*
- *Hold hiring managers and recruiters accountable for diversity and inclusion efforts as part of their performance evaluations.*

Feedback Loops

- *Establish feedback mechanisms for candidates to report any perceived bias or discrimination during the hiring process.*
- *Use this feedback to continuously improve your process.*

Data-Driven Decision-Making

- *Analyze hiring data to identify any disparities in candidate selection, progression, or offers.*
- *Use this data to address potential bias and discrimination.*

Inclusive Culture

Foster an inclusive company culture that values diversity and equity at all levels, making it more attractive to a diverse talent pool.

Legal Compliance

Ensure strict adherence to anti-discrimination laws and regulations at every stage of the hiring process.

Minimizing bias and discrimination is an ongoing effort, and it requires a commitment from the entire organization. By implementing these strategies, continuously monitoring progress, and fostering a culture of inclusion, a large organization can create a fair and equitable hiring process that benefits both the organization and its employees.

4) How do you minimize bias working with AI tools?

Minimizing bias when working with AI tools in the HR and hiring process is essential to ensure fairness and equity. Here are some strategies we recommend.

Select and Audit AI Tools Carefully

Conduct a thorough evaluation of AI tools before implementing them. Look for vendors who have a strong commitment to diversity and inclusion and can demonstrate that their tools are designed to minimize bias.

Diverse Data Training Sets

Ensure that the AI tools are trained on diverse and representative datasets. This helps prevent the amplification of existing biases in the tool's recommendations.

Regularly Audit and Update Algorithms

Periodically review the AI algorithms to identify and address any potential bias. Make necessary adjustments to minimize bias, and ensure that the AI tool is kept up to date with evolving best practices.

Transparency and Explainability

Choose AI tools that provide transparency and explainability in their decision-making processes. This allows you to understand how the AI is arriving at its recommendations and whether bias might be present.

Bias Detection and Mitigation

Implement bias-detection mechanisms within the AI tools to identify and flag instances of bias. These mechanisms can help you take corrective action.

Regular Training and Testing

Train the AI algorithms to recognize and minimize bias by providing feedback on decisions made by the tool. Continuously test the tool to ensure it's making fair and unbiased recommendations.

Human Oversight

Maintain human oversight throughout the hiring process. AI tools should support, not replace, human decision-making. HR professionals should review AI-generated recommendations and make the final decisions.

Diverse and Inclusive AI Teams

We encourage diversity within our own teams responsible for developing and maintaining AI tools. Diverse teams are more likely to identify and address bias effectively.

Educate and Train HR Staff

Provide training for HR staff on how to use AI tools effectively and how to interpret the results, emphasizing the importance of maintaining an unbiased approach.

Auditing and Reporting

Regularly audit and report on the performance and impact of AI tools in the hiring process. Share these reports with leadership and stakeholders to demonstrate a commitment to fairness.

Feedback Mechanisms

Establish feedback mechanisms for candidates who feel they may have been subjected to bias in the hiring process due to AI tools. Act on this feedback to improve the system.

Legal Compliance

Ensure that AI tools used in the hiring process adhere to all relevant anti-discrimination laws and regulations.

Continuous Monitoring and Improvement

Stay informed about the latest developments in AI and machine learning and regularly assess the performance of AI tools. Continuously work to reduce bias as technology and best practices evolve.

*Minimizing bias when working with AI tools in HR requires a proactive and vigilant approach. **It's important to view AI as a tool that can enhance decision-making rather than replace it, and to ensure that it aligns with the organization's commitment to diversity and inclusion.** Regular assessment and adjustment are key to maintaining a fair and equitable hiring process.*

5) What do you recommend to current job seekers with respect to uploading resumes (optimize qualification)?

For job seekers looking to optimize their resumes for AI-based recruitment systems, here are some key recommendations:

Use a Clear and Professional Format

Format your resume in a clean, professional, and easily readable layout. Avoid using overly complex designs or fonts that might confuse AI systems.

Keyword Optimization

Tailor your resume for each job application by including relevant keywords from the job description. AI systems often scan for these keywords to match your qualifications to the job requirements.

Use Standard Job Titles

When listing your job titles, use industry-standard terms that are easily recognized by AI systems. Avoid using internal or company-specific titles that may not be understood.

Highlight Achievements and Skills

Focus on showcasing your accomplishments and skills prominently in your resume. AI systems look for specific achievements and qualifications when ranking candidates.

Avoid Unnecessary Graphics and Symbols

Minimize the use of graphics, symbols, or unusual characters in your resume. These elements can confuse AI algorithms.

Include Relevant Certifications and Education

Make sure your certifications, degrees, and education details are clearly presented. AI systems consider these qualifications when assessing candidates.

Customize Your Resume

Tailor your resume for each job application to emphasize the qualifications and experiences most relevant to the specific role.

Provide Quantifiable Results

Whenever possible, use quantifiable data to describe your achievements. For example, mention how you increased sales by a specific percentage or reduced project completion time.

Use Standard Section Headings

Employ standard section headings such as "Work Experience," "Education," and "Skills." AI systems are more likely to recognize and categorize your information correctly.

Proofread for Errors

Carefully proofread your resume to eliminate spelling and grammatical errors. AI systems may penalize resumes with numerous mistakes.

Include Your Location

Mention your current location or the location where you are seeking employment. This can be crucial for AI systems that filter candidates based on location.

Keep It Concise

Limit the length of your resume to 1-2 pages, focusing on the most relevant information. AI systems prefer concise and to-the-point resumes.

Include Industry-Specific Jargon

If your industry uses specific jargon or terminology, incorporate relevant terms into your resume. This can demonstrate your familiarity with the field.

Avoid Unrelated Information

Exclude information that is not relevant to the job you're applying for, such as hobbies or personal details. AI systems prioritize job-related content.

Upload in Standard Formats

When uploading your resume, use common file formats like PDF or Word (.doc/.docx) to ensure compatibility with AI systems.

Regularly Update Your Resume

Keep your resume up to date with your most recent experiences and qualifications. This ensures that AI systems accurately reflect your current profile.

Remember that while optimizing your resume for AI systems is important, it's also crucial to create a human-friendly version that will impress hiring managers during the later stages of the recruitment process. Balancing AI optimization with human appeal is the key to a successful job search.

Any other surprises working with AI hiring tools?

Developing and deploying AI hiring tools in organizations has presented several surprises and challenges. While these tools offer numerous benefits, they also come with their own set of complexities. Here are some surprises we have encountered:

Initial Resistance

Some employees and hiring managers initially resisted the use of AI tools in the hiring process. They were concerned about potential job displacement or were uncomfortable with the idea of technology making important hiring decisions.

Data Quality Issues

AI tools rely heavily on data, and in some cases, the data used for training AI models may contain biases or inaccuracies. This can result in AI systems making biased or incorrect decisions. We have to audit the data and adjust for any biases that may exist.

Algorithm Fairness

Despite our efforts to choose AI tools with fairness in mind, we discovered that some AI models still had biases. Addressing and mitigating these biases required ongoing attention and fine-tuning.

Over Reliance on AI

Some hiring managers began to over-rely on AI recommendations, assuming that they were infallible. This created a challenge in ensuring that human judgment remained an integral part of the decision-making process.

Candidate Experience

While AI tools can streamline the initial screening process, we found that some candidates were less satisfied with the impersonal nature of AI-driven communication. Ensuring a balance between automation and personalized communication became a priority.

Cost Implications

The implementation and maintenance of AI tools can be costly, and the organization needs to carefully consider the return on investment, especially in comparison to traditional hiring methods.

Evolving Technology

The field of AI is rapidly evolving, and keeping up with the latest advancements and ensuring our tools remain up-to-date requires ongoing efforts.

Data Privacy and Security

We needed to be diligent about protecting candidate data and ensuring compliance with data privacy regulations. Safeguarding sensitive information was a top priority.

Integration with Existing Systems

Integrating AI tools with existing HR systems and processes can be more complex than anticipated. Ensuring a seamless flow of information and processes was an ongoing challenge.

Training and Change Management

Training HR staff and hiring managers to effectively use AI tools and embrace the change was a significant undertaking. Change management strategies became crucial to ensure a smooth transition.

While AI is a powerful tool in HR, it must be thoughtfully integrated into the hiring process, and continuous monitoring and adjustments are necessary to maximize its benefits and minimize potential pitfalls.

Since the tech companies and AI experts we have spoken with for the Report are focused on minimizing and mitigating bias in recruitment software, none denied or dismissed bias in AI systems. This however does not reflect the overall talent intelligence tech companies. We understand from our discussions with recruitment consulting experts that most talent tech companies are mostly focused on managing systems' data security- and privacy challenges.

5 Algorithmic Hiring Tool Experiments — Methodology

In this Project, we simulated a job hiring scenario akin to a traditional recruitment process without the use of AI tools. Ayse Semiz-Ewald, HR Director and Vice President of Diversity, Equity, and Inclusion, conducted a mock screening for the role of Project Manager, as detailed in Appendix A. To source diverse candidates, we announced the research Project on LinkedIn, directing interested individuals to a landing page on the [impactmania](#) website with a resume upload function. The posting was shared within our network and various community groups to attract a broad range of candidates.

Between August 22 and September 13, 2023, we received 88 resumes, each reviewed and labeled individually. This exercise aimed to gain insights into the human recruiter's sourcing and selection process. From this pool, a dozen resumes were selected for a hypothetical interview, mirroring the typical progression to the hiring manager, who would then finalize the list for personal interviews.

Next, the same 88 resumes underwent processing by an open-source Applicant Tracking System (ATS), managed by Dr. Tejo Chalasani, co-founder, and CEO of [Utpatti.ai](#). This step aimed to discern whether a recruitment software system would select the same candidates.

Furthermore, we collaborated with [Palqee](#), a privacy and data governance technology company. Sabrina Palme, CEO; Andre Quintanilha, Chief Privacy Officer; and Hartley Jean-Aimee, Chief Technology Officer, employed their expertise to test and audit a proprietary AI system. Together, we explored "hidden bias" experiments, testing local and international resumes with their synthetic dataset.

5.1 Experiment I (A)

5.2 . Overview of Manual Hiring Process

A talent acquisition manager is requested to publish a job opening, typically a strategy meeting occurs with the hiring manager to discuss the job profile and requirements for this new hire.

The responsible person posts and promotes the job vacancy on various sites. Human Resources (HR) employees usually wait between 7 - 14 days to do the screening at once to save time. Most recruiters, at larger firms, have 20 to 40 jobs open, so time management is a process priority.

In line with typical manual screenings, the 88 resumes were categorized as follows:

- A-candidates fulfill all the requirements. There are no questions open, for example, there is a work permit and no gaps in their resumes. They check all the boxes.
- B-candidates are those that look good, but there are open questions. If you don't have that many A-candidates, you will look at B-candidates.
- C-candidates are those that are moved directly into the rejection pile because they have no or not enough criteria matches to meet the requirements. There are "knock-out" criteria, for example, they have no work permit. Candidates in this category are typically rejected via an automated email.

Date	October 2023
Performed by	Ayse Semiz-Ewald
Test Topic	CV manual selection

5.3 Outline of Resume Selection Process for an Invitation to an Interview

The Recruiter screened the resumes based on the provided Project Manager job profile.

I would screen for knock-out (KO) criteria first, these are must haves. Then I would look for should haves, and rate the candidates based on that. Out of 88, there are 14 A-candidates. Two candidates seem too senior and will most likely not match the job's salary range, so I would start the process with the 12 candidates.

— Ayse Semiz-Ewald,
Vice President Diversity, Equity & Inclusion at a German public company

Results of the 88 received resumes

- 14 A-Candidates of which 12 were moved to the next round
- 34 B-Candidates
- 40 C-Candidates

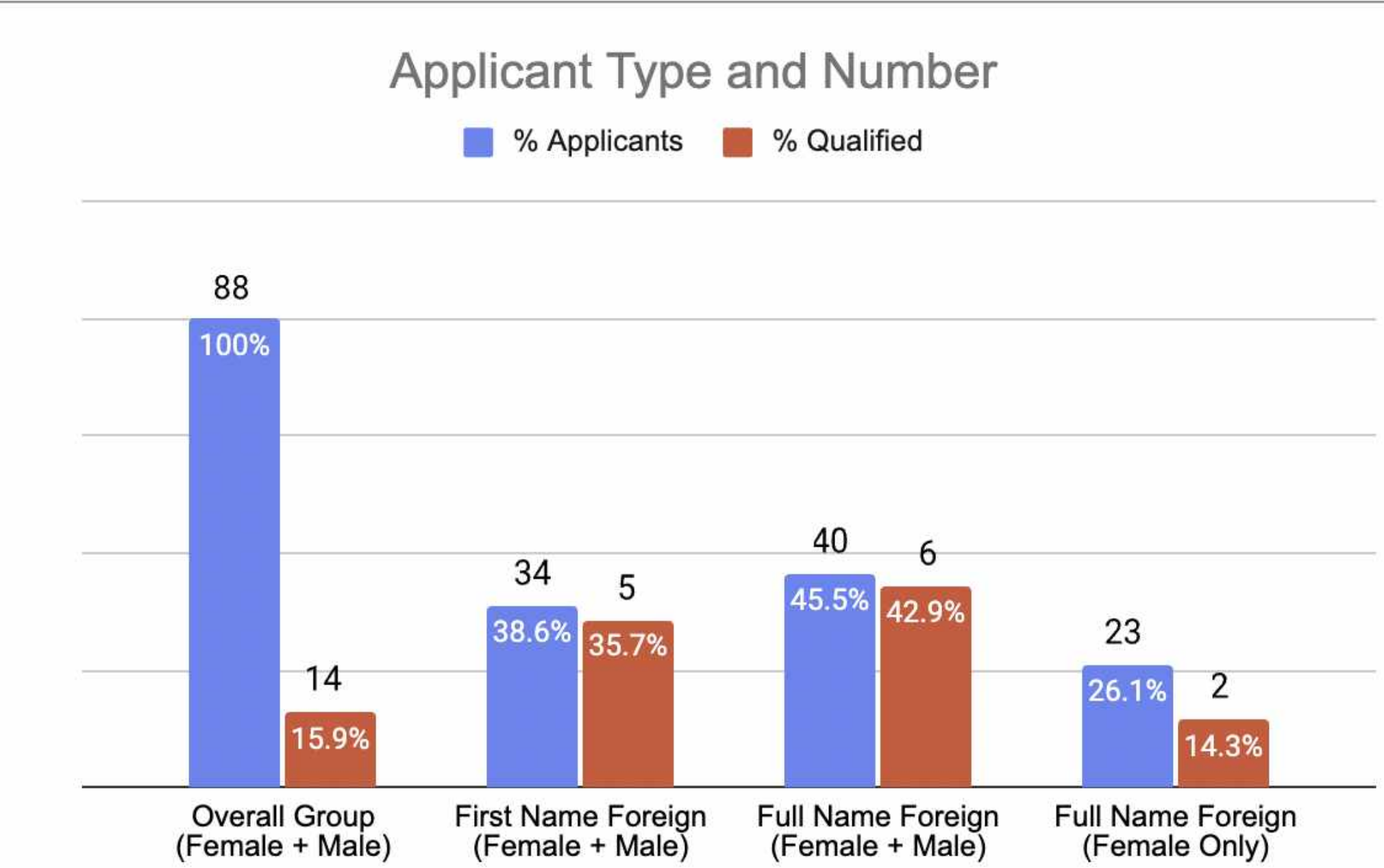


5.4 The Project’s Selected Applicants Reflect the Diversity of Total Received Resumes

The manual selection of candidates in Project’s Experiment I (A) resulted in a similar ratio of non-European names of the total resumes received. The recruiter assessed the resumes exactly as they were uploaded – with names included.

Of the 88 received resumes, 34 or (38.6%) have ethnic-sounding, non-European first names; 14 job applicants selected for interview of which 5 candidates (35.7%) have ethnic-sounding, non-European first names.

Of the 88 received resumes, 40 (45.5%), have ethnic-sounding, non-European first and last names. Of the 14 selected for an interview, 6 candidates (42.9%) have ethnic-sounding, non-European (first and last) full names. Note, out of the 14 qualified candidates, only two (2) female applicants with full ethnic names were selected for an interview.



6 Experiment I (B)

How does an Application Tracking Systems (ATS) perform in comparison to the Project's recruiter's manual selection?

Do migrant women's resumes receive a differential treatment in an open source ATS?

6.1 System

<https://github.com/srbhr/Resume-Matcher>

6.2 Introduction

The utilization of AI-based predictive technologies in candidate screening and selection processes has become a common and well-documented trend. A simple online search on popular platforms or inquiries related to AI-based hiring systems will yield numerous results. **AI is now integrated into various stages of the candidate selection process, encompassing activities such as resume scanning, keyword matching, candidate ranking, and even behavioral assessments.**

However, it's important to recognize that AI systems, as extensively discussed in the survey paper titled "A Survey on Bias and Fairness in Machine Learning,"¹ are susceptible to introducing biases into decision-making processes. These biases can manifest in various forms and can significantly impact the fairness and equity of AI-driven candidate selection systems that rely on machine learning and artificial intelligence.

To quickly assess the influence of AI systems on applicant tracking systems, our small research initiative aimed to conduct an evaluation of several prevalent commercial ATS solutions extensively utilized throughout Europe. The primary approach we adopted was to treat each of these systems as a black (opaque) box, meaning that we focused on their input - output behavior without delving into their internal workings.

¹ Mehrabi, Ninareh, Fred Morstatter, Nripsuta Saxena, Kristina Lerman, and Aram Galstyan. "A Survey on Bias and Fairness in Machine Learning," ACM computing surveys (CSUR) 54, no. 6 (2021): 1-35. <https://arxiv.org/abs/1908.09635>

In line with this methodology, we utilized a meticulously curated set of resumes, as elaborated in the section Experiment I (A), and subjected them to an empirical evaluation. Our objective was to compare the performance of these resumes when processed by the AI-powered ATS systems against a quantitative benchmark established through simulated assessments by professional recruiters, as detailed in the section Experiment I (A).

In particular, our investigation centered on examining whether resumes from migrant women underwent differential treatment in comparison to other resumes within these AI-driven systems. This aspect aligns closely with the core aim of our study, which is to uncover potential biases, whether intentional or unintentional, in the evaluation of resumes. Specifically, we sought to determine if the demographic characteristics of being a migrant woman influenced the outcomes in a manner that might reflect bias or disparities within the ATS processes.

The idea of testing the popular ATS systems we had initially chosen proved to be an insurmountable challenge. The primary obstacle that hindered our efforts was the significant difficulty in gaining access to these systems, especially considering our intention to assess them for potential bias. The closed nature of these systems presented a formidable barrier, as they were not readily accessible for external evaluation. Typically, these systems are closely guarded by their respective providers, with access granted exclusively to their clientele. Our primary research objective was to rigorously examine these systems for bias in their decision-making processes, which necessitated a level of access that we were unable to secure.

The closedness of these ATS systems presented a unique set of challenges, and this is further elucidated in the subsequent section of our study. This section delves into the specific systems we had endeavored to test and provides insights into why it was, regrettably, an unattainable goal. **The inaccessibility of these systems stemmed from their proprietary and often confidential nature, which limits external parties from scrutinizing their functionality.**

Furthermore, due to their commercial and competitive nature, ATS providers are generally guarded about revealing the inner workings of their systems, making them particularly resistant to external evaluation. Our efforts to test these systems, as detailed in the upcoming section, are a testament to the complexities and constraints we encountered in our quest to uncover potential biases in these widely-used AI-driven applicant tracking systems. In lieu of the commercial ATS systems that posed access challenges, we opted for an open source alternative whose source code is publicly available. **This strategic choice significantly eased the testing process in comparison to the proprietary commercial ATS solutions. However, it's important to note that the open source system in question relies on a set of AI engines, the intricate details of which are not publicly disclosed.** Consequently, while we were unable to delve into the precise inner workings of the AI algorithms in use, we effectively achieved our overarching objective of assessing the system as a black (opaque) box. The design and structure of this open source system are outlined in detail below, while the subsequent sections provide comprehensive insights into the experimental setup employed for conducting our empirical study.

Our research endeavors culminate with the presentation of findings and the formulation of recommendations aimed at mitigating the existing issues prevalent within AI systems. These suggestions encompass both short-term solutions, which can immediately empower candidates to enhance their prospects when interfacing with AI systems, and long-term policy recommendations that advocate for the development of commercial AI systems that are amenable to unbiased testing. **This multifaceted approach aims to address the immediate challenges faced by candidates in their interactions with AI systems, while also advocating for the creation of a regulatory framework that fosters transparency, fairness, and accountability within the AI industry.** By offering practical short-term strategies alongside forward-thinking policy recommendations, we aspire to not only identify bias in AI systems but also to catalyze positive change and improve the landscape of AI-driven applicant tracking systems for both applicants and organizations.

6.3 Commercial ATS

In our pursuit of testing commercially used Applicant Tracking Systems (ATS), we embarked on a mission to select a handful of systems commonly employed across Europe. To accomplish this, we leveraged search engines to identify systems currently in active use. Here is a list of the systems we initially considered for evaluating bias in our experiments:

1. ICIMS
2. Greenhouse
3. Ceipal ATS
4. Breezy HR
5. Jazz HR
6. Personio
7. Workable
8. Recruitee
9. FreshTeam
10. HireEZ

Regrettably, despite our intention to assess ICIMS, Greenhouse, Ceipal ATS, FreshTeam, and HireEZ, we encountered insurmountable obstacles in the form of an inability to create free accounts. These systems, it seemed, posed entry barriers that hindered our testing efforts.

As for the remaining systems, while it was technically feasible to establish free accounts, we made a conscious choice to refrain from using them. Our decision was prompted by concerns related to potential General Data Protection Regulation (GDPR) issues that such usage could potentially trigger. Notably, if we were to employ these systems and input the actual resumes collected by our team, we were left with uncertainties regarding the consequences of our actions. **Key questions revolved around the storage duration of the resumes and the purposes for which the stored resumes would be utilized by these systems.** In light of these uncertainties, we opted to exercise caution and abstain from using these systems.

It is essential to emphasize that the selection of systems for our experiments was a representative sample chosen from the wide array of available ATS systems in the market. This selection aimed to illustrate the challenges and, in some instances, the impossibility of effectively testing commercial systems. Our choice was not directed at a specific provider but was rather an illustrative effort to underscore the complexities involved in scrutinizing such systems.

In place of commercial systems, our decision was to assess an open source system, the source code of which is openly available on a public code repository. In the upcoming section, we provide a detailed exploration of this open source system, as well as a comprehensive account of the experiments we conducted using this platform.

6.4 Open Source System

For our research, we employed a specialized tool called "resume-matcher," which is an open-source system available at <https://github.com/srbhr/Resume-Matcher>. **The core objective of utilizing this system was to thoroughly examine the system for any potential biases it might exhibit when scoring resumes, specifically focusing on those of female candidates with migrant backgrounds compared to others.** To provide a more comprehensive overview of how this system functions, let's delve into its operational process:

1. Input Documents: The "resume-matcher" system begins its operation by accepting two fundamental types of documents as input. These documents include a **resume** and a **job description**, both typically provided in the ubiquitous PDF format.

2. Keyword Extraction: To enable an accurate comparison and assessment, the system undertakes a multi-step process. **First, it parses and thoroughly scrutinizes both the resume and the job description using machine learning algorithms.** The objective of this step is to extract and identify the most pertinent keywords that convey the essential information within each document. **To further refine the**

keyword extraction process, the system incorporates "textacy" (<https://textacy.readthedocs.io/en/latest/>) a text analysis library, which assists in extracting key terms and identifying the principal themes within the job description. This thematic identification is critical for the subsequent matching process.

3. Similarity Scoring: The most crucial phase in the operation of the "resume-matcher" system is its similarity scoring. In this step, the system employs a powerful tool named "Qdrant" (<https://qdrant.tech/>) which is essentially a vector similarity search tool. **The primary function of "Qdrant" is to analyze and assess the degree of similarity between the input resume and the job description.** The result of this process is an absolute score, which quantifies the extent of alignment or compatibility between the content of the resume and the criteria and expectations outlined in the job description. This numerical score essentially serves as a comprehensive evaluation of a candidate's suitability for the given position.

In the context of our research, we harnessed the capabilities of the "resume-matcher" system to critically evaluate its performance in scoring resumes. We paid particular attention to the potential emergence of biases, specifically when assessing female candidates with migrant backgrounds in comparison to other candidates. This in-depth analysis allowed us to gain valuable insights into the system's behavior and its impact on candidate assessment and selection.

This experiment comprised a selection of candidate resumes, chosen at random from both migrant and non-migrant female groups. The rationale behind this specific dataset was to examine whether the migrant background of candidates would have a discernible impact on the scoring outcome in comparison to the non-migrant status, whilst putting the gender attribute to be common in both the groups. **The results of this experiment revealed a notable disparity between the scores assigned by the AI system and those assigned manually.**

6.5 Experiments Purposes

The experiments were devised with a dual purpose. Firstly, our aim was to explore the potential existence of biases within the open source resume matcher that was under evaluation.

Secondly, we aimed to assess its performance in comparison to the scores assigned by our recruitment team, as detailed in Experiment I (A).

During the evaluation process, our recruitment team meticulously evaluated the entire pool of resumes, allotting each one a score denoted as either A, B, or C. Here, A represented the highest level of relevance to the job posting, while C denoted the lowest level of relevance.

6.6 Approach

To conduct these experiments, we began by creating a job description tailored for the position of a project manager. Subsequently, we gathered a set of 88 resumes from actual individuals. The candidate pool included 46 resumes from migrant female candidates, 10 from non-migrant female candidates, 7 from non-migrant male candidates, and 25 from migrant males. However, for our experimental analysis using the resume-matcher system, we were able to utilize 84 of these resumes, **as four (4) of them were not in the PDF format compatible with the system**. Furthermore, our recruitment team also assigned specific tags to the resumes, distinguishing between categories such as female, male, migrant, and non-migrant. This tagging process allowed us to execute a series of tests, focusing on specific comparisons. These resumes were input into the resume-matcher system to obtain scores in each experiment, enabling a comprehensive assessment of the system's performance and its potential biases in these diverse candidate scenarios.

We conducted three separate comparisons, each involving a subset of six (6) candidates randomly chosen from the pool of migrant female candidates and six (6) from three (3) different candidate sets:

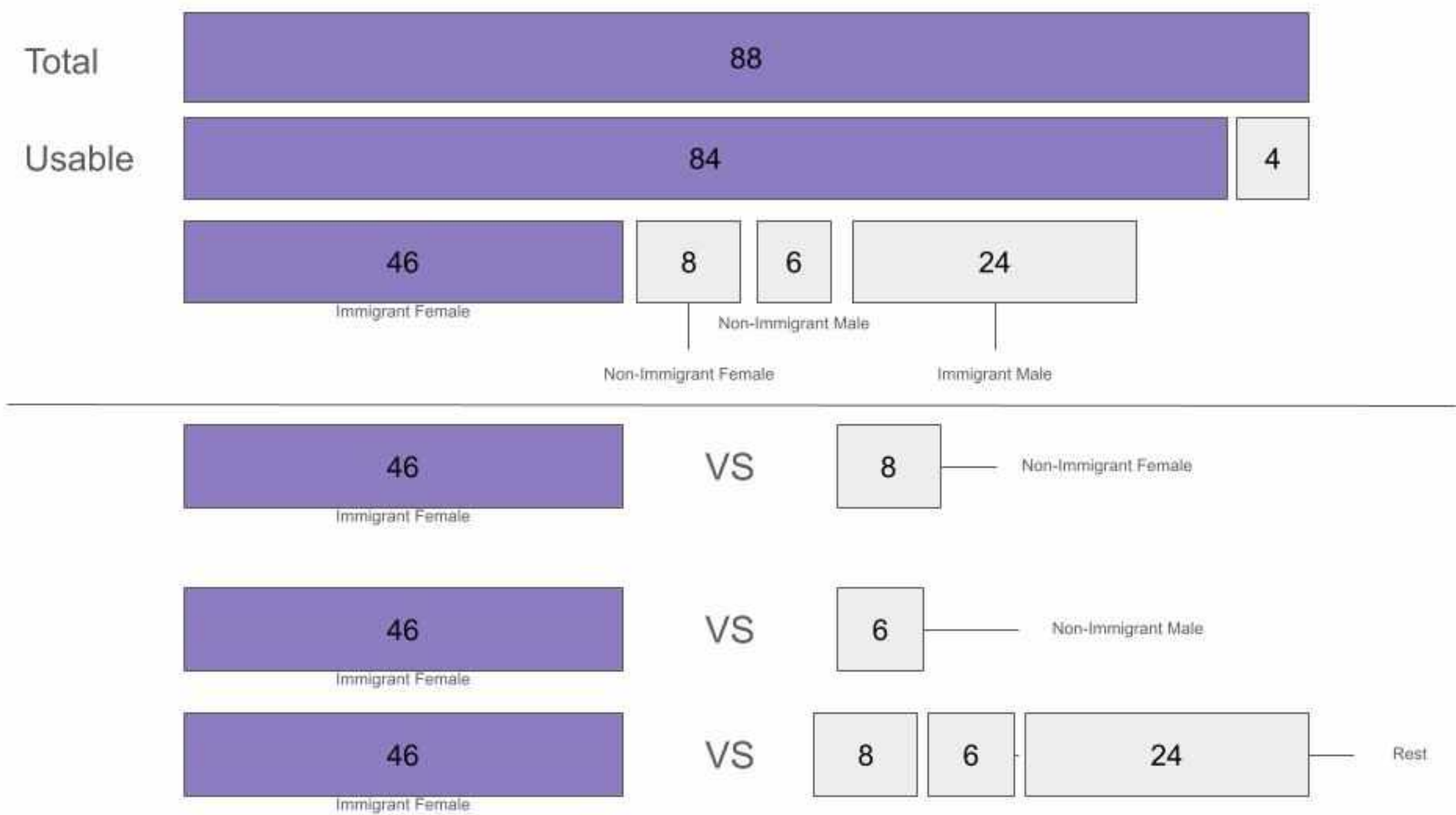
1. Migrant female vs. Non-migrant female,
2. Migrant female vs. Non-migrant male,
3. Migrant female vs. Rest (Non-migrant female + Non-migrant male + migrant male).

Date October 2023

Performed by Dr. Tejo Chalasani

Test Topic CV manual selection vs CV ATS selection

6.7 Resumes breakdown for ATS Experiment



6.8 Experiment I (B)

This experiment comprised a selection of the Project’s resumes, chosen at random from both migrant female and non-migrant male. The rationale behind this specific dataset was to examine whether the migrant background of candidates would have a discernible impact on the scoring outcome in comparison to the non-migrant status, whilst putting the gender attribute to be common in both the groups. **The outcomes of this Experiment uncovered a discrepancy between the ratings assigned by the AI system and those manually assigned.** In Experiment I (A), where the resumes were categorized, the ATS only identified four (4) candidates within the "A-Category." It’s important to note that all resumes in the A-Category showcased experience in project management, and, in some instances, included relevant certificates. Interestingly, the ATS selected four candidates originally labeled as "C-Category" during the manual selection process, representing those deemed less suitable.

Below are the results from each of the experimental set:

Migrant Female vs Non-Migrant Female

# SNo	# Score	Manual ...	Select	Demographic
80	0.57	A		Non-migrant female
21	0.36	B	Ethnic first + last name	Migrant female
28	0.33	C		Non-migrant female
56	0.32	C		Non-migrant female
76	0.27	B		Non-migrant female
36	0.26	A		Non-migrant female
88	0.25	A	Ethnic first name	Migrant female
1	0.25	B	Ethnic first name	Migrant female
53	0.23	B	Ethnic first + last name	Migrant female
63	0.22	C	Ethnic last name	Migrant female
42	0.11	C	Ethnic last name	Non-migrant female
51	0.08	A		Non-migrant female

This experiment comprised a selection of candidate resumes, chosen at random from both migrant female and non-migrant male. The rationale behind this specific dataset was to examine whether the migrant background and gender of candidates would have a discernible impact on the scoring outcome in comparison to the non-migrant status. Similar to the previous results, **this experiment revealed a notable disparity between the scores assigned by the AI system and those assigned manually.**

Migrant Female vs Non-Migrant Male

# SNo	# Score	Manual ...	non-European name	Demographic
44	0.4	B	Ethnic first + last name	Migrant Female
54	0.37	B		
24	0.32	A		
4	0.3	C	Ethnic first + last name	Migrant Female
66	0.28	A	Ethnic first + last name	Migrant Male
34	0.28	B		
23	0.26	A		
19	0.26	B		
82	0.23	C		
53	0.23	B	Ethnic first + last name	Migrant Female
27	0.19	B		
58	0.19	C		

The subsequent three (A, B, C) sets of experiments involved the random selection of six (6) candidates from the migrant female group and six (6) candidates from the rest of the candidate pool. In the first and last sets, the scoring results closely mirrored the manually assigned grades.

However, due to the relatively small sample size, we must exercise caution in drawing substantial inferences from the alignment between the system’s scoring and the manual grading.

Test A: Migrant Female vs Rest 1

# SNo	# Score	Category	Select	Demographic
80	0.57	A		
16	0.5	A	Ethnic last name	Migrant Female
70	0.4	C		
75	0.36	B		
4	0.3	C	Ethnic first + last name	Migrant Female
11	0.3	B	Ethnic first + last name	Migrant Male
76	0.27	B		
8	0.26	B	Ethnic first + last name	Migrant Male
20	0.25	B	Ethnic first + last name	Migrant Male
53	0.23	B	Ethnic first + last name	Migrant Female
37	0.18	B	Ethnic last name	Migrant Male
22	0.15	C		

Test B: Migrant Female vs Rest 2

SNo	# Score	Category	Select	Demographic
14	0.35	C		
78	0.34	C	Ethnic first + last ...	Migrant Male
6	0.32	A	Ethnic first + last ...	Migrant Female
17	0.27	B		
48	0.27	C	Ethnic first + last ...	Migrant Female
23	0.26	A		
86	0.25	C		
20	0.25	B	Ethnic first + last ...	Migrant Male
31	0.24	B	Ethnic first + last ...	Migrant Female
87	0.2	C	Ethnic first + last ...	Migrant Male
22	0.15	C		
65	0.13	C	Ethnic first + last ...	Migrant Female

Test C: Migrant Female vs Rest 3

#	SNo	#	Score	Category	Demographic
	44		0.4	B	Ethnic first and last name Migrant Female
	85		0.38	B	
	15		0.31	B	
	3		0.29	B	Ethnic first and last name Migrant Male
	34		0.28	B	
	10		0.28	B	Ethnic first and last name Migrant Male
	8		0.26	B	Ethnic first and last name Migrant Male
	86		0.25	C	
	53		0.23	B	Ethnic first and last name Migrant Female
	58		0.19	C	
	42		0.11	C	
	68		-0.02	C	Ethnic first and last name Migrant Female

6.9 Experiment I (B) Findings

Our most significant discovery in this study revolved around the impact of resume parsability on scoring. **Notably, we observed that numerous resumes, despite possessing relevant experience and closely aligning with the job description’s requirements (and consequently graded as ‘A-Candidates’ by manual scoring), received lower scores.** This phenomenon ultimately underscores the critical importance of a resume’s parsability – the system’s ability to effectively read and extract the pertinent keywords and information. **In essence, the accuracy and efficiency of this parsing process emerged as a pivotal factor influencing the scoring outcomes.**

While our findings were not statistically significant, it’s worth noting that we did not detect any discernible bias within the application of a system like resume-matcher. This observation stemmed from the fact that the scoring generated by the system was consistently absolute. Irrespective of the setting or context in which a specific resume was evaluated, it consistently received the same score when compared to a given job description.

Nonetheless, it’s essential to acknowledge the potential existence of concealed attributes that may exert an influence on the ranking mechanisms in numerous commercially employed ATS. To shed light on this aspect, **we conducted Experiment II, and provided results concerning how these “hidden” attributes could potentially impact rankings.**

7 Experiment II

Do Application Tracking Systems (ATS) have bias towards migrants?

7.1 Introduction

Despite efforts to reduce AI bias risk, the black (opaque) box effect remains a significant challenge in improving AI fairness. Applicant Tracking Systems (ATS) are often trained to disregard protected attributes, such as gender, age, and migrant status when ranking a resume. **Additionally, computational and statistical methods can help to monitor biased decision-making in AI systems but they have limitations. They tend to focus only on statistical relevance and do not assess context or how systemic and human biases, like the use of different language styles in a resume, might influence an ATS's output.**

In the previous Experiment I (B), no statistically relevant differences were detected in the resume ranking of migrant applicants. The question remains whether other, context-related attributes, particularly those hinting at an individual's migrant status, could lead to biases in the ATS.

To assess this, we leveraged Palqee's PAM to generate resumes tailored for a U.K.-based job advertisement. The primary objective with PAM is to assist AI companies in enhancing the trustworthiness of their models through Explainable AI solutions and ensuring compliance with the forthcoming EU AI Act (Appendix B), as well as industry-specific regulations governing AI usage.

PAM introduces a contextual layer to the bias risk assessment process, which helps in understanding why an AI system makes certain predictions. This approach not only facilitates explainability but also provides a deeper understanding of system limitations, contributing to more robust AI governance and compliance.

Experiment II centered on distinguishing between local (in this Experiment, local is U.K.) and international resumes, focusing on three subtle attributes that hold the potential to influence resume ranking scores: **Language Proficiency, Overseas Work Experience, and International Education.**

It's important to note that PAM is currently in the Alpha phase, indicating that the system is undergoing further development and validation before its market release.

7.2 Experiment II Findings

Our analysis has yielded the following insights:

High Likelihood of Bias Towards Migrants

- When comparing local (U.K.) and international resumes, the ATS **consistently assigns higher scores to local resumes**, irrespective of the presence of subtle attributes.
- International resumes that incorporate a subtle attribute **denoting migrant status show on average a decline of 2-3 points** (of 100) in their score, as opposed to local resumes (such as highlighting that the applicant is a British native), which experience an approximate 1-point decrease.
- **Statistical analyses show significant differences between local and international resumes.** The most substantial mean difference is -5.41 points, observed between international resumes containing subtle attributes and local resumes without subtle attributes.
- Of the three subtle attributes studied, **"International Education"** exerts the most pronounced negative impact on resumes scores, with **a notable 80% of international resumes receiving lower rankings.**
- Comparing resumes scores based on Nationality, English/British resumes and Indian resumes ranked the highest and resumes from Japanese applicants the lowest. **This suggests potential preference to ethnic groups that have a higher representation in the U.K.**

7.3 Approach

1. **Configuration of PAM:** PAM is provided with parameters. The intended purpose of the AI: 'Resume Ranking System,' the region: 'U.K.,' and the job advertisement: 'Project Manager'.
2. **Reference Data Resume Generation:** PAM generates a set of reference data resumes.
3. **Subtle Attribute Integration:** PAM proceeds to introduce subtle attributes into the resumes from the reference dataset.
4. **Ensuring Suitability:** All generated resumes, are checked to inherently possess the qualifications that align with the requirements of the role.
5. **Classification into 'Local' and 'International' Resumes:** The dataset is categorized into 'local' (U.K.) and 'international' resumes, enabling a comprehensive evaluation of potential biases towards applicants with differing migrant status.

7.4 Migrant Status and Subtle Attribute Category Analysis

To gain deeper insights into the influence of migrant status and the presence of subtle attributes on resume scores, we categorize the resumes into four groups. These groups are determined by the combination of migrant status and the presence or absence of subtle attributes within the resume. Subsequently, we conduct an ANOVA (Analysis of Variance) test, to detect statistical significance in differences among those groups.

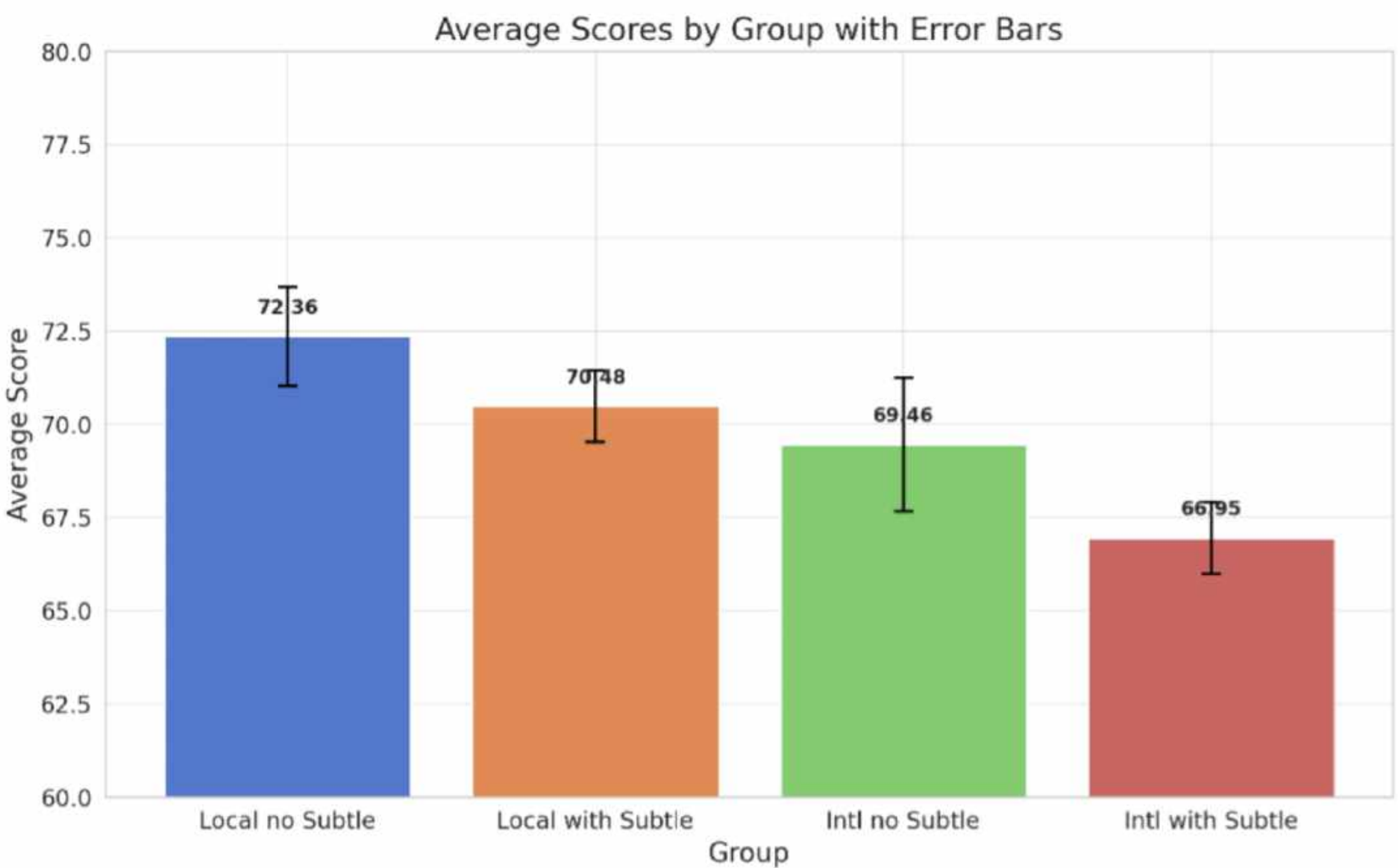
The results of the ANOVA test are as follows:

- **FF-value: 3.54**
- **P-value: 0.0175**

Given that the P-value is less than 0.05, we can reject the null hypothesis. This suggests that there is a statistically significant difference in the scores between at least two of the categories.

To determine further how specific resume groups differ from each other, we performed the Tukey’s Honest Significant Difference (HSD) test (Appendix D). This post-hoc test compares the means of each group with every other group, providing more granularity.

The below bar chart shows the average scores for each group with error bars. The error bars represent the standard error of the mean (SEM) for each group. The SEM measures how much we expect the sample mean (average) to vary if we were to take multiple samples from the population.



Observations:

- **Highest Average Score:** Resumes in the "Local Status but no Subtle Attribute" group attain the highest average score, as indicated by the tallest bar.
- **Lowest Average Score:** International resumes featuring a Subtle Attribute receive the lowest average score, indicated by the shortest bar.
- **Significant Differences:** Notably, there is no overlap in the error bars between the "Local no Subtle Attributes" and "International with Subtle Attribute" resumes, as well as between the "Local with Subtle Attribute" and "International with Subtle" resumes. This absence of overlap shows the significant scoring differences between these groups.
- **Some Overlap:** In contrast, there is slight overlap in the error bars among groups, such as "Local with Subtle Attribute" and "International no Subtle Attribute". This overlap suggests that the difference in average scores between these two groups is less pronounced, which can be also observed in Tukey's HSD test table (Appendix D).

Considerations

International resumes containing subtle attributes have a statistically significant difference in scores compared to all other groups. **This finding suggests potential bias in the ATS towards international applicants, or migrants, applying for a U.K. based project management role based on aspects that are likely unrelated to the qualifications of the applicant and more related to the nature of their international background.**

7.5 Subtle Attribute Comparison for International and Local Resumes

We compare resumes based on the subtle attribute, International Education, Language Proficiency, and Overseas Work Experience, to assess the ATS for potential bias towards migrant applicants and to discern which subtle attribute exerts the most significant impact on the scores. The Appendix D Average and Median Score Comparison and Standard Deviation Bar-Plot Chart show the comparison. Resumes without a Subtle Attribute Key (None) are the Reference Data.

Observations:

1. **Reference Data Scores:** Resumes without subtle attributes (Reference Data) have the highest average scores for both international and local applicants.
2. **Local vs. International:** Local (U.K.) applicants with subtle attributes score higher on average and median than international ones.
3. **Impact of Attributes:** Resumes with “language Proficiency” or “Overseas Work Experience” score higher than those with “International Education.”
4. **“International Education” Effect:** This attribute significantly lowers scores for international applicants, with an average decrease of 3.3 points, from 69.46 to 66.16.

Considerations

For the scope of this experiment we tested with three subtle attributes specifically to assess bias towards migrants. There may be more attributes that can influence the outcome. Further it does not consider the impact of a combination of factors, such as migrant- and gender- bias which could lead to greater discrepancies in the results.

7.6 Analysis of “International Education” Subtle Attribute

Building upon our earlier findings, the “**International Education**” attribute has the **most significant negative impact** on score. Notably about 80% of resumes with this attribute scored lower compared to those without any subtle attributes.

The most significant score shift among local applicants was -13.89 points, dropping from 64.83 to 50.94 due to the addition of “International Education.” Notably, we identified this particular resume as an outlier, given the addition of a comment specifying that the applicant had never studied abroad, likely contributing to the substantial score drop.

For international applicants, the most substantial score change amounted to -12.30 points, from a 77.95 score to 65.66 upon the addition of the subtle attribute. this change seems linked to language modifications in the resumes, which included adjustments to reflect international education and experience.

7.7 Influence of Nationality on Scores

In this section, we examine the influence of applicants' nationality on the scores assigned by the ATS. Appendix D show the results and visualize the scores attributed based on the nationality of the applicants.

Several key observations emerge:

- **Indian and English applicants' resumes** scored the **highest** on average, with Indian applicants leading.
- **Japanese applicants** consistently received the **lowest scores**, showing a slight improvement only in "International Education."
- Resumes including subtle attributes generally scored lower across most nationalities.
- **"Overseas Work Experience"** had a **lesser negative impact on scores**, and in some cases, like for Indian applicants, it positively influenced the scores.

Considerations for Bias

The high scores of Indian applicants may relate to the U.K.-based job role, as Indians are the third-largest ethnic group in the U.K. (2.3%). Notably, the analysis excluded Black British or Afro-Caribbean applicants, who make up 3% of the population. For a more thorough evaluation, future assessments can be expanded to include this group for a more thorough evaluation.

7.8 Conclusion

In Experiment II, we successfully addressed the issue of the black (opaque) box effect. It provided a possible explanation on why the experiences of migrant applicants with an ATS in Chapter 6 contrast with the statistically insignificant bias findings from Experiment I(B). **Current bias detection methods often overlook subtle factors that could influence ATS outcomes and instead just assess results based on name heritage and citizenship status. This oversight poses a risk of exacerbating challenges for migrants in the application process, potentially due to factors unrelated to their qualifications for the role.**

8 Participants' Discussion on Project's Findings

On Thursday, November 2, 2023, we held an online meeting for the Project's participants that gathered 23 guests.

We aimed to communicate the initial findings of the Project with the participants for three reasons:

1. to provide them with feedback on how the Project managed their data and input.
2. to assess and directly gather their responses to the preliminary research findings.
3. to create a space for participants to share additional perspectives, whether confirming or contrasting the research findings, and engage in discussions with other participants regarding how their individual experiences align or differ.

During this meeting, the Project's team presented the initial research findings. **The main points: in Experiment I (B) we found that the ATS can't process certain resume formatting. In Experiment II, the AI hiring tool did not view "international work experience" as favorable as "local experience."**

Approximately 10 participants openly shared their personal experiences and challenges related to job hunting in Germany. **These individuals candidly discussed the difficulties they encountered in securing employment, despite possessing the necessary qualifications and skills. The underlying source of their frustration predominantly revolved around the persistent biases and discrimination they faced due to their names and backgrounds.**

One (1) participant shared an account of changing her Muslim name in an attempt to enhance her job prospects. As her career progressed, she gradually transitioned back to using her original first name while retaining her mother's more widely accepted European last name. Interestingly, a Recruiter affiliated with the Project acknowledged a noticeable increase in her personal interview invitations once she added her husband's German last name to her Muslim name. This experience served as a vivid example of the challenges faced by many job seekers in Germany.

The Project's findings not only validate the experiences shared by the participants but also provide valuable insights into the reasons behind their ongoing struggles, despite the presence of a shortage of skilled workers in the job market.

9 Recommendations

The methodology implemented in this report embraced a multifaceted approach. **Our strategy involved hands-on experimentation with algorithmic hiring tools** conducted by the Project's AI experts and talent acquisition leaders. Additionally, **we engaged in candid discussions with talent acquisition leaders from some of Germany's prominent global corporations. We learned about the latest development in AI hiring tools with some of the world's leading experts in talent intelligence technology.**

This extensive exploration provided a comprehensive view of one of the initial stages in a non-transparent recruitment process. Our emphasis was on examining the challenges unique to the **experiences of educated women migrants** during the job application process. By adopting a broad perspective, we aimed to uncover aspects of the recruitment landscape that impact diverse candidates.

We recommend clear communication from companies about the use of AI systems, the methods for processing candidates' requested data, and the criteria influencing decision-making.

In the broader context, businesses stand to gain substantial support by aligning motivated and capable non-traditional workers to address labor shortages.

Consider this report as the beginning of a journey toward the development of hiring practices that **prioritize inclusivity over exclusivity, shaping a future where matching is optimized to embrace a diverse range of individuals that make up our community.**

9.1 Automated Hiring Tools Can Both Support and Hinder Job Seekers' Accessibility to the Labor Market

We offer a set of recommendations aimed at addressing both short-term and long-term considerations. These recommendations encompass practical steps that candidates can take to enhance the effectiveness of their resumes within AI-based ATS. Simultaneously, we advocate for comprehensive, long-term measures directed at ensuring that commercial ATS become more amenable to test.

9.2 Short-Term Recommendations for Candidates and Companies

In the short term, we propose a series of practical recommendations aimed at empowering candidates to improve their interactions with AI-based ATS. These recommendations are designed to enhance the transparency and effectiveness of the application process while assisting **candidates** in optimizing their resumes. Here's an expanded perspective on these suggestions:

1. **Transparency in AI Screening:** To foster a more transparent and candidate-friendly application process, we recommend that **employers** clearly communicate to candidates that their applications will be screened by AI-based ATS. This transparency ensures that applicants are aware of the automated nature of the initial screening, thus setting clear expectations.
2. **Candidate Support Tools:** Candidates can significantly benefit from access to readily available support tools, such as Textio, Resume-Matcher, and Resume-Ranker. These tools are designed to assist **candidates** in the preparation and formatting of their resumes. By leveraging these resources, candidates can align their resume content with the specific job descriptions. This alignment not only enhances their chances of passing the initial ATS screening but also ensures that their qualifications are effectively communicated to potential employers.

Textio, for instance, offers invaluable assistance in optimizing the language and phrasing used in resumes, aligning them with industry-specific norms and best practices. Resume-Matcher and Resume-Ranker provide comprehensive guidance on tailoring resumes to match the qualifications sought in job postings. These resources empower candidates to present themselves in the best possible light, increasing their chances of making it through the initial AI-based screening process.

By adopting these short-term recommendations, **employers and candidates can work collaboratively to streamline the application process and ensure that candidates' qualifications are accurately reflected in their resumes. This approach not only improves the applicant experience but also enhances the overall efficiency and effectiveness of AI-based ATS.**

9.3 Long-Term Recommendations for Policymakers

For the long-term, we advocate for comprehensive measures that promote transparency, fairness, and continuous improvement in AI-based ATS. Here are detailed insights into our long-term recommendations:

1. **Transparency and Accessibility for Testing:** It's imperative that ATS based on AI should be made available for, at the very least, black (opaque) box testing. This involves opening these systems to external scrutiny, research, and evaluation. **By allowing independent experts, researchers, and oversight bodies access to these systems, it ensures a more robust assessment of their functionalities. This transparency not only fosters accountability but also helps identify and rectify potential biases and shortcomings. Furthermore, by making these systems amenable to black-box testing, it facilitates the creation of a collective effort to improve their fairness and equity.**
2. **Periodic Audits for Bias Mitigation:** To address the evolving nature of biases and to prevent the accumulation of unfairness, we recommend that regular and systematic audits of AI-based ATS be conducted. **These audits should involve a comprehensive examination of the system's decision-making processes, algorithmic operations, and outcomes. The aim is to identify, quantify, and rectify any biases or disparities that may have emerged over time.** Periodic audits serve as a proactive approach to bias mitigation and ensure that the systems remain aligned with evolving ethical and legal standards.

By embracing these long-term recommendations, organizations can foster transparency and accountability in their recruitment processes. This approach not only enhances the trust candidates have in AI-based ATS but also reflects a commitment to fair and equitable hiring practices. It is a forward-looking strategy that promotes continual improvement and adherence to evolving standards of fairness and ethical use of AI technology in recruitment.

10 Conclusion

Equity Demands More than Unbiased AI

We arrived at the conclusion that bias in AI systems is not merely a technology problem, since machine learning algorithms are trained on historical data which are inadvertently shaped by societal structures, reflecting and perpetuating existing power dynamics, and inequalities. Even if the previously mentioned technical recommendations are institutionalized, job applicants optimize their resumes, and the system recommends a fairly diverse workforce — ultimately a company's hiring manager may still select the candidate based on similarity of past hires.

Technology can definitely become better advisors to humans making better decisions once we correct existing datasets, conduct continuous bias audits, and add human oversight by a professional diverse team of people.

However, the overriding key recommendation we would have is that the AI field should diversify itself. A diverse and inclusive AI talent pool, especially from under-represented communities would anticipate and build a more equitable system. This will require investment in education, mentorship, and access to opportunities. Only then will we have an environment where sophisticated systems are created by people that represent our union.



11 Glossary

Algorithm: a process or set of rules to be followed in calculations or other problem-solving operations by a computer system.

Applicant Tracking Systems (ATS): recruiting tools that may or may not use Artificial Intelligence (AI) to source and select job candidates.

Artificial Intelligence (AI): is the simulation of human intelligence processes by computer systems.

Artificial Neural Network (ANN) : Modeled after the human brain, these mathematical structures use layered data sets to convert input into output, commonly applied in pattern recognition and forecasting across various fields such as science, medicine, telecommunications, and business.

Automated hiring systems (AHS): technology that establishes automatic workflows for what would normally be manual recruiting or human resources activities.

Black (opaque) box : a system or process that uses information to produce a particular set of results, but the inner workings is confidential or difficult to understand.

Ethnic-sounding names : typically non-Western European or American-English sounding names.

Generative AI : a form of neural network-based machine learning trained on vast data sets that can create new text, image, video, or audio content.

Human Resources (HR): the department of a company that deals with the hiring, administration, and training of staff.

Machine learning (ML): a form of AI and computer science focused on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.

Migrant: a person not born in the country he/she/they currently live and work in. For this Report, we looked at ethnic-sounding names on resumes.

Natural Language Processing (NLP): a form of AI that allows machines the ability to read, to understand, and to interpret human language.

Talent acquisition: the process of hiring (often with algorithmic tools) sourcing, screening, and selecting candidates.

Talent intelligence: the process where companies use AI to collect and analyze data regarding talent and skills.

12 Organizations



This Report was prepared over the course of four months (August - November 2023) by impactmania. For more information and biographies of the team members: <https://www.impactmania.com/im/ai-hiring-eu/>. Or email info@impactmania.com. The Project is part of the Initiative: Fairness and Intersectional Non-Discrimination in Human Recommendation <https://cordis.europa.eu/project/id/101070212>.

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DISCLAIMER

This Report has been carefully crafted using a blend of existing research, external sources, and both open-source and proprietary systems, deemed accurate and reliable as of the time of writing. It is important to note that while we strive for accuracy and completeness, we cannot guarantee these aspects. This Report is not to be construed as constituting a representation or warranty, and all involved stakeholders shall not be held liable or responsible for any errors or omissions therein.

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APPENDIX B

1 EU AI Act

The European Union's "Ethics Guidelines for Trustworthy AI" delineates seven governance principles: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, nondiscrimination and fairness, (6) environmental and societal well-being, and (7) accountability.

https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence?&at_campaign=20226-Digital&at_medium=Google_Ads&at_platform=Search&at_creation=RSA&at_goal=TR_G&at_advertiser=Webcomm&at_audience=ai%20legislation&at_topic=Artificial_intelligence_Act&at_location=DE&gclid=Cj0KCQjw9fqkBhDSARIsAHlcQYSCGxAEvgVRMEXmPyMNdyjkk9jy_rZUX5w6RYP-KT4A4ZvvHLalluYaApGREALw_wcB

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2 OECD AI Policy Observatory. Compromise Amendments on the Draft Report Proposal for a regulation of the European Parliament and of the Council on harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts. September 2023. European Parliament Committee on the Internal Market and Consumer Protection Committee on Civil Liberties, Justice and Home Affairs. <https://oecd.ai/en/>.

3 ISO 9000

The ISO 9000 family is a set of five quality management systems (QMS) standards by the International Organization for Standardization (ISO) that help organizations ensure they meet customer and other stakeholder needs within statutory and regulatory requirements related to a product or service. https://en.wikipedia.org/wiki/ISO_9000.

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<https://www.onelogin.com/learn/what-is-soc-2#:~:text=SOC%20%2C%20aka%20Service%20Organization,data%20in%20a%20secure%20manner>.

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Appendix A - Project Manager Job Description

The Project's job posting and resume upload function were published on <https://www.impactmania.com/im/ai-hiring-eu/>.

Job Description: Project Manager

Position Overview

As a Project Manager, you will play a pivotal role in planning, executing, and delivering projects on time, within scope, and within budget. With your strong organizational and communication skills, you will lead cross-functional teams, collaborate with stakeholders, and ensure the seamless implementation of our initiatives.

Key Responsibilities

- Develop comprehensive project plans that outline project scope, objectives, tasks, timelines, resources, and budget requirements.
- Lead and motivate cross-functional teams, assigning tasks, setting priorities, and ensuring clear communication channels throughout the project lifecycle.
- Communicate effectively with internal and external stakeholders, managing their expectations and providing regular updates on project progress.
- Identify potential risks, develop mitigation strategies, and address issues as they arise to ensure projects stay on track.
- Monitor project budgets and expenses, tracking costs and making adjustments as necessary to maintain financial targets.
- Maintain a high standard of quality in project deliverables, ensuring they meet or exceed client expectations.

- Create and maintain detailed project documentation, including project plans, status reports, meeting minutes, and other relevant records.
- Facilitate change management processes as required, ensuring smooth transitions for stakeholders affected by project changes.
- Contribute to the refinement of project management processes and best practices, striving for greater efficiency and effectiveness.

Qualifications

- Bachelor's degree or equivalent practical experience.
- Excellent communication, interpersonal, and leadership skills.
- Demonstrated ability to manage multiple projects simultaneously and prioritize effectively.
- Problem-solving mindset with a keen eye for detail.
- Solid organizational and time management skills.

Appendix B - Participants

Breakdown of Resumes Received through Project Landing Page

Incoming resume upload	Demography	Category based on manual selecton	Talent Acquisition notes
1	Migrant Female	B	No PM experience
2	Migrant Male	A	Experience, Consulting Experience
3	Migrant Female	B	Technology entrepreneur, venture and BD; no client experience
4	Migrant Female	C	Not enough experience, junior profile
5		C	No PM Experience, Finance Background
6	Migrant Female	A	Experience and training
7	Migrant Female	A	PM Experience, PM training or certification
8	Migrant Male	B	Analytical, PM, Might be too Senior or too technical and lack soft skills
9	Migrant Male	B	Analytical, PM, Might be too Senior or too technical and lack soft skills
10	Migrant Male	B	Good experience, but Business Dev focus, might be not engaged after a short time
11	Migrant Male	B	More Product than Project Management
12		B	Marketing Profile, Not PM Experiences
13		A	PM Experience
14		C	No PM experience, no PM training or certification
15		B	
16	Migrant Female	A	PM experience, Client Mangement experience, might be too senior -> salary expectations
17		B	Junior Profile, if we would be open for Junior PM would be interesting, would need to check with HM
18		B	Business Development backgorund, might not be engaged for a long time
19		B	Brand, Product Management
20	Migrant Male	B	Experience in managing many
21	Migrant Female	B	PM experience, right soft skills
22		C	No relevant experience
23	Migrant Female	A	Consulting experience, Client Management, but might be too senior
24		A	Experiences as PM and Program M
25	Migrant Male	B	Interesting, BD focus, might not be engaged after a short time
26		B	Tech, no client management
27		B	Marketing, Start-Up, BD
28		C	"Senior Leadership" experience, might be bored with this job
29		C	No relevant experience
30		C	Messy CV, no time to read that much and search for relevant info
31	Migrant Female	B	BD and entrepreneurship focus
32		B	BD and entrepreneurship focus
33	Migrant Female	B	Law backgorund, senior expert, no pm expertise
34		B	Engineering, no PM experience
35		B	Entrepreneurshio, no PM background
36		A	PM and colsulting experience, Client Management
37	Migrant Male	B	No PM experience, Investment and Product focus
38	Migrant Male	C	Technical Profile
39	Migrant Female	C	UX Designer
40	Migrant Female	C	CV is not convincing, dates are missing, summary not compelling
41	Migrant Female	C	No relevant experience
42		C	No relevant experience
43		C	No relevant experience
44	Migrant Female	B	More Tech Agile than PM
45		B	No PM experience
46		B	No PM experience
47	Migrant Female	A	PM experience, might be too senior - > salary expectations
48	Migrant Female	C	PM experience, Creative Profile

Breakdown of Resumes Received through Project Landing Page

Incoming resume upload	Demography	Category based on manual selecton	Talent Acquisition notes
49		B	Experience not in Corporate environment
50		C	Tech, BD, Entrepreneurship
51		A	PM experience,
52		C	No PM experience
53	Migrant Female	B	Not clear what experiences are relevant, no discription
54		B	No relevant experience, No PM certification
55		C	No relevant experience, No PM certification
56		C	No relevant experience, No PM certification
57	Migrant Male	C	Entreprenerial profile, no PM certification
58		C	Too Senior profile, won't match salary expectations, worked as PM 20+ years ago
59		C	No relevant experience
60		C	No relevant experience
61		C	No relevant experience, No PM certification
62	Migrant Female	C	No relevant experience, No PM certification
63		C	No relevant experience, No PM certification
64	Migrant Female	C	Can't read the CV, not in English or German
65	Migrant Female	C	No relevant experience, No PM certification
66	Migrant Male	A	PM experience, mentions PM skills on CV
67	Migrant Male	C	No PM experience
68	Migrant Female	C	No PM experience, no PM tools mentioned
69		B	Comms experience relevant, but no PM experience
70		C	Technical Profile, No PM experience, no certification
71	Migrant Male	C	Technical Profile, No PM experience, no certification
72		B	A few relevant experiences, no PM job before
73		A	Relevant PM experience and PM training, horrible CV
74		B	Few relevant experiences, no PM certification
75		B	Not enough experience in PM, no PM training
76		B	No relevant experience
77	Migrant Male	C	No relevant experience, horrible CV
78	Migrant Male	C	No relevant experience, no PM training
79	Migrant Female	C	No relevant experience, no PM training
80		A	Relevant PM experience and PM training
81		C	No relevant experience, no PM training or certification
82		C	No relevant experience, no PM training or certification
83	Migrant Female	C	No relevant experience, no PM training or certification
84		C	No relevant experience, no PM training or certification
85		B	More technical profile
86		C	No relevant experience, no PM training or certification
87	Migrant Male	C	No relevant experience, no PM training or certification
88	Migrant Male	A	Relevant experience

Breakdown of Resumes Received through Project Landing Page

40 total Migrants with non-European sounding names:
23 Migrant Females with non-European sounding names,
17 Migrant Males with non-European sounding names.

A total of 23 Participants from 1:1 Interviews, three (3) Focus Groups,
and Questionnaire

- | | |
|--------------------------------|--------------------------------|
| 1. M. (female, non-native) | 13. H. (female, non-native) |
| 2. V. (female, non-native) | 14. M. (male, non-native) |
| 3. M. (female, non-native) | 15. E. (female, non-native) |
| 4. N. (female, native) | 16. J. (female, non-native) |
| 5. P. (male, non-native) | 17. I. (female, German native) |
| 6. M. (female, non-native) | 18. H. (female, non-native) |
| 7. A. (female, non-native) | 19. D. (female, non-native) |
| 8. E. (female, non-native) | 20. C. (female, German native) |
| 9. M. (female, non-native) | 21. E. (female, non-native) |
| 10. M. (female, non-native) | 22. D. (female, non-native) |
| 11. C. (female, non-native) | 23. Z. (male, non-native) |
| 12. J. (female, German native) | |

Appendix C - EU AI Act

The forthcoming EU AI Act ¹, expected to be fully effective in 2026, is a comprehensive law that regulates the use of AI systems in the European Union. Taking a risk-based approach, AI systems that are considered 'high-risk' will need to implement a range of requirements to comply with the Act. This includes, but is not limited to, measures for AI governance, quality management (QMS), technical documentation, risk management as well as post-market monitoring.

To a large degree the EU AI Act has been designed based on the guidance of the Organisation for Economic Co-operation and Development (OECD) ² as well as standards organizations such as International Organization for Standardization (ISO) ³. While comprehensive in scope, the aim is to align the AI Act as much as possible with existing regulations and standards to minimize additional admin burden. Here the EU government suggests, for example, that organizations which already have ISO 9001 certification for their Quality Management System (QMS,) ensures compliance with the Act's QMS requirements as well, given that the scope encompasses the AI system. Service Organization Control Type 2 (SOC 2) ⁴ is a popular American information security standard. Its European counterpart is ISO 27001. Both are broad in scope, however ISO 27001 is more popular in Europe and internationally and can be implemented by any type of organization, whereas SOC 2 is popular in the U.S. and specifically for Business-to-Business (B2B) Software as a Service (SaaS) providers.

¹ EU AI Act

The European Union's "Ethics Guidelines for Trustworthy AI" delineates seven governance principles: (1) human agency and oversight, (2) technical robustness and safety, (3) privacy and data governance, (4) transparency, (5) diversity, nondiscrimination and fairness, (6) environmental and societal well-being, and (7) accountability.

[https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence?&at_campaign=20226-Digital&at_medium=Google_Ads&at_platform=Search&at_creation=RSA&at_goal=TR_G&at_advertiser=Webcomm&at_audience=ai%20legislation&at_topic=Artificial_intelligence_Act&at_location=DE&gclid=Cj0KCQjw9fqkBhDSARIsAHlcQYSCGx](https://www.europarl.europa.eu/news/en/headlines/society/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence?&at_campaign=20226-Digital&at_medium=Google_Ads&at_platform=Search&at_creation=RSA&at_goal=TR_G&at_advertiser=Webcomm&at_audience=ai%20legislation&at_topic=Artificial_intelligence_Act&at_location=DE&gclid=Cj0KCQjw9fqkBhDSARIsAHlcQYSCGxAEvgVRMEXmPyMNdyjkk9jy_rZUX5w6RYP-KT4A4ZvvHLalluYaApGREALw_wcB)

<https://www.europarl.europa.eu/news/en/press-room/20230505IPR84904/ai-act-a-step-closer-to-the-first-rules-on-artificial-intelligence>

Revised proposal of EU AI Act from EU Parliament, including provision that ISO 9001 certified companies, have a compliant QMS according to the Acts requirements: https://www.europarl.europa.eu/meetdocs/2014_2019/plmrep/COMMITTEES/CJ40/DV/2023/05-11/ConsolidatedCA_IMCOLIBE_AI_ACT_EN.pdf (see page 25). NB: This is a draft version; the final text is currently under review.

² OECD AI Policy Observatory. Compromise Amendments on the Draft Report Proposal for a regulation of the European Parliament and of the Council on harmonized rules on Artificial Intelligence (Artificial Intelligence Act) and amending certain Union Legislative Acts. September 2023. European Parliament Committee on the Internal Market and Consumer Protection Committee on Civil Liberties, Justice and Home Affairs. <https://oecd.ai/en/>.

³ ISO 9000

The ISO 9000 family is a set of five quality management systems (QMS) standards by the International Organization for Standardization (ISO) that help organizations ensure they meet customer and other stakeholder needs within statutory and regulatory requirements related to a product or service.

https://en.wikipedia.org/wiki/ISO_9000.

⁴ Service Organization Control Type 2 (SOC 2)

SOC2 is a cybersecurity compliance framework developed by the American Institute of Certified Public Accountants (AICPA). The primary purpose of SOC 2 is to ensure that third-party service providers store and process client data in a secure manner.

<https://www.onelogin.com/learn/what-is-soc-2#:~:text=SOC%20%2C%20aka%20Service%20Organization,data%20in%20a%20secure%20manner.>

White House Executive Order

Then, on October 30, 2023, the U.S. President Biden issued an Executive Order on safe, secure, and trustworthy Artificial Intelligence:

The Executive Order addresses Workers in a specific section: “Develop principles and best practices to mitigate the harms and maximize the benefits of AI for workers — by providing guidance to prevent employers from undercompensating workers, evaluating job applications unfairly, or impinging on workers’ ability to organize.”⁵

Based on input from one of the Project’s advisors, companies often refrain from providing feedback on resumes due to concerns about potential legal consequences. The General Act on Equal Treatment (AGG) in Germany has only been in place since 18 August 2006. The Act is to prevent or to stop discrimination on the grounds of race or ethnic origin, gender, religion or belief, disability, age or sexual orientation.⁶

⁵ “FACT SHEET: President Biden Issues Executive Order on Safe, Secure, and Trustworthy Artificial Intelligence” United States of America White House Briefing Room, October 30, 2023. <https://www.whitehouse.gov/briefing-room/statements-releases/2023/10/30/fact-sheet-president-biden-issues-executive-order-on-safe-secure-and-trustworthy-artificial-intelligence/>

⁶ Sommer, Maureen Roycroft. Translated by Lisa Gow. “Guide to the General Equal Treatment Act: Explanations and Examples.” Antidiskriminierungsstelle des Bundes, November 2019. https://www.antidiskriminierungsstelle.de/SharedDocs/downloads/EN/publikationen/agg_wegweiser_engl_guide_to_the_general_equal_treatment_act.pdf?__blob=publicationFile

Appendix D – Experiment II

Date

October 2023

Performed by

Hartley Jean-Aimee, Sabrina Palme,
Andre Quintanilha

Test Topic

CV AI Scanner Scoring for “Hidden” Bias

Test variables

Defined by Test Team:

- Type of protected attribute
- Number of subtle attributes

Defined by PAM:

- Subtle attributes
- Size of reference data set
- Size of subtle attribute data set
- Distribution of local vs. international CVs

Variables

Protected Attribute	Migrant vs. Native (local vs. international)
Subtle Attribute	Language Proficiency, Overseas Work Experience, International Education
# of Subtle Attributes tested	3
Total Data Set Size	100
Local CVs	60
International CVs	40
Reference Data Set Size	25
Language Proficiency Data Set Size	25
Overseas Work Experience	25
International Education	25

Results from Tukey's HSD test:

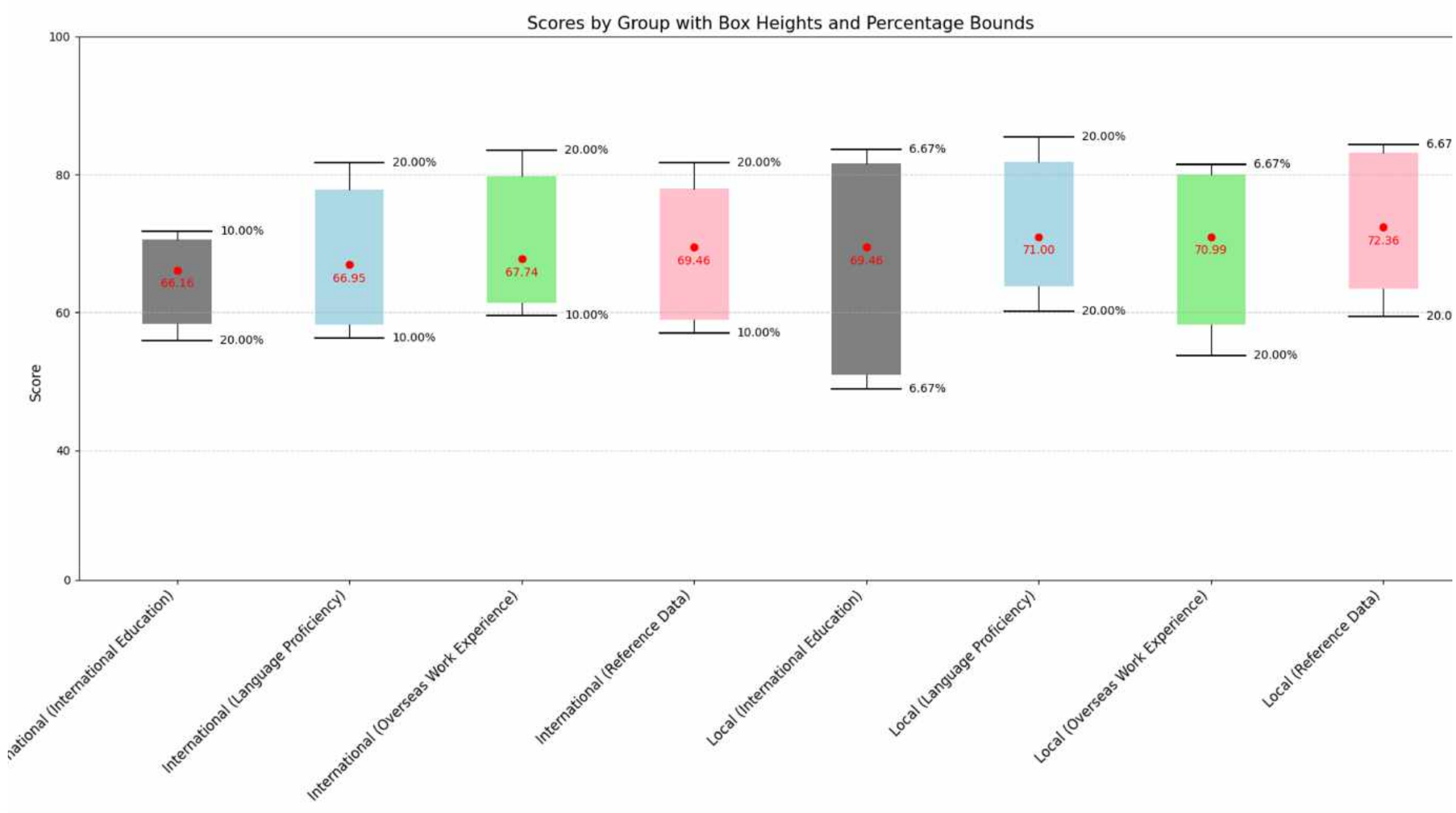
Group Comparisons	Mean Difference	Lower Bound	Upper Bound	Significance
Intl no Subtle - Intl with Subtle	2.51	0.28	4.74	Yes
Intl no Subtle - Local no Subtle	-2.90	-6.05	0.25	No
Intl no Subtle - Local with Subtle	-1.03	-3.30	1.24	No
Intl with Subtle - Local no Subtle	-5.41	-8.49	-2.34	Yes
Intl with Subtle - Local with Subtle	-3.54	-5.74	-1.34	Yes
Local no Subtle - Local with Subtle	1.87	-0.18	3.93	No

Subtle Attribute Comparison for International and Local Resumes

Average and Median Score Comparison based on Subtle Attributes and Migrant Status

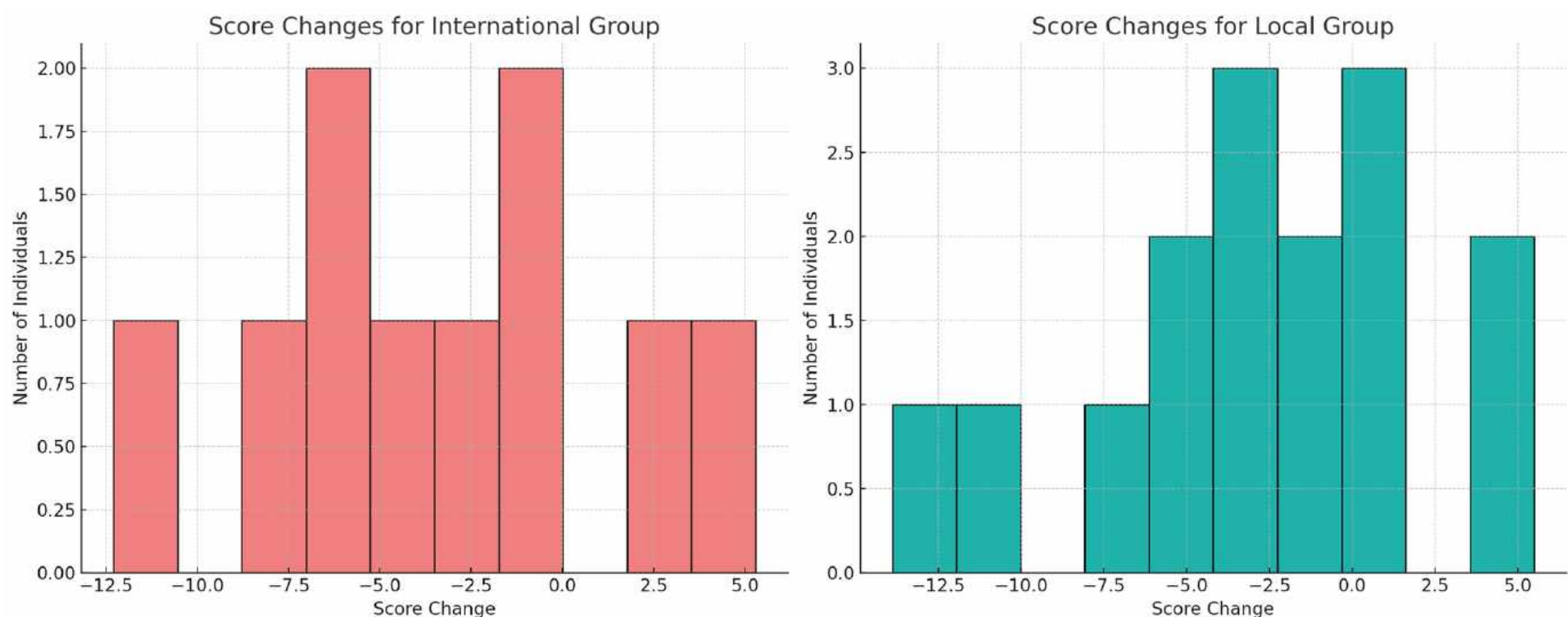
Subtle Attribute Key	Migrant Status	Average Score	Median Score
None (Reference Data)	International	69.46	69.54
None (Reference Data)	Local	72.36	73.25
International Education	International	66.16	67.04
International Education	Local	69.46	71.89
Language Proficiency	International	66.95	65.89
Language Proficiency	Local	71.00	70.12
Overseas Work Experience	International	67.74	65.56
Overseas Work Experience	Local	71.00	72.52

Standard-Deviation Bar Plot Chart



Analysis of “International Education” Subtle Attribute

The histograms below give a visual representation of the score fluctuations for both local and international applicants when comparing the reference resume to the resume with the inclusion of the "International Education" attribute.



- For **international applicants**, most of the score changes are negative (i.e., a decrease in score).
- For **local applicants**, the distribution is slightly more varied, but there's still a predominant decrease in scores.

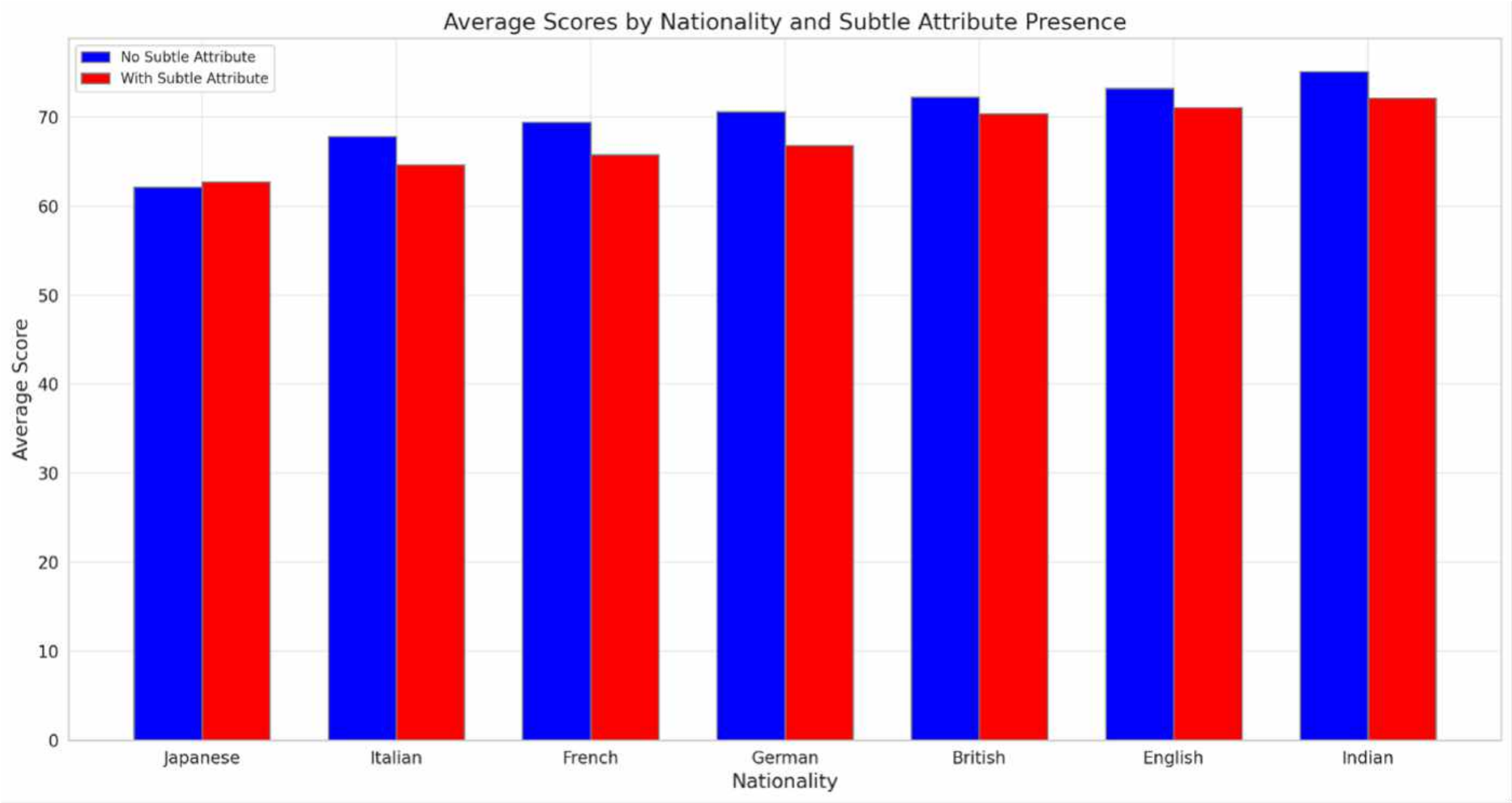
Influence of Nationality on Scores

Scores for each Nationality by Subtle Attribute:

The table below compares the average scores for each nationality, considering the subtle attributes incorporated into the resumes.

Nationality	Language Proficiency	International Education	Overseas Work Experience
British	70.98	69.50	70.69
English	71.11	69.16	72.97
French	65.89	67.04	64.37
German	65.07	69.90	65.36
Indian	73.25	68.11	75.10
Italian	66.44	62.10	65.41
Japanese	60.00	64.51	63.58

Influence of Nationality on Scores



Ideal Experimental Setup

This page describes the ideal experimental setup needed to test the Biases in ATSs considering them as a Black Box.

We would like to detect and show bias in ATS tracking systems.

- By showing that theoretically there will always be bias, even if it is reduced.
- By finding individual examples that give different results after simple masking or more intricate input manipulation (thus proving it is not unbiased towards individuals)
 - By showing that it is super easy to manipulate the ranking by changing the output. (We would be showing the system is not robust)
- By showing that ATS systems are on a group level more discriminatory than our “ground truth” aka the ranking made by the recruiter team. (We will likely find this to be true because our recruiters are biased in favor of the marginalized groups).
- By zooming out to look at the whole AI pipeline. The introduction of power imbalance into data science. (Or, more accurately, describe the lack thereof). Justice, equity, equality and fairness aren’t the same.
 - Feeling like you are discriminated against, is already enough to harm marginalized personas in the hiring process; for instance, I do not reply to tech functions through ATS systems anymore because at some point I realized I was discriminated against.

Input

A set of M application tracking systems $S = \{S_1, \dots, S_M\}$,

A set of K editable job descriptions $J = \{J_1, J_2, \dots, J_K\}$,

A set of N editable pdf resumes $R = \{R_1, \dots, R_N\}$,

with $M, K, N \in \mathbb{N}$

Output

There are several output options, depending on the ATS used.

Option 1. A full ranking of all resumes

Let the set of all permutations of R be denoted by $\text{Perm}(R)$. An ATS could output a ranking of R , denoted by $\sigma \in \text{Perm}(R)$, with

$$\text{Perm}(R) = \{ \sigma: R \rightarrow R \mid \sigma \text{ is a bijection} \}.$$

Option 2. A set of k (unordered) resumes

Let the powerset of R be denoted by $\mathcal{P}(R)$, this powerset contains all possible subsets of R . An ATS could output the top- k resumes. We define $\mathcal{P}_k(R)$ as the subset of all possible subsets of R with cardinality k .

Can also be seen as a binary mapping on each individual resume R_i .

Option 3. A set of k (ordered) resumes

More or less a combination of the two described above. A subset of k resumes (option 2), which is ranked (option 1).

Mathematical description of ATS tracking

We can view an ATS as a black box algorithm that inputs the set of job descriptions and the set of resumes, and outputs a ranking of R for each of the job descriptions in J .

For a job description J_k , we will use a tracking system S_j .



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