EXPLORING THE IMPACT OF THE ALGORITHMS ON MANAGEMENT HIRING DECISION AND BIAS

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ABSTRACT

This research seeks to grasp the effect that trust in algorithm word has on the decisions made by hiring managers when it comes to selecting candidates. Specifically, this research will focus on whether trust in algorithms affects how much emphasis hiring managers put on important traits such as Experience, Education, and Qualifications. Ultimately, the goal of this research is to assess whether algorithm formulas or traditional assessment methods are currently producing better hires for organizations. Understanding the impact of trust in algorithms will help determine which method is best for employers to use moving forward. Also, how managers cope with bias and what role they play during the hiring selection. The data collected from the experiment will help identify and analyze Artificial Intelligence's impact on hiring managers' decisions. The study will also use the data from the experiment to test the hypothesis. Ultimately, this will help us to determine if Artificial Intelligence can reduce bias in the recruitment process and provide employers with more accurate insights into applicants' abilities. This study is expected to lead to more efficient and effective use of Artificial Intelligence in recruitment while helping employers make more informed decisions. We hope this research will pave the way for a more equitable hiring process by reducing bias and providing an objective evaluation of applicants' abilities. By having such a variety of diversity in Industries, Race and Gender, this research is a piece of real world that every employer can replicate for their hiring or training employees. We look forward to seeing how AI can improve the recruitment process. By accurately assessing applicants and considering their abilities, employers can make informed decisions that benefit both applicants and employers.

To my loving family, Paraskevas, Panagiotis Arber, Paris Bexhet & Aggelos Jon,

your love and support gave me wings!

To all Unicorn women that can do it all. You can have a family,

a career and achieve your dreams.

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CHAPTER 1

BIAS IN HIRING

Introduction

Artificial Intelligence is the go-to tool for hiring and selecting talent in almost every company nowadays. To escape the labeling of discrimination and chances of bias, CEOs of companies turned to the shiniest and most attractive "savor" Artificial Intelligence algorithms. Big corporations are spending millions of dollars on algorithms that are not perfect and reflect more bias. Lawsuits and payout settlements show that AI brings different issues to our corporate world: more calculated hidden discriminations and bias. According to MIT Sloan Management Review (2023), the risks are more real and abundant as AI becomes more powerful. Google Gemini is the most recent example of inaccurate historical portray such as a woman pope, African Nazis, and Vikings with Asian features. Misuse or errors will place companies on reputational damages with financial losses and legal issues. Managerial bias is another layer of concern. Most companies in the USA do not have much diversity because of conscious or unconscious bias, which resides in their consciousness, making them hire the same group of people. According to Baker, Larcker et al, (2023) studies show discrepancies between reports some companies provide regarding DEI and their hiring practices. They pretend they are increasing diversity, so their clients see them as compassionate and increase their investments. Also, some managers have more trust in AI than others and that tends to be an issue as well. EU countries have already started building laws to protect against these issues and the USA is following in its steps. Ongoing work from legislators, scholars, and industry professionals is necessary to address these concerns.

Measuring the impact and risks of AI will tackle future issues and prepare us for the unknown (Smuha, Ahmed-Rengers, et al, 2021). Policies and guidelines need to be instituted to ensure that AI is developed and employed in a way that respects ethical boundaries and societal norms. There must also be rigorous, ongoing scrutiny of AI-related practices to ensure they remain fair and non-discriminatory, especially in domains as crucial as hiring. Technically, Algorithms aim to weed out candidates who may display undesirable behaviors or characteristics that could potentially negatively impact the company. They should help reduce the bias inherent in hiring decisions by providing a more objective and data-driven approach. While AI algorithms can be an invaluable tool for companies looking to recruit and retain top talent, there is also the potential for these algorithms to introduce more bias into the hiring process.

In his book, Dastin (2022) points out the importance of not looking at AI as the holy grail but ensuring the data used is fresh and that more inclusive language is used for the algorithms. We should also investigate bias in selection. If the AI algorithms are trained on historical hiring data, they might perpetuate biases against certain groups. This could worsen inequality instead of helping to eliminate it. The first issue would be invasion of Privacy. AI tools may analyze candidates' online presence or personal data to assess fit, which raises privacy issues. The second issue would be lack of human touch. According to Lindquist & Dautaj, (2021) AI lacks the human touch and that brings doubt in people. Reliance on AI could lead to a dehumanized hiring process, missing nuances and qualities only human interactions can reveal. Finally, accountability in decision-making. It is essential to have clear lines of accountability when AI is used in hiring, especially in the case of legal challenges regarding unfair practices.

For example, algorithms may privilege types of candidates based on their demographic characteristics or educational background, which could lead to a lack of diversity in the company's workforce. Unfortunately, Diversity Disparity in High-Power Sectors is the challenge. According to Washington (2020), our society must have DEI programs to ensure diversity is enforced and calculated. Across various industries, a stark contrast persists between the diversity in the universities. These settings and the homogeneity are evident within the professional workforce. This disconnect suggests an underlying systemic issue, particularly in investment banking, information technology, and pharmaceuticals. While universities churn out a diverse array of graduates, many sectors remain dominated by Caucasian males, with reports indicating over 90% representation in some fields. That draws the question to why CEO are not doing more work on building a diverse environment in their corporation? Do they not see it important enough?

Investment banking, traditionally seen as a bastion for the elite, continues to grapple with diversity disparity. The high-paced, high-stress environment paired with the legacy of exclusivity has perpetuated a workforce that skews heavily towards Caucasian males. However, according to Ely & Thomas, (2020) lack of advance in diversity in industries shows that many CEO do not see it compelling or beneficial. Despite diverse programs and initiatives, this sector needs help to reflect the multi-dimensional nature of the business world. The IT sector, often perceived as the face of modern innovation, paradoxically remains among the least diverse. Women and minorities are significantly underrepresented, particularly in leadership and technical roles. This industry's culture, recruitment practices, and educational outreach have all been criticized for favoring a narrow demographic.

Like its fellow sectors, the pharmaceutical industry is predominantly Caucasian, and male dominated. From research and development to executive leadership, the influence of diversity is scarce, raising concerns about whose interests these drugs serve and who benefits from the wealth of this lucrative industry. The overwhelming factor contributing to the lack of diversity across these sectors is bias. Whether conscious or unconscious, bias influences hiring practices, promotions, and workplace culture. It manifests in various forms, and it is important for companies to identify them and correct their actions. Ignoring the fact that the pharmaceutical industry requires diversity can no longer be afforded by executives of these companies per Damm-Ganamet, DesJarlais, et al. (2020).

Despite these challenges, companies are increasingly turning to AI algorithms as an effective way to improve their hiring practices and reduce bias. By carefully analyzing and optimizing their algorithms over time, companies can maximize the benefits of AI while minimizing any discriminatory effects. According to Benbya, Pachidi, & Jarvenpaa, (2021) companies can accomplish all business goals such as automation of the process, innovation and insight decision making. With continued innovation in this area, we can look forward to a future where hiring algorithms help companies select candidates, based on their qualifications and skills rather than outdated assumptions or stereotypes. These practices have become the norm in the past decade as companies feel overwhelmed by the number of candidates and the need to reduce mundane procedures. Many researchers have been interested in the past few years in looking into the pros and cons of using algorithms and how to recognize the bias from hiring managers. Their findings have contradictory results, and some create more smoke than clarity.

This research aims to see if the Artificial Intelligence algorithm word would trigger something in hiring managers. Do they trust algorithms or ignore them and continue engaging based on their experience and gut feeling? The research is based on an experiment run in two groups called (Treatment and Controlled). Both groups are presented with the same job description and the same five candidates. The position "we are hiring " is Analyst, Equity research. This position is an entry-level position in the Equity Group. It requires an advanced degree such as Masters in Finance, Economics, Data Science, or Computer Science. 2-5 Years of experience in quantitative research and portfolio management. Solid programming skills in Python and SQL. Also, a must is knowledge of Financial Statements and regulatory filings. The resumes for the five candidates are made up of experiences for the study but purposely instructed to have unique names from different races and genders in order to highlight and identify any bias.

Our first candidate's name is Juan Gonzales. He is of Latino heritage and has a Ph.D. in mathematics, CFA-licensed, FINRA Licenses, Computer Programming and Coding Certificates. He was a Vice President and Chief Investment Officer for Bank of America and has ten years of experience at the executive level. Juan Gonzales is not only highly educated but bilingual and with experience in the international arena. This shows that he is a dedicated individual constantly learning and improving himself. Someone with a diverse skill set could be an asset to any company.

Our second candidate, Mike Chung, is a highly qualified candidate with a diverse background. In addition to his Chinese heritage, he holds a master's degree in mathematics and finance technology. This unique combination of skills gives him an edge in programming and quantitative analysis. With six years of experience in various Investment firms, Mike has developed a strong understanding of the industry and its ever-changing landscape. He can analyze market trends and make informed decisions based on data-driven insights. His ability to think critically and problem-solve has made him an asset in his previous roles.

Our third candidate is Latisha Nzeribe. She is of African heritage. She holds a master's in mathematics and finance and programming skills in Python, Stata, MySqlr, and other programs. She has three years of experience in Investment companies and has worked on various projects.

Latisha is a highly skilled and experienced candidate who brings a unique perspective. She has lived in Nigeria for most of her life. She has an extensive understanding of African culture, which can be valuable in international companies looking to expand their reach into African market.

In addition to her cultural background, Latisha has impressive academic credentials and strong analytical and problem-solving skills. This makes her a valuable asset for any company looking to make data-driven decisions.

Our fourth candidate is David Bennet. He is Caucasian, born and raised in Maine. He has a bachelor's degree in computer science and mathematics and two years of experience in entry-level software company positions. David is an ambitious and driven individual who is always seeking to expand his knowledge and skills in computer science.

During his two years at the software company, David worked on various projects, from web to mobile app development. He also gained experience in programming languages like Java, Python, and C++.

Our fifth candidate is Amanda Johnson. She is Caucasian, born in Boston, Massachusetts. She holds a bachelor's degree in financial mathematics. She has no programming experience and has two years of internship at a bank. Amanda Johnson's background in financial mathematics has given her a strong foundation in critical thinking and analytical skills. With her experience working in the banking system, she possesses practical knowledge and valuable financial exposure. As an aspiring programmer with no coding experience, Amanda brings a fresh perspective to the field by combining her mathematical expertise with a willingness to learn and adapt.

The Control group was told that a Human Resource Manager hand-selected the five candidates and The Treatment group was told that an AI algorithm selected the five candidates based on the job description requirement. They were presented with the job description first to see the requirements and what the job entails and then review each candidate one at a time. The interview questions asked to both groups were semi-constructive. They were asked to provide a confirmation on if they were bringing in the candidate for a second round of interview or not and based on what qualifications Education, Experience or Both. Overall, algorithms can potentially improve hiring selection and reduce bias in selection processes. AI recruiting gives companies a competitive advantage (Black, Esch, 2020). However, many questions remain about how this can be accomplished and what factors need to be considered. Whether managers embrace these new technologies or not, the future of AI in hiring will undoubtedly continue to impact how companies select and recruit their employees.

Therefore, we ask:

RQ 1- To what extent is there a bias in hiring managers before AI word is mentioned?

Human instinct often pushes us towards familiar people, ideas, and beliefs. However, when hiring a candidate for an important position, are employers doing their due diligence? Most companies in the USA have a higher percentage of Caucasians and more men, and even some departments don't have diversity at all, and that applies to gender, ethnicity, and race. Diversity is vital when companies want their employees to feel part of an inclusive environment. (Byrd & Scott, 2024). How is that possible in a country that fosters the best universities in the world with students from different parts of the world? Are they casting the broadest possible net, or do certain conscious or unconscious biases already exist in managerial hiring decisions before AI algorithms enter the equation? Do they prefer to fill the position internally because of people they know or feel they are a good fit due to cultural adaptation? Are managers only hiring people with limited skills for the position, or are they looking at other candidates with more complex skills? Do managers only hire candidates that look, and sound like them? Do they associate diversity with future problems in a team? It is worth examining these questions to ensure that positions get filled based on transparency instead of entrenched doubts.

According to Hardy Tey, Cyrus-Lai, Martell, Olstad, & Uhlmann (2022), there are many biases in managers' decisions specifically for those managers that have been in the industry for several years. The dangerous habit these managers inherit when being in the industry for many years is that they are used to specific sets of teams and how a corporation should look and sound. How dynamics are played, and who should be considered for particular roles. Companies often recruit from a narrow pool of universities or through networks that need more diversity. As employees recommend and refer individuals like themselves, these practices reinforce homogeneous hiring. Biases affect how performance is perceived and who is considered 'leadership material.' Consequently, the upper echelons of these sectors remain homogenous as majority groups continue to promote from within their ranks. Corporate culture often caters to the majority, creating an exclusive workplace that can be alienating or hostile to those who do not fit the mold. This can deter diverse candidates from applying or staying in these industries. The goal of companies should be creating value to the organization by including different groups of people. (Moon, Christensen 2020)

Human Resource departments need to work on shaping things around and changing the norm. They need to stop searching their candidate's online social media profiles and post or ask for their salary history or any other questions related to personal information. Social media data should not be used in the hiring process. Information found in social media can reveal ethnicity, gender, disability status, family status, and other information that could be a liability for HR. In her article, Chang (2012) brought in examples of some applicants' experiences that went to the extreme, as there were reports that hiring managers were asking applicants to provide passwords for their social media.

Some handed in the passwords and watched the hiring managers turn around and log in to their Facebook accounts. These managers read private messages and public posts out loud in the applicant's presence by invading their privacy and considering it a 'necessity'.

That is another form of adding biases in hiring and the possibility of discrimination. After reading those posts, we cannot say the information did not impact the manager's opinion about hiring the candidate. It could have doubled the manager's bias by knowing more than they needed to know about the candidate. These are situations that companies need to be aware of because they would harm their reputation and build more discrimination in the hiring process. Equip hiring managers and HR personnel with the necessary training to recognize and overcome unconscious biases, fostering a culture of inclusivity. Review hiring data and processes regularly to detect and address any patterns indicating potential discrimination. This includes tracking the diversity of applicant pools and new hires. According to Hargittai (2020), managers say it was easy to find when asked why they chose to see a candidate's social media content. However, knowing little about the content of what candidates refer to makes it a problem and a liability for the company. The picture below shows factors that build more bias in managerial decisions.

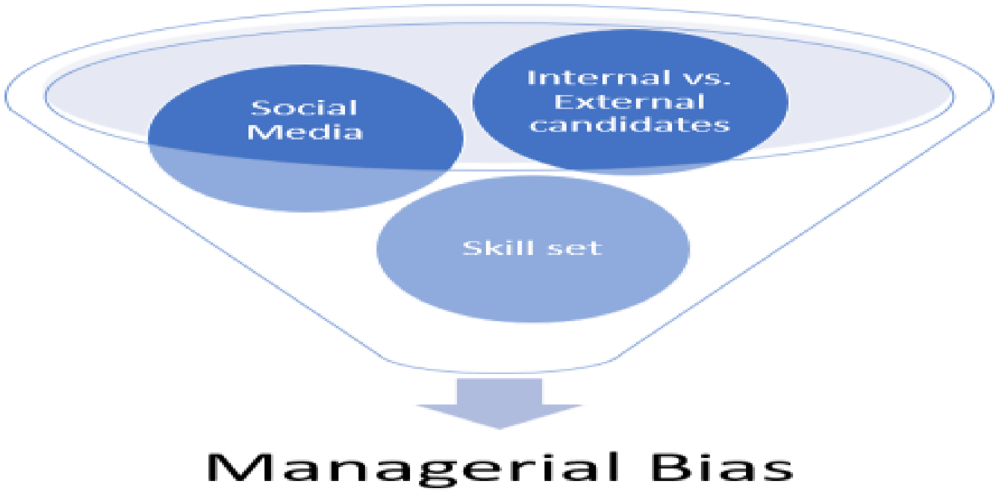

Figure 1. Factors That Make Up Managerial Bias

RQ 2 - How does the word Artificial Intelligence algorithm impact the managers' hiring decision-making?

AI algorithms are becoming an increasingly prominent peak in the future of hiring, but how do managers respond to this significant shift? Many can be uncomfortable entrusting recruitment decisions with a machine - and understandably so. However, those who understand AI's capabilities and want to improve automation (Glikson and Woolley, 2020) will likely find it hugely impactful in their decision-making process, while others may choose to neglect its potential among candidates altogether. This research is expected to contribute to the literature regarding managerial decision-making and the impact of AI algorithms as a tool. There is a lot of interest in companies and how their Human Resource Departments continue their hiring process. Further, this will show in more detail how seasoned managers decide on future candidates for their team. If they choose the candidates based on the company's needs or the comfort level, they feel with the candidate's background or maybe how they fit “the box”.

The practitioners must keep attracting talented candidates while having effective team communication (Demir, McNeese & Cookee, 2017) and ensure that they are not discriminating against certain groups. With university environments teeming with a rich tapestry of genders and races, industries must reflect on their practices and commit to fostering diversity within their realms. As society recognizes the value of diverse perspectives in driving innovation and performance, industries must shift from complacency to action in dismantling the biases that maintain the status quo. We can only reconcile the disparities and create an equitable and thriving professional landscape. Diversity in thought, experience, and background is not merely a moral imperative—it is a proven business advantage, and it is high time that every sector treats it as such.

Avoiding reputation risks associated with hiring discrimination is imperative for any company. It requires a concerted effort to ensure fair, unbiased recruitment practices while continuing to foster a corporate culture grounded in equality and respect. Recognizing potential dangers, implementing preventive strategies, and frequently reviewing hiring processes are vital to maintaining and enhancing a company's reputation. Overall, using algorithms in hiring processes can help companies eradicate bias while still effectively evaluating and selecting candidates based on their skills and qualifications. Many studies show that AI is impacting hiring decision-making globally (Nahar, 2024). By understanding algorithms, managers can make more informed decisions about who to hire, leading to a more diverse and inclusive workforce that meets the needs of today's globalized economy. Ultimately, algorithms have the potential to improve hiring decisions and help companies thrive in today's rapidly changing business landscape.

Artificial Intelligence in Hiring

"Governing AI poses a set of interwoven challenges. These challenges begin with agreeing on what AI is." (Cheng, Varshney & Liu, 2021, p. 1). Artificial Intelligence machineries are made of algorithms and data. Algorithms are designed and integrated by developers. Developers have become increasingly integral in the world of Artificial Intelligence (AI) as algorithms are designed and integrated to create powerful machinery. Companies have been relying heavily on algorithms to run their systems and thus have sought developers to assist them in building faster selection processes that use specific criteria, such as skills, education level, years of experience and industry knowledge. This shift has allowed AI applications to make more efficient decisions while providing accurate results with improved speed. As algorithms become more sophisticated, developers will need to create and monitor algorithms to ensure they are performing properly and efficiently.

The foundation of a trustworthy and fair algorithm rests on thorough validation. Bartosiak and Modlinski (2022) highlight the importance of coworkers being harsher when evaluating their peers when the algorithm suggests disciplinary actions, which shows they are affected by the algorithm and probably do not consider other factors. It indicates that if that algorithm has built-in bias, it harms the team. We need to be able to trust the AI algorithms. Companies seeking to maintain the integrity of their algorithms, particularly those employed in critical decision-making processes such as candidate selection, must engage in a diligent algorithm validation process. To attain this level of thoroughness, companies are increasingly considering the engagement of independent contractors. These experts bring an external perspective invaluable for confirming the algorithm's purposes and scrutinizing the data unbiasedly. The objective is to validate the algorithm's functionality and guarantee that it operates fairly, consistently, and without inherent biases that could lead to discrimination. Below, we outline the goals and contractor qualifications essential for an effective algorithm validation process.

The algorithm should perform as intended, without moral impact (Bigman & Gray, 2018) meeting the predefined requirements set by the company. It should produce results that are in line with the goals, accurately reflecting the parameters and constraints defined during its development. The algorithm must be free from biases that could potentially discriminate against certain groups or individuals. This includes but is not limited to racial, gender, and socio-economic biases. The validation process should scrutinize various aspects of the algorithm to identify any form of discrimination coded, whether intentionally or inadvertently. Professionals tasked with this crucial responsibility should have the following qualifications. A profound understanding of algorithms is paramount. Contractors should possess relevant experience in developing, deploying, and evaluating complex algorithmic solutions. They must be well-versed in machine learning, artificial intelligence, and data analytics. More is needed to understand how an algorithm function. Contractors must also have strong analytical skills to discern patterns and implications in the data, predicting how diverse scenarios might impact the algorithm's behavior. The ability to give unbiased assessments is critical. Contractors must prove a history of objective evaluation practices and a commitment to neutrality to ensure that personal beliefs or external pressures do not sway their work.

Algorithms are only as good as the data they process with chances of them being hostile. (Maninger & Shank, 2022). A thorough understanding of data collection, cleansing, and management practices is necessary. Contractors should be skilled in evaluating the datasets for completeness, representativeness, and potential contamination that could bias the output. As guardians of fair practices, they must uphold the highest ethical standards, ensuring that validation processes are transparent and adhere to societal norms and legal requirements regarding discrimination and fairness. By achieving these validation goals and engaging qualified independent contractors, companies can move closer to employing algorithms that are fair, unbiased, and aligned with ethical employment practices. This will contribute to the fairness of automated systems and enhance public trust in using such advanced technologies within critical sectors.

Our next important component in hiring is job postings. It is fundamental for the recruitment process; it provides the employers with greater control over managing the selection of candidates. According to (Samek, Squicciarini, & Cammeraat, 2021), AI demand has increased in all sectors of industries. Such algorithms can extract essential details from applicants, including skills, Education and Experience that match those required for the role. Thanks to this technology, companies can identify suitable applicants more quickly and efficiently than non-automated processes. Simply entering all pertinent data into an online form allows job seekers an opportunity to be presented before management personnel with relevant information that meets the organization's requirements. By leveraging these technologies, businesses can generate a robust candidate pipeline in minimal timeframes.

"Recruitment activities include writing job descriptions, posting job advertisements, or scouting potential candidates by evaluating resumes" (Li, Lassiter, Oh & Lee, 2021, p.167). The tasks AI suggested to assist are candidate sourcing, the discovery of these candidates, outreach screening for the skills, and ranking of the qualified candidates. Once a hiring company posts its job description, applications float in, and selecting the candidates through hundreds and thousands of resumes can be a real challenge and overwhelming due to the volume. Additional tasks to automate with AI are the interview scheduling for prospective hires and sending reminders or follow-ups—engaging in communication with candidates and doing background checks. Based on feedback from managers, AI can discover future positions or candidates within the company that can be a good fit. Many companies also prefer to have templates of offer letters and submit them via AI.

Based on several experimental studies by other scholars with the increase of social concerns and reported cases, there is a need to discover more about the possibility of collaboration between sophisticated AI algorithms and hiring managers. According to Dell'Acqua (2022), managers prefer to have AI inform humans, but if it is justified, they will override the algorithms. In other words, have them as a tool to understand a large amount of data but not in complete control of decision making. It is a valid reason to pursue this research by looking into previous solutions provided by others. Inclusivity has been a goal for many companies in the past few years.

With the rise of social media, there is more pressure than ever to make sure everyone feels equal. Technology is seen as a revolutionary tool that can help assist the audience by enhancing good behavior and showing more positive thinking that would drive inclusivity. However, some studies have suggested that AI can make conceptual models of AI collaboration to create a more inclusive environment. The use of technology is encouraged and seen to help everyone feel included. Inclusivity is essential because it creates a feeling of belonging and drives innovation. When everyone feels included, they are more likely to be creative and come up with new ideas. Inclusivity is essential for companies because it helps create a strong community and drives innovation. (Aytemiz, Shu, Hu & Smith, 2020).

In previous studies, white male pictures were coming up when people searched for a CEO candidate. Historically, companies had more white male CEOs than other races or females, but over a decade now, boards and leadership have shifted to be more inclusive by hiring women and other races. Also, another example was the jobseekers search on Google. If the search engine sensed that a female job seeker was searching, it produced fewer ads and positions than when a male searcher was looking and reported lower pay for women. Many online data showed that men make more money than women, proving the lower pay search results. Xu, Mu& Liu (2017) state, "In recent years, with the development and maturation of such technologies as cloud computing, big data, and deep learning, the industrialization of artificial intelligence (AI) has been developed accordingly." (pg. 1) This raises many questions about how much has improved and whether it is for the best.

CHAPTER 2

LITERATURE REVIEW

Research on AI in hiring has yielded mixed results. Some academics have raised concerns about the potential for algorithm bias, while others suggest that AI can be a valuable tool if used carefully. "While rapid advances in artificial intelligence (AI) hiring tools promise to transform the workplace, these algorithms risk exacerbating existing biases against marginalized groups." (Tilmes, 2022, p.1). Research indicates that AI may be more accurate than human reviewers in identifying high-quality candidates. In the past few years, AI has improved and grown rapidly. We also see high competition in the industry, with CEOs of companies like CHATGPT, OpenAI, and Google introducing new features and improved versions of their products. However, algorithm design is complex, and data quality can vary significantly from one dataset to another. Below are some of the papers reviewed.

In their paper, Upadhyay & Khandelwal (2018) point out efficiency and positive impact in the recruitment process with AI assistance that would benefit the companies and the candidates. They mention more perks, such as automation of repetitive tasks handled by AI, will give the recruiters more time to build relationships with applicants. Another suggestion is scanning social media and collecting other information about candidates not included in the application or resume. These are advantages to the hiring team to know more about their personality and other traits. Also, according to the article, "AI is intelligently programmed to avoid unconscious bias. AI-powered systems can ignore the primary source of bias like names, schools attended, gender, age, and race." (p 257). Upadhyay and Khandelwal's (2018) findings on using AI in recruitment are valuable in providing employers with solid evidence supporting the use of AI to create a fairer system that focuses on individual potential. The high volume of processed applications has brought many changes to the competition by increasing revenue, profitability, and candidate acquisition. However, the negative impacts of this technology are experienced by some candidates who have been left anxious and even paranoid about their chances of being hired. Overall, the authors offer a glimpse into a future where AI can create a more efficient and effective recruitment process.

Dattner, Chamorro-Premuzic, Buchband & Schettler's article focuses on the potential backlash this new technology can have on the privacy of job seekers. The authors raise the question of how easy it is to cross the line between legal and illegal use of this information. They argue that even if this information is available online, it is not ethical to use it and might bring legal issues for the companies. Using the place of birth, native language, and race is a liability for the company if the applicant does not want to provide them voluntarily. The authors bring up several valid points about the dangers of this new technology and its potential to invade the privacy of job seekers. While this new technology has the potential to be very helpful for companies, it is crucial to be aware of the risks involved in using it. (Dattner, Chamorro-Premuzic,Buchband & Schettler,2019) "Facebook and Twitter often show people's intelligence and personality, including their dark side and sexual preferences" (pg. 4).

Efficiency and Positive Impact

Concerns have been raised that using artificial intelligence (AI) in hiring may lead to selection bias. According to (Deshpande, Pan, & Foulds, 2020), studies and many field experiments have shown the effect and presence of bias in workplaces from managers or automated systems. The trick is how to overcome this challenge in the future. AI systems are often trained on data sets that contain human bias, which can be perpetrated in the predictions made by the AI system. In the European Union, a law protects individual privacy, limiting personal data use in hiring decisions. The United States does not have a similar law; therefore, it is more challenging to regulate the use of AI in hiring. Some experts have advised against using AI in hiring as it may increase selection bias. However, others argue that AI can be used to reduce bias in hiring by providing objective criteria for selection. Ultimately, it is up to each company to decide whether to use AI in their hiring process.

Yarger, Playton, and Neupane's paper critically analyze potential bias in software applications used in AI. The paper first suggests that bias can already be embedded in the algorithms and the data population. To address this issue, the authors suggest that data scientists and software engineers must ensure design choices' consistency. They must ensure that design choices reflect a broader context of society so that they are diverse. The paper further suggests lacking diversity will bring more class, Gender, and race disparities. Some additional suggestions include adding more assurance layers and new techniques to secure an unbiased process. "Talent acquisition is the long-term planning approach for finding and acquiring skilled specialists to meet organizational labor requirements." (p.2)

Privacy Issues

In conclusion, the paper offers a critical analysis of potential bias in software applications used in AI. "Feminist thought and methods can aid in providing an ethical and moral compass for designing and auditing AI systems." (p. 10). The paper provides valuable suggestions on how to address this issue. The paper argues that AI brings potential harms to the table through discriminatory practices and unequal access to opportunity. The authors suggest ways to mitigate these risks, chief among them being increased transparency and accountability in AI development and implementation. They also recommend measures to promote inclusivity in the workforce, such as removing indicators of Gender, race, and other protected status from job applications.

While these suggestions are well-intentioned, it is vital to consider the potential unintended consequences. For example, anonymizing the job application process may disadvantage marginalized groups relying on personal connections to secure employment. Similarly, while blind skill testing may seem like a fair way to assess candidates, it could inadvertently perpetuate existing inequalities if designed and administered to favor particular groups. As such, companies need to address any effort that risks associated with AI must be carefully planned and diligently executed to avoid exacerbating existing social tensions. As Han points out in her paper review, companies considering using AI as a recruiting tool need to be aware of the potential challenges that come with it. One of these challenges is the risk of discrimination cases, damaging a company's reputation.

Potential Bias

Programmers can help prevent this by ensuring that data used in previous algorithms is not contaminated and that new data is applied. Constant training for the HR management team on bias can also help prevent discrimination issues. Companies can use AI as a successful recruiting tool by being aware of these potential challenges and taking steps to avoid them. "As your company decides if using AI as a recruiting tool might increase effectiveness, do not just smell the roses. Consider the thorns and how much they might prick" (p 4). Due diligence is the recipe for successful hiring. Programmers have been training machines to do their work for them since the 1950s; it was not until recently that algorithms began to play such a prominent role in the hiring process.

Thanks to the advent of artificial intelligence (AI), hiring teams now have access to many tools to help them identify and select the most qualified candidates; however, many concerns are also addressed. "As these new technologies significantly impact people's lives and careers but often trigger ethical concerns, the ethicality of these AI applications needs to be comprehensively understood." (Hunkenschroer & Luetge, 2022, p. 1) One of the most popular AI-based hiring tools is an applicant tracking system (ATS), which uses natural language processing (NLP) to extract critical information from resumes and job descriptions. ATS systems are often criticized for their masculine-sounding language, discouraging female candidates from applying for certain positions. However, there is evidence that these systems can be trained to use more gender-neutral language. Another criticism of AI-based hiring tools is that they require minimal training for HR representatives. However, this criticism is undermined because most AI-based hiring tools have comprehensive user manuals and online tutorials.

Competitive Advantage

Eubanks (2022) stresses that we must be open-minded about AI. In conclusion, AI gives hiring teams a competitive advantage in several tasks, including screening resumes, identifying qualified candidates, and reducing unconscious bias. As long as the teams welcome AI, many benefits will create a fruitful collaboration among them. All these papers bring many facts, benefits, pros, cons, and uncertainties that our society faces now in the workforce. We see conservatives and liberals trying to make their points for their concerns. It is impossible not to address them first or use them as a foundation to understand where we want to see the future heading toward a more sophisticated and unbiased reality. These issues are impacting individuals' futures financially, morally, and psychologically. Feeling underrepresented or not good enough does numbers with morals.

"According to the World Economic Forum's 2022 Global Gender Gap Report, only 31% of leadership positions globally are held by women, and workplace gender parity is declining." (Newstead, Eager & Wilson, 2023, p. 2). The glass cliff is defined as when women are given leadership roles during uncertain times in a company, and if the plans fail, the blame is on them. It happens because leadership sees them as fragile, emotional, and incompetent. Studies have shown that companies choose men over women during difficult times for those positions regardless of the skills or experience needed. Women are then left with anxiety, self-doubt, and survivor guilt when the company bounces back up. Companies need to change their mindset and give everyone an equal chance regardless of gender identity. We have seen outstanding performances by women leaders during pandemic times, which shows that they're just as competent, if not more than men, in leadership roles.

The impact of artificial intelligence on society is a hotly debated topic. While some believe AI will lead to greater efficiency and progress, others worry it will cause mass unemployment and create new social divides. There is no doubt that AI is already having an impact on the world of work. In recent years, we have seen a rapid increase in the use of AI in recruitment, with many companies now using algorithms to screen job applicants. It has led to concerns that AI may favor certain groups of people over others, for example, those with higher levels of education or who come from privileged backgrounds. Some also argue that AI could lead to Mass unemployment as machines increasingly replace human workers. (Khan, 2022)

Artificial Intelligence machines amplify race, Gender, disability, and our abilities and behavior. We should consider AI as an intelligent automation to enhance the high selection performance of candidates. (Vrotis, Christofi & et al 2022) However, it is worth noting that previous technological revolutions have also led to rapid changes in the labor market. While there have been some negative impacts, such as increased inequality, these changes have been positive for society. Therefore, while some risks are associated with adopting AI, it is essential to remember that the potential benefits far outweigh the negatives. Many questions are raised, such as: How can we let AI decide the future of humans? How can a computer know more than a manager about what is needed in their team? Can human decision-making be enough to trust in hiring? How did companies evolve so far without AI? How can everyone understand how algorithms work? Can we even tell when they fail when we have a lot of data?

Race and Gender Amplification

All these questions are addressed differently by everyone. It is a global war for talent regarding recruiting methods (Chen, 2023). It is no secret that different generations have different strengths and weaknesses. For example, those born before 2000 tend to be better at strategic thinking, while those born afterward rely more on technology. However, it is essential to remember that each generation has something to offer. Just because someone is younger doesn't mean they are automatically less capable than those older. Our society tends to resist change, even when that change is for the best. Instead of looking at different generations with suspicion or mistrust, we should learn to embrace our differences and work together for the common good.

Literature Gap

The infiltration of Artificial Intelligence (AI) in recruitment processes has been substantial, almost unnoticeable, and often without the full awareness of the individuals who may count on its accuracy and fairness – the hiring managers. In the literature on AI and human resources, a gap exists, not in the application of AI but in understanding the trust that hiring managers place in these technologies. With a vast array of automated processes, such as filtering, ranking, and sometimes even interviewing potential candidates, it is imperative to ask: Do hiring managers believe in the decisions suggested by AI algorithms? Are they aware of the extent of AI's role in their hiring decisions? What factors influence the level of trust that hiring managers have in AI-powered recruitment tools?

We want to drill down into the level of experience or exposure they had during their career and how confident they are in trusting algorithms they didn't build or data they didn't vet. Also, another important part of the study is the gender and race indicators. Do they pay attention to the names on the resumes or even try to guess their Gender or ethnicity? Observation and questions will be part of the interview with each participant. Open questions will help me identify the source of each manager's hiring method. In conducting such research, we aim to close the trust gap, allowing AI to be used more effectively and ethically in hiring. The findings can help design transparent, understandable, and trusted AI systems by those who rely upon them for hiring talented individuals.

CHAPTER 3

STUDY 1

Measurement Map

The map measurement below portrays the relationship and the outcome of both hypotheses concerning AI selection. According to Fan, Cheng, et al (2017) maps help visualize studies and provide some future expectations. In our case it will help visualize what we can expect from both Hypotheses. What will be the results, and how will the candidates' hiring process be expected to go? The map measurement will help us recognize the possible outcome in a more simple and organized way. It can be very beneficial for HR professionals since it helps them to decide which of the two hypotheses is most suitable for their company. Ultimately, this approach could lead to better and more successful candidate selection processes in future hirings.

Furthermore, this map measurement also serves as a tool to analyze the pros and cons of both Hypotheses. It can provide HR professionals with more details on which one of the Hypotheses is more suitable for their company's candidate selection process and give them an easy way to compare both possibilities. In addition to that, it also enables HR professionals to identify any potential risks associated with the decisions they make. Mapping designs can help to build priorities for the studies. (Schaid, Chen & Larson, 2018). This can be especially beneficial for HR professionals in ensuring that their candidate selection process is efficient, effective, and safe. The mapping measurement can help us understand how different outcomes are related to AI selection and help HR professionals streamline and optimize their recruitment processes.

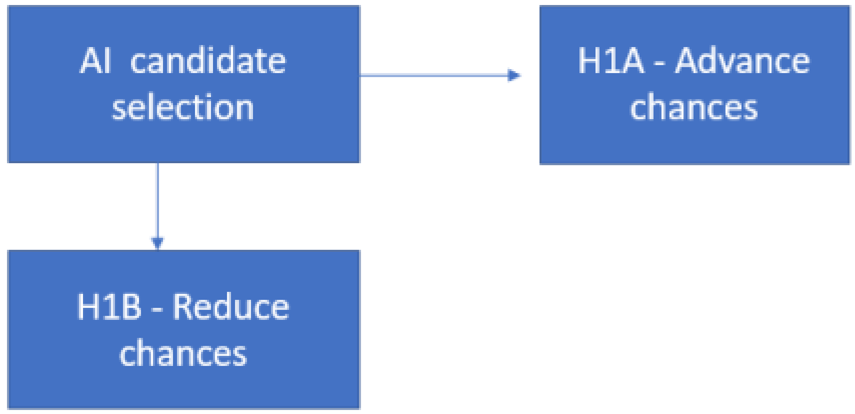

Figure 2. Measurement Map for The Proposed Study

Hypotheses

H1A – Candidates recommended by algorithm have a greater chance to advance in the hiring process than ones recommended by human HR managers.

Based on this Hypothesis, the data will show if managers' trust in the algorithm drives their hiring desires in candidates. Depending on their experience and confidence in AI, people tend to use and prefer the outcome from algorithms rather than human intervention. Their confidence could be a result of the awareness of discrimination. So, algorithms have the potential to help eliminate bias and discrimination while providing a fair and unbiased decision-making criterion. There is growing evidence that algorithms are increasingly used in managerial decisions, particularly regarding hiring and candidate selection. While this may seem like a positive development, there are concerns about whether algorithms drive managers' trust in algorithms and whether this trust in algorithms may lead to managers preferentially hiring algorithms over candidates. According to Porter & Donthu (2006), a great number of people put more trust in technology to avoid bias.

Some might even consider AI has disrupted the HR process. (Minbaeva, 2021). At the heart of this debate is whether algorithms are objective and unbiased or if they introduce bias into decisions that can have far-reaching consequences for businesses and individuals. While some argue that algorithms can be free from human prejudice and discrimination, others claim that algorithms are inherently biased by the data used to create them. Whether algorithms drive managers' trust in algorithms and decisions remains an open question. However, algorithms will continue to play a growing role in managerial decision-making in the years to come, and their impact on hiring decisions must be carefully considered.

H1B – Candidates recommended by algorithm have a lower chance of advancing in the hiring process than those recommended by human HR managers.

Based on this Hypothesis, the data will show that if managers hire candidates selected by an algorithm, they do not understand or trust and rely on their judgment. The algorithms used in the hiring process are based on various criteria, including skills, experience, and qualifications. While these algorithms may effectively identify candidates with the potential to succeed in a given role, they may not always consider other factors crucial to an employee's success, such as work-life balance or cultural fit. As such, HR managers need to continue to rely on their judgment when evaluating potential hires rather than simply trusting algorithms' recommendations. By doing so, they can ensure that the best candidates are selected for each position and ultimately improve the quality of their organization overall. According to Lee (2018), "With the algorithmic evaluation decisions, most participants expressed negative emotion. Some responses suggested that the fact that a machine evaluated a person was demeaning and disrespectful" p (11).

On their journal description, Chen, Chen, Pittman, et al. (2022), mentioned that many years of experience in managerial roles lessens the bias. Also, with years of experience, these managers create an independent decision-making process based on their gut feeling. While algorithms may help narrow down candidates based on their qualifications, it is up to HR managers to weigh all the factors and make the final decision. Ultimately, this ensures that the best candidates are selected for each position and helps companies succeed. So, suppose you're looking to build a successful career in human resources. In that case, it's essential to continue developing your skills and experience while relying on your instincts when evaluating potential hires. For experienced managers, it is second nature when it comes to selecting people to hire on their team. First, they know their managerial style and have seen the people's personalities and skills that work with their style. It sounds selfish and may be selfish in some ways, but their goal is to build a team that will work according to their style and complete the projects in the future. Higher management only measures performance based on the successful completion of projects.

In an era where data is hailed as the ultimate oracle, tempering this faith with human judgment is essential. A manager's role is not to replicate the machines' cold, calculated decision-making but to complement it with their human faculties. Some research shows that policies and other regulations impact hiring managers' decisions (Araten-Bergman, 2016). Organizations thrive only by understanding and respecting each other's capabilities—algorithms and arithmetic on one side, intuition, and experience on the other. To disregard the value of intuition is to strip the workplace of an element that, combined with data-driven insights, can transform good decisions into great ones. We must remember that while data may guide us, human wisdom often lights the way forward. In a world that demands efficiency and precision, we must not forget the immeasurable value of the manager's intuition. It is, after all, their unique human touch in the otherwise binary domain of decision-making.

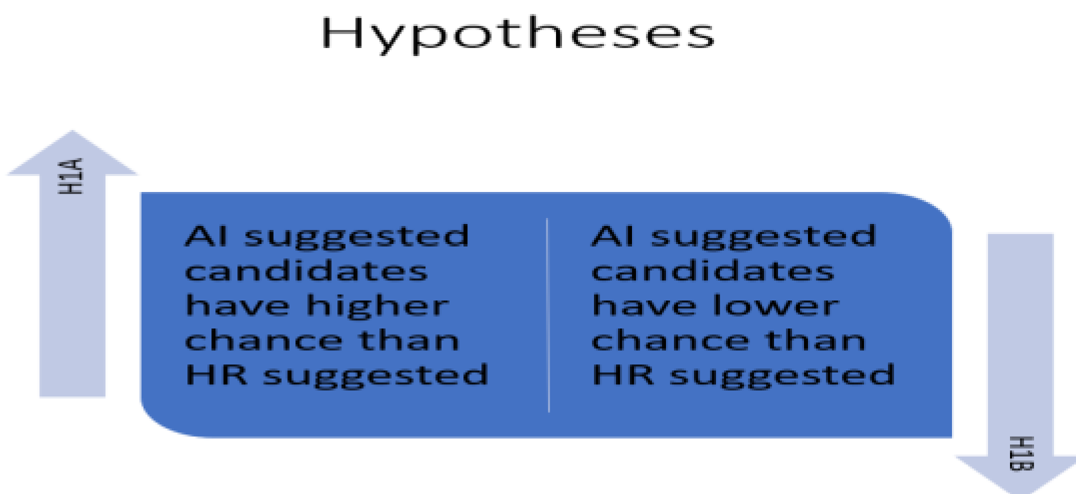

Figure 3. Hypotheses Suggestions

Methodology – Study Design and Procedures

Empirical Method and data Sources for this research is based on an experiment done in two groups. Each group has 30 participants. These participants are a mix of seasoned managers from different industries, genders, and races. The first group is called the Controlled Group. This group is told that the HR manager handpicked the applicants as suitable candidates. Would you bring them in for a second round of Interviews? The second group is the Treatment group. This group is told that applicants were chosen by an algorithm used by the company's HR department. Would you bring them in for a second round of Interviews? The same job description is presented with five resumes to both groups. The three stages of this experiment are aiming to discover three aspects. How do managers decide when they are told that AI is selecting vs HR? Do they try to guess certain features of the applicants, such as ethnicity or Gender, or do they look strictly at the qualifications? The job description and five candidates resume used for the experiment are listed in the appendix. The experiment focuses on three variables listed below:

- AI vs. No AI
- Race
- Gender

Information collected on the participants includes the industry they are working in, their current Title, Years in managerial positions, their group age, Gender, and Race. A brief open questions conversation is to establish their trust in AI algorithms, such as their percentage amount of trust in AI. Based on their response, the follow up question is if their trust based on their research or experience, and to elaborate more to get a good sense of where they stand with algorithms? Also, I asked if their work is impacted by AI and what do they think about it.

Data Collection

The methods used to recruit the respondents for the research to gather data are essential steps in the research process. Selecting the right participants for the study is crucial to ensure that we obtain reliable and relevant data. The recruitment process involves identifying and inviting potential participants to participate in the research. The first step is to define the target population, which refers to individuals with similar characteristics that align with the research objectives. This could include age, gender, occupation, or other demographic information.

According to Canals (2017), selecting the correct group of participants is essential to studies because academics must ensure the participants meet the requirements and will bring in many inputs for the study. So far, participants have been from large Investment companies such as Fidelity Investment, State Street Financial Services, Putnam Investment, and PanAgora Asset Management—pharmaceutical companies such as Takeda, Merck, and Novo Nordisk. Technology industries include Boston Technologies, Broadridge Technology, Axis Technology, and Universities such as Suffolk University, Boston College, Temple University, and Boston University. Many Doctorate Students at Temple University are in their first and second year and are EDBA students. Diversity was a priority regarding Gender, race, and industry. Also, a handful of participants were from nonprofit organizations.

These industries and participants were used mainly because I worked in the sectors and am familiar with how they think and approach hiring. Also, they have managed people for over a year, qualifying them as hiring managers. Having experience managing and hiring people is one of the critical criteria of this research. Also, having these managers replicate the methods and logic they use in their everyday work is the best example of how corporations hire. These industries and participants were chosen as they are highly competitive markets with a high demand for skilled professionals. Furthermore, these sectors have seen rapid growth in recent years and have become attractive for job seekers. The fact that participants are experienced managers makes it easier for anyone in the future to replicate the experiment for their hiring process. To have an innovation process in hiring, executives must find hiring managers who influence organizational performance. (Sing, Gupta et al, 2021)

In addition, the individuals working in these industries possess diverse skills essential for any hiring manager. These include effective communication, problem-solving abilities, and leadership skills. These industries also require individuals to be adaptable and have a strong work ethic, making them highly desirable for hiring managers. Moreover, working in these industries has exposed these participants to different business models and strategies, allowing them to understand the complexities and challenges of running a successful organization. This experience makes them well-equipped to identify top talent that can contribute positively to a company's growth. Managers who have hired people for an extensive period are the best participants. With time, their hiring skills have improved drastically (Chan & Wang, 2018). Overall, these industries and participants provide valuable insights into the hiring process and the qualities that employers look for in potential candidates. Their experience and expertise make them credible sources for discussing effective hiring practices and tips for job seekers looking to stand out in competitive markets. As such, their input is essential for creating a comprehensive guide for both hiring managers and job seekers alike.

Every participant was asked in person if they were interested in participating in a study on how AI is involved in the hiring process and how it affects the participants and the new hires. They were made aware of the anonymity of data and how this study will contribute to companies hiring in the future. As a result, all participants agreed to participate in the study, which provided valuable insights into their experiences with AI in hiring. Some mentioned feeling intimidated by being evaluated by an algorithm rather than a human, while others expressed concerns about potential biases in AI-powered systems. Some managers feel intimidated by AI and risk losing their future jobs to AI. (Cao, Duan, et al 2021). The data collected from these participants revealed that AI is widely used in hiring. All interviews are done the same way in person.

Data Analysis

The study is focused on the data collected from the experiment. The interviews were conducted in person to ensure that all factors could be observed and accounted for. Each interview lasted between 30-40 minutes, providing ample time to gather necessary information. A conference room was booked for each meeting, and the participants were asked not to use their phones or any other distractions during the process. Furthermore, conducting the experimentation in a controlled setting allowed for consistent results (Fabijan, Dmitriev, et al. 2017). This was essential in analyzing the data and drawing conclusions. The conference room also provided a neutral environment for the participants to make their decisions without any external influences. It is important to note that the participants were asked not to use their phones or other distractions during the process. This was to ensure that they could focus solely on the task at hand and avoid any bias or external factors influencing their decision.

They were presented with the job description, and once the description was read, each resume was given one at a time to be reviewed. The participants were asked to decide if they would bring them in for a second round of interviews or not. Each decision was described as based on meeting the requirements for education, experience, or both. In the meantime, during the experiment, every participant was observed, and notes were kept if they made any comments trying to identify gender, ethnicity, their education level, school even languages they spoke, or anything related to the candidates based on the name placed in the resume. Once they had finished their decision for all resumes, the material was put aside, and they were asked if they noticed the name on top of the resume. Did they try to guess the gender or ethnicity of the applicant based on the information listed on the resume? Was their opinion about the candidates changed in anyway after they saw their education, schools they attended or qualifications.

The experiment highlighted the bias that can exist or gets build up in the hiring process, where decisions are often influenced by factors such as name, gender, or ethnicity rather than education or experience. This is a critical issue to address, especially in today's diverse and inclusive workplaces. Companies need to recognize this unconscious bias and actively work towards reducing it. Employers should focus on evaluating candidates based on their qualifications, skills, and experience instead of superficial factors such as name or appearance. One way to address this issue is by implementing blind hiring practices, where personal information such as name, gender, and ethnicity are removed from resumes before they are reviewed. This ensures that candidates are evaluated solely on their abilities and qualifications, promoting a fair and equal opportunity for all applicants. Moreover, companies can provide training and education for their hiring managers to recognize and overcome unconscious bias. On their study Flory, Leibbrandt, et al, (2021) removed all identifiers of the applicant as a result the companies managed to hire more diversity but also showed productivity and innovation. Practices similar to this study including workshops, seminars, or diversity training programs can educate employees on the importance of fair hiring practices and encourage them to evaluate candidates objectively.

Education alone did not necessarily mean they would automatically be accepted; several other factors, such as job experience, communication skills, and even the resume format, could influence their decisions. Furthermore, it became evident that each participant had a different set of criteria and strategy to determine who they would bring in for an interview to join their team. Their Gender and age were leading factors in how they decided. Human Resources has experienced a real evolution since the introduction of AI (Votto, Valecha & et al. 2021). The fact that Artificial Intelligence has been in the news lately has brought more insight information to the public and each employee. Almost all participants knew that AI is always involved in selecting the candidate at some point in the hiring process, either in the beginning or middle of the process. Their companies have been using algorithms for over a decade, so this was no news to them.

Overall, the data collected, and analysis generated from this experiment provided an excellent opportunity to learn more about how people make decisions when evaluating potential employees. Organizations can use studies as an example to build workplaces where employees feel inclusive. Woods & Tharakan, (2021) highlight the importance of these studies to be used to identify areas of improvement in current recruitment processes or even to create new strategies that will help companies find the best-qualified applicants and increase their chances of success. Furthermore, the data can be used to continue researching how individuals make decisions in various contexts. Analysis from research into recruitment decision-making provide compelling opportunities for companies to re-evaluate and fine-tune their recruitment processes. By adopting a more empirical approach and continuing to research decision-making, companies can better identify areas for improvement and develop cutting-edge strategies to attract the most qualified candidates, ultimately fostering tremendous company success and innovation. This data can be utilized by companies looking to gain insight into what factors affect the selection of job candidates for their organization.

Results

The data collected from the experiment on the Controlled and Treatment Groups had a total number of participants (N=60). Each group had (N=30) participants from different backgrounds of ethnicity such as (Africans, African Americans, Asians, Asian Indians, Middle Eastern, Latinos, European Caucasians, American-born Caucasians, Cape Verde, Caribbean), Gender (Male & Female), professions (Professors, Head of Departments, CEO, Scientists, Directors, Attorneys, Sales, Architects) and industries such as (Investment, Education, Biotech, Advertisement, Consulting, Science & Technology, Telecom, Banking, Transportation). Experiments need to have a large number of diversities to have more inclusive and vital results. (Tiwarim, 2022).

Variable	Definition
Controlled group	Is the group of participants that were told the resumes were selected by a HR Manager.
Treatment Group	Is the group of participants that were told the resumes were selected by a AI algorithm.
Years in Industry	Number of years in managing other employees.
Age	Group age
Gender	Female / Male
Race	African, African - American, Asian, Caucasian, Cape Verdean, Caribbean, Indian, Latino, Middle Eastern
Trust in AI	Establish the trust participants had in AI and algorithm in general.
Admitted	When participants admitted they saw the names and tried to guess gender, ethnicity, and race.
Denied and became defensive	During observation, participants tried to guess out loud the gender, ethnicity but when asked in the end, denied and became defensive.

Table 1. Variable Definitions

Participation

During our conversation, the first item to establish was the trust in AI algorithms among all participants. How much do they trust AI algorithms in hiring the selection of candidates? Due to AI being so much on the news, almost every participant knew their companies used third-party vendors with algorithms in the earlier candidate selection steps. We noticed that male participants had a higher trust percentage than female participants, regardless of the industry, their understanding of AI, or how much AI was involved in their day-to-day activities. The Gender of participants' trust stood out. Women tended to have a deficient level of trust. They expressed doubts about AI efficiency and fairness. If they could not understand a tool, they felt vulnerable to accepting its results without having a way to verify the data or the algorithm. According to Gillespie, Lockey, Curtis, Pool, and Akbari (2023), the general public lacks awareness of how much AI is involved in everyday activities; however, a high interest has been shown lately in learning to understand and use it to improve their life. Also, our other interesting results were when looking at the results on race, Caucasian vs Others in both groups Treatment and Controlled there was no significant indicator on trusting AI.

Regarding guessing the Gender and ethnicity, both groups and both genders had the same results. They all tried to think and imagine the person on the other side of that resume. There was no difference between Caucasians vs. Other regarding AI trust. They tried to guess based on the name listed on the resume. It is an indication that automatically, the moment the brain is introduced to an identification factor about someone on the other side of the resume, it will start guessing the information about the applicant. According to Kristal, Nicks et al. (2023), "blinding" resumes would be the best approach to avoid any discrimination that could happen from bias created. Our study has shown the same results for Caucasians vs. Other. One factor that stood out was the group age of Caucasians 20-40 became defensive and denied reading names; the rest admitted and elaborated as a normal brain activity however absolutely would not affect their hiring decision. We noticed that qualifications were always a priority for all participants. The table below shows the results of the observation.

Variables	Independent Varianles	Observation Results
Treateatement Group		
Gender	Female vs. Male	Female participants showed a low level of trust in AI. Male participants expressed higher trust in AI.
Race	Caucasian vs. Other	Race has not been a big indicator in AI trust.
Gender & Ethnicity guessing	Female vs. Male	Both genders tried to guess the applicants gender and ethinicty.
Gender & Ethnicity guessing	Caucasian vs. Other	Caucasians ages 20-40 were more prone to deny and become defencive. Other races admitted guessing.
Controlled Group		
Gender	Female vs. Male	Female participants showed a low level of trust in AI. Male participants expressed higher trust in AI.
Race	Caucasian vs. Other	Race has not been a big indicator in AI trust.
Gender & Ethnicity guessing	Female vs. Male	Both genders tried to guess the applicants gender and ethinicty.
Gender & Ethnicity guessing	Caucasian vs. Other	Caucasians ages 20-40 were more prone to deny and become defencive. Other races admitted guessing.

Table 2. Variable and Undependable Variable Definitions

To further understand the data, T-tests and P-values were calculated to compare the trust in AI between both groups, Controlled and Treatment, and Individually. There is no significant difference in % of trust in AI between the Controlled and Treatment groups, as shown in the picture results below. This result indicates that AI is embedded in every company's hiring process over time and doesn't increase or decrease the applicants' chances. It has been established as the norm and is well accepted. However, there is a considerable difference between both control and treatment groups for Gender. Women trusted AI less than men across both Control and Treatment. These results can impact hiring in cases when women are the hiring managers but also spark the interest on studying the origin and the impact. Knowing that AI has selected candidates can bring distrust in the selection and increase the bias in hiring. When there is a gap of doubt, we need a bridge to fill the void (Chowdhury, Budhwar & et al. 2022)

In today's technology-driven world, the relationship between humans and Artificial Intelligence (AI) has become a subject of extensive study. Notably, the discovery that women trust AI less than men has sparked significant dialogue. Why does this gender disparity exist? Moreover, more importantly, how does it impact decisions, notably in the hiring process? Research has uncovered these intriguing patterns, but their reasons still need to be discovered. It is not just about a woman's predisposition to trust AI less than her male counterpart but rather about how this trust deficit affects strategic decision-making. The phenomenon casts a light on an unexpected bias that colors the perception of AI and its resultant choices in a hiring scenario. Mistrust can be built due to history of being unfair to certain people and human involvement in AI algorithm casts the doubt in people (Kreps, Lushenko & Rao, 2023) in our case women.

Women Trust in AI

Women's trust in artificial intelligence has emerged as a significant concern in the age of technology. The reluctance to rely on AI systems can stem from many factors rooted in the complexity of AI technologies and the socio-cultural narratives that shape women's interactions with these systems. One critical aspect lies in the representation of gender within AI development. Historically, the tech industry has been male dominated, resulting in AI algorithms and systems that may not adequately reflect the perspectives and experiences of women. This lack of representation has occasionally led to AI decision-making biases, further eroding women's confidence in these technologies. Furthermore, the opacity of AI algorithms contributes to this distrust. When the decision-making process of AI is not transparent, it becomes challenging for users, especially women who have faced systemic biases, to understand how conclusions are being drawn and to trust the validity of those outcomes. Instances of unfair treatment, particularly where AI systems inadvertently perpetuate gender disparities, also fuel these trust issues. These can range from gender discrimination in recruitment AI tools to the portrayal of female voices as assistants in various virtual AI platforms, strengthening the stereotype of women in subservient roles. We can only gain the trust when we calibrate the knowledge behind technology (Zhang, Liao & Bellamy, 2020)

Consequently, does this inherent skepticism among women make them less likely to hire AI-selected candidates? Moreover, if so, are they doing so based on their biases? Are women consciously or unconsciously devaluing the choices made by AI, thus favoring candidates selected by humans instead? Perhaps most importantly, we must ask ourselves about this preference's ethical implications. Can we categorize it as discrimination, or is it merely a form of self-protection against a rapidly evolving, AI-dependent future? Individuals must understand that AI and automation will help them and not conflict with their future goals (Chiou & Lee, 2021). Indeed, these are challenging questions to answer. However, understanding and addressing these issues could lead us to a future where both genders widely accept, trust, and utilize AI equally. It is essential to bridge this trust gap between gender and AI, particularly in scenarios where it could play a crucial role in decision-making. Ultimately, it is not just about closing the gender disparity but also about leveraging the full potential of AI for the betterment of society as a whole. The issue of gender disparity was brought to light by many researchers.

Understanding the basis of this disparity could be the key to open the great benefits of AI. In their hiring decisions, are women allowing these trust issues to impact their choice of candidate? Our inherent biases are in play, shaping our perceptions of value and capability.

Moreover, are women subconsciously resisting the decisions generated by AI in favor of their judgment? In doing so, are they subverting the very essence of AI or maybe impartiality? Beyond these questions stands the ethical dimension of this issue. Is this distrust leading to discriminatory practices within the spectrum of AI-driven decisions? These questions warrant probing, for they not only shed light on gender dynamics within the world of technology but also challenge us to explore how we can bridge this trust gap to harness the full potential of AI. It is more than just a conundrum; it is understanding the nuances of trust in the AI era - an insight worth millions. Reliance in technology is important for all (Chiou & Lee, 2021) and if companies can achieve that, hiring managers will follow.

The answer to these questions lies not just in research but in action. By acknowledging and addressing this gender disparity, we can move towards a future where both genders have equal trust in AI and its decisions. In an interesting study by (Chong, Zhang, et al, 20222) they asked the question if AI mistrust is rooted in self-confidence as well. It is time to break free from the shackles of bias and embrace AI's possibilities for a better tomorrow. Let us work towards building a world where AI serves as an ally, not a hindrance, in our journey towards progress and development. So, let us take the first step:

challenge our biases and embrace AI as an equal partner in shaping our future. So, let us continue to research and explore this fascinating relationship between humans and AI and build a world where there is more inclusivity and equality, where trust knows no gender boundaries. It is not about gender or AI but about progress and growth for all. We should learn to adapt and evolve together with AI by our side. The possibilities are endless, and we are just getting started.

It is time to move beyond discussing the trust gap between women and AI and take action to narrow it. Building trust is difficult in many levels but it is more difficult when it comes to AI (Siau & Wang, 2018). To build a future where AI and humans coexist in harmony, we must actively address this issue and work towards closing the gap. We can only accomplish this change but creating diversity and inclusion training for AI developers, creating more diverse datasets for AI algorithms to learn from, and promoting transparency in AI decision-making processes. Furthermore, organizations must prioritize gender diversity in their hiring processes and ensure that AI is not perpetuating any existing biases. This can be achieved by regularly auditing and monitoring the performance of AI systems and implementing safeguards against biased decision-making.

Raising awareness and educating individuals about the potential of AI and its role in society can also help bridge the trust gap. By dispelling myths and misconceptions, we can build a more informed and inclusive society that embraces AI as a tool for progress rather than a threat.

In conclusion, the trust gap between women and AI it is an urgent matter and needs societies attention. Companies can no longer afford to ignore the fact. It not only highlights gender dynamics within the tech industry but also raises important questions about ethical implications and potential discrimination. Society has to be cautious but also keep in mind and visualize the potential of AI improving our lives (Beauxis-Aussalet & Behrisch, 2021). By actively addressing this issue and working towards building a more inclusive and equitable future, let's bring AI and utilize its ability to full potential and pave the way for progress and growth for all. So, let us continue challenging our biases, promoting diversity and inclusion, and embracing AI as an equal partner in shaping our world.

The possibilities are limitless, and it is up to us to make the most of them. Let us bridge the trust gap and build a brighter future for all genders. So let us not only talk about it but also take action to create a world where AI knows no gender boundaries, only potential. Let us continue to push the boundaries and break free from limitations – with AI by our side. Together, we can shape a better tomorrow, one that is truly inclusive and equitable. Additionally, AI developers and policymakers must instill a culture of transparency, accountability, and ethical standards to build trust with all users regardless of gender. This involves creating clear guidelines on how personal data is collected, used, and protected by AI systems. It also means promoting diversity and inclusion in the development of AI algorithms to avoid unintentional biases that may affect women disproportionately. Trust is built along the way when accountability is shown (Beauxis-Aussalet & Behrisch, 2021).

On their article, Omrani, Rivieccio, et al (2022) mention that in the heart of the digital revolution, trust takes center stage in how we embrace and interact with Artificial Intelligence (AI). AI impacts our lives in myriad ways, and its acceptance varies drastically across different demographics. One insightful revelation from a recent study of over 30,000 individuals in the EU28 indicates that women display significantly less trust in AI than men. This gender gap in AI trust is more than just a statistical observation; it underlines the need to understand and address gender-based apprehensions concerning AI utilization. Women's lower trust in AI could stem from various concerns, such as AI's ethical usage, potential for misuse, and implications on privacy and personal data. The less trust shown by women in AI also highlights potential fears of losing control or being misrepresented by these advanced technologies. For AI to reach its full potential, it's essential to bridge this trust gap and make AI more accessible and trustworthy for everybody, women included. Addressing these concerns will not only propel the widespread adoption and successful implementation of AI systems but will also ensure a more inclusive and equitable digital future. The technology industry must take note of this disparity and work actively to include women in AI development and decision-making processes, assuring their unique concerns are considered and their trust is earned.

According to Ahn, Almaatouq, Gulabani, & Hosanagar, (2021) More is needed for AI systems to be intelligent; they must earn our trust. Highlighting gender differences in the acceptance of AI is crucial for developing strategies to bridge this trust gap. It's been found that increased trust in AI only sometimes directly translates into enhanced performance. This is true across genders, but it is particularly pertinent in the context of women's lower trust levels. This highlights an important research area that needs addressing. It's not just about making AI systems more trustworthy; it's about understanding what drives trust in different groups and how to enhance it strategically. For AI to have a meaningful and positive impact, we need clarity on when and how to increase trust - especially among the women who are currently more skeptical. By understanding the factors influencing women's trust in AI, we can work towards strategies that result in greater adoption of AI systems among women and more significant impact from these systems. Let's collaborate to demystify the world of AI and make it more accessible and trustworthy for everyone. As we continue integrating AI into our everyday lives, we must address any trust gaps. This ensures fair and equal use of AI for all individuals and enables us to reap the benefits of this rapidly advancing technology fully.

Trust can be built but you need to know how to build the trust in AI. (Vereschak, Bailly & Caramiaux, 2021). Addressing these issues is even more critical regarding specific roles, such as those related to technology or engineering. Research has demonstrated that women are significantly underrepresented in these fields, leading to a lack of diversity and reducing the likelihood of innovative solutions being generated. Organizations must be aware of potential biases concerning AI-based hiring decisions to create a more equitable hiring process and encourage greater diversity across technology and engineering roles. By considering the findings of our t-tests, companies can ensure that their hiring practices are as fair and unbiased as possible.

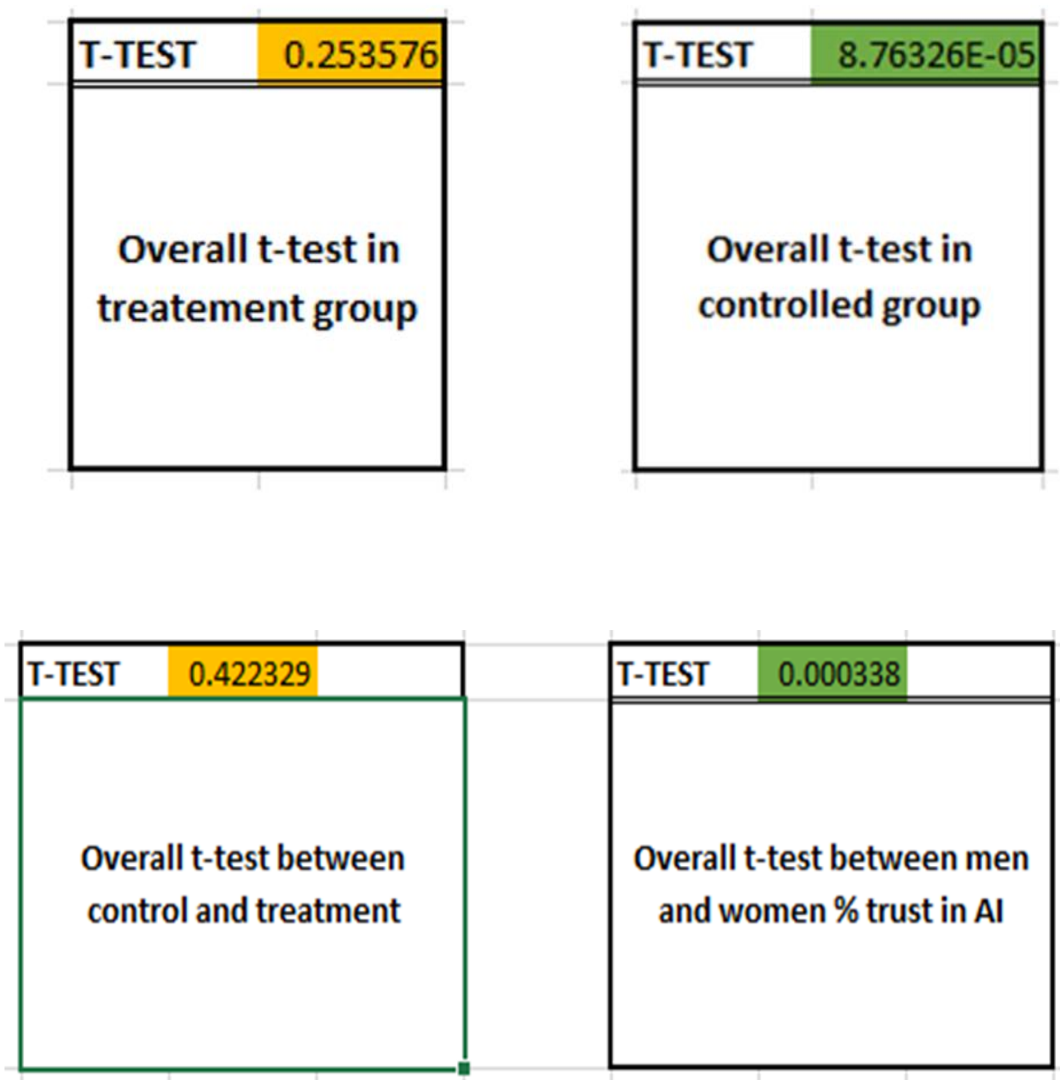

Figure 4. T-Tests Results for AI Trust

Moving forward with the experiment, the following item to establish was to bring them in for a second round of interviews or reject them. Each candidate was reviewed one at a time against the job description by the participants of both groups. There were two main factors for rejection or acceptance: Education and Experience. The participants were deciding if the requirements for Education and Experience are the same as in the job description. Running the T-test and looking at the p-value, we saw no significant difference between the Treatment and the Control group. The appendix below shows the p-values of our calculation.

No Experience							
	Treat	Control	Diff	p-value	Mean	DF	t-value
Total	0.3533	0.3533	0.0000	0.5000	0.35333	29	0
Male	0.3600	0.3692	-0.0092	0.4554	0.35556	29	0.11
Female	0.3467	0.3412	0.0055	0.9423	0.34375	29	-1.62
Mike	0.3333	0.3333	0.0000	0.5000	0.33333	29	0
Amanda	0.4667	0.4667	0.0000	0.5000	0.44828	29	0
Latisha	0.4333	0.4333	0.0000	0.5000	0.39286	29	0
David	0.5000	0.5000	0.0000	0.5000	0.51852	29	0
Juan	0.0333	0.0333	0.0000	0.5000	0.03846	29	0

Figure 5. T-Test Results for No Experience

Another variable to investigate was Education; if it did not necessarily match the requirements, it would have an impact. P-value showed no significant difference from the experiment data. The appendix below shows the p-values of our calculation.

No Education						
	Treat	Control	Diff	p-value	DF	t-test
Total	0.1200	0.1200	0.0000	0.5000	29	0
Male	0.1385	0.1467	-0.0082	0.5000	29	0
Female	0.1059	0.0933	0.0125	0.7926	29	-0.893
Mike	0.0333	0.0333	0.0000	0.5000	29	0
Amanda	0.0333	0.0333	0.0000	0.5000	29	0
Latisha	0.0667	0.0667	0.0000	0.5000	29	0
David	0.1889	0.4667	-0.2778	0.5000	29	0
Juan	0.0000	0.0000	0.0000	0.5000	29	0

Figure 6. T-test Results for No Education

When the tests were run to see the impact that No Education / Experience had on the participants, the p-value showed no significant impact. The appendix below shows the p-values of our calculation.

No Experience / Education							
	Treat	Control	Diff	p-value	Mean	DF	t-value
Total	0.0867	0.0867	0.0000	**0.5000**	0.08667	29	0
Male	0.0933	0.0769	0.0164	0.3650	0.08148	29	0.35
Female	0.0800	0.0941	-0.0141	0.7532	0.08750	29	-0.69
Mike	0.0000	0.0000	0.0000	0.7179	0.00000	29	-0.58
Amanda	0.0333	0.0333	0.0000	0.5000	0.03448	29	0
Latisha	0.0667	0.0667	0.0000	0.5000	0.07143	29	0
David	0.3333	0.3333	0.0000	0.5000	0.37037	29	0
Juan	0.0000	0.0000	0.0000	0.5000	0.00000	29	0

Figure 7. T-Test Results for No Experience / Education

Discussion

The expectation from this research was to establish the impact algorithms have on hiring managers when they select candidates. AI algorithms handle the first selection of resumes, and most companies already see an improvement in the process. According to Madriakis (2017), AI has affected many parts of hiring and made the process more practical and efficient. However, the research revealed a potential risk of bias in managers when they hear AI algorithm word. Their concern was that AI systems might prefer specific characteristics over others, such as Gender or race. It could limit the ability of recruiters to make fair decisions and create an unfair advantage for some applicants over others. Additionally, it can lead to a need for more diversity in the workplace.

Overall, regarding the first research question, we had on to what extent there is a bias in hiring managers before AI word is mentioned; this research showed no significant impact. Managers are aware that their companies are already using AI in one way or another during the selection process before it comes to them. Regarding the second research question on how the word Artificial intelligent algorithm impacts the managers' hiring decisions, the research showed no significant impact. We concluded that AI algorithms have positively and negatively affected hiring managers, but not all have the same trust in AI.

The Gender of the hiring managers showed a significant difference in how much they trust AI. We have to work harder and be more proactive on building trust in AI (Bedue & Fritzsche, 2022). The finding drew questions on how we can improve this issue and we came with a few suggestions. Addressing AI trust issues among women it has to involve all layers of management and AI components in organizations such as ecosystem, including developers, companies, policymakers, and end-users. Here are proposed solutions for cultivating a more trustworthy AI environment: Increase Diversity in AI Teams to gain different perspectives. Bringing diverse voices to the table can lead to developing AI systems that are not biased toward one gender or another. Recruitment and retention of female AI professionals must be a priority.

Implement Transparent AI Algorithms for all to see. Transparency in how AI algorithms operate and make decisions can demystify the technology for the public. This clarity helps users, including women, understand and trust AI processes. On their studies, Kim, Giroux & Lee (2021) mentioned that with trust will build with consumers evaluation of the information and validation. Regular and Independent Audits to make sure nothing goes unnoticed. Conducting thorough audits can help to detect and mitigate gender biases that may exist in AI systems. These audits should be conducted by independent bodies to ensure impartiality. Encouraging open discussions for everyone to express their concerns. Providing forums where women can discuss and voice their concerns about AI will help developers understand issues directly from those affected and work towards addressing them. Building trust in AI among women involves acknowledging and rectifying past and present gender biases in technology. By fostering inclusivity, transparency, and accountability within AI systems, we can create a technological landscape that commands the trust and confidence of all users, irrespective of gender.

According to Peng, Nushi et al. (2022), while AI algorithms provide efficiency and streamline the selection process, they can also contain bias, leading to an unfair advantage for some candidates. Therefore, it is crucial for companies to be aware of the potential for bias in AI algorithms and to take steps to ensure that their recruitment process remains fair. It can be done by better incorporating human decision-making into the hiring process or ensuring that AI systems are trained using data sets representing diverse backgrounds. Ultimately, this will help create a more equitable hiring process and promote diversity in the workplace.

The word cloud represents the responses from all participants.

Figure 8. Word Cloud Representing Participant's Responses

Limitations

As mentioned by (Cam, Chui, and Hall - 2019), there is a period of adaptation to AI and hiring managers that is critical to understanding the benefits or doubts of AI. Every study has more potential and better results if the number of participants is more significant. We have 60 participants in this study, and it is hard to find managers from different backgrounds and industries agreeing to take the experiment. Companies are de-layering management positions, making it even harder for managers to find time and take on social experiments. Thus, the limitation of this research is that it needs to include a large and varied enough sample size to make general conclusions about how AI bias affects hiring managers. Despite this limitation, results are meaningful and can be used as a baseline for future research. This will allow further exploration of how AI bias affects hiring managers in different industries and countries. It will also be interesting to investigate what strategies can be used to reduce AI bias in the hiring process. This material could then form the basis of new recommendations on best practices for recruitment. Ultimately, this research provides a starting point for further investigations into the impact of AI bias on hiring managers.

In the grand scheme of human progress, a few innovations pack the punch of artificial intelligence. Curiosity in AI designs and unique approaches has piqued the interest of younger generations (Zhang, Bai & Ma, 2021). From medical diagnosis to entertainment curation, AI has carved its niche in the parts of our modern world. Given its versatility and reach, it is little surprising that the realms of employment and business are not exempt from AI's steadily encroaching touch. Among the most salient points of AI's application is in recruitment and hiring, an arena fraught with historical biases and calls for reform. However, as we ponder the integration of AI into the hiring process, we find ourselves teetering on the precipice of two daunting prospects: the promise of enhanced equity and the peril of perpetuating hidden biases. The Quantum jump towards equity and the narrative favoring AI-driven hiring practices sing an anthem to progress and fairness. Arguably, AI—being a creature of cold logic—ought to be blind to the superficial traits that have, for eons, seeped into human recruitment decisions. By parsing through vast datasets and applying algorithms touted to be free from human foibles, AI hiring platforms promise a utopia where merit alone is the currency. In these aspirations, AI shines brightest, wielding a potential to remodel hiring practices fundamentally and, in doing so, address systemic inequalities.

Proponents argue that these AI systems do not discriminate based on gender, race, or socioeconomic status. Their vision is clear, their judgments untainted. The prospect of a recruitment process distilled to the scientifically sound principles of job requirements and objective data instills hope – a sort of technological restorative justice promising to lend the overlooked and the undervalued an unbiased chance. Echoes of the Human Hand however, for all its promises, AI hiring tools are not the stone of impartiality being hurled into the pond of recruitment—dispersing ripples of equality far and wide. No, this metaphor crumbles under the weight of tangible studies that reveal cracks in AI's impartial veneer. The issue of 'AI perpetuating human bias's is not a hypothetical one but an entrenched reality that multi-million-dollar algorithms struggle to untangle. Consumers are looking for a precision in AI processes (Zhu, Zhu & et.al, 2023).

The folly lies in the data sets fueling these learning machines—data that, itself, is born of human decisions colored by the very biases AI seeks to transcend. When AI learns from past hiring practices, it inherits past biases, gravitating towards candidates that resemble successful hires, perpetuating existing imbalances. The argument is not that AI is inherently biased—far from it—but that its current incarnations risk reflecting and even amplifying the very deficiencies it aims to combat. The balancing Act is unveiling the Path to Fairness. The task at hand is daunting but far from impossible. If you adapt the client needs with the right program and responses, it shows progress in collaboration with AI tools (Chen, Li & Wang, 2023). It is unraveling the conundrum of AI bias in hiring demands a multi-faceted approach that acknowledges AI not as a monolithic 'other' but as a tool beholden to its creators. Companies and developers must vigilantly dissect and reconfigure the data inputs feeding AI systems, infusing platforms with a conscious effort to include and empower all candidates.

Transparency is critical in the methodologies governing AI-driven recruitment and in the outcomes arising from them. Trust is a hobbled thing, and it is not easy to understand how AI culminates in its choices without opening the black box and sifting through its machinery. We must heed the call to scrutinize AI with a discerning eye, never ceding to the allure of a modern marvel at the expense of the human narratives it seeks to evaluate. Reimagining the Spectrum of Success in the roadmap forward is one of collaboration, where human intuition meets artificial acumen to forge a synergy that is at once innovative and humane. AI in hiring should not be seen as a wholesale replacement for human recruiters but as a companion, a guide—a mirror held up to reflect and rectify our biases. The future we foresee differs from one where AI reigns supreme in recruitment or abdicates the responsibility to human judgment. Instead, it is a union where AI equips us to redefine what success looks like in a rich spectrum that defies simplistic molds. It is a future where diversity is not a buzzword but an integrated facet of businesses' growth and evolution. AI will push for changes in our society and infrastructure soon but in a positive way (Grace, Salvatier & et. al, 2018).

The Final Verdict in on the Pursuit of Parity is to think of AI as one of the best disruptions (Chopra & Bhilare, 2020). Our conclusions, however, are not carved in stone; they are the product of an ongoing dialogue that we need to engage in vigorously and sincerely. As the dust settles on this ongoing transformation of hiring practices, we hope that we do not simply fold our aspirations into the binary code of an AI system and expect it to right our age-old wrongs. We must engage with AI as active participants in a social experiment, just as those we entreat to participate in our AI research studies. Every click, every data point, and every hiring decision is a brushstroke on the canvas of our collective future. We must ensure that the masterpiece that emerges is a testament to technological prowess and a beacon of justice, equity, and the enduring triumph of the human spirit.

CHAPTER 4

CONSCIOUS OR UNCONSCIOUS BIAS CAN DRIVE HIRING DECISIONS ON PARTICULAR GROUPS

Introduction

Conscious and unconscious biases are tangible, and every human being harbors them. Our experiences, societal norms, and cultural backgrounds shape these biases. But what happens when these biases drive hiring decisions? It's no secret that hiring the right candidate is a crucial decision for any organization. It can make or break the success of a company. However, conscious or unconscious biases often influence these decisions, leading to unfair recruitment practices. For instance, a study from MIT where two exact resumes, one with a "white-sounding name" Brendan, and one with an "African American sounding name" Tamika submitted, found that resumes with "white-sounding" names received 50% more callbacks than identical resumes with "African American-sounding" names. It shows how unconscious biases based on race can impact hiring decisions. According to Bertrand & Mullainathan (2004), a name can queue all the negative unconscious biases a manager carries and will apply to the hiring decision. Let’s drill down to each of them to understand better why they exist and the reason behind it.

Conscious Bias

One might ask, what are conscious biases and how do I know I have them? Conscious biases are beliefs we hold about a particular group of people. Identifying the hidden hustle of conscious Bias that occupies us as individuals is paramount. The pervasive influence of unconscious Bias has gained the spotlight in recent years, with many businesses and institutions discussing its impact and, more crucially, how to mitigate it. However, the more insidious cousin of unconscious Bias—conscious bias—lurks in the shadows, often escaping the public eye while wielding a heavy influence on individual actions and societal structures. In this portion of our study, we intend to illuminate conscious Bias, dissect its nature, and impact, and offer a roadmap to identify and address it daily. Sometimes, understanding the impact of the duality of Bias crosses our minds. When we think of Bias, we often picture subtle, subconscious preferences that influence our decisions without realizing it. However, what about the biases that are recognized and sometimes defended? Conscious biases are those we know, yet they command a significant portion of our cognitive, emotional, and behavioral landscapes. Unlike unconscious biases, which involve social stereotypes without conscious awareness, conscious biases are the ones we actively hold and sometimes champion. "Research in social psychology on prejudice, stereotyping and discrimination shows that although many biases are conscious and deliberate, the expression of bias is often unintentional because people hold negative attitudes and stereotypes at a non-conscious or implicit level." (Stone & Moskowitz, 2011, p.774).

The conscious element in these biases makes them particularly challenging to overcome. When aware of our prejudices, we must grapple with social expectations, personal experiences, and myriad justifications that have solidified these biases into beliefs. They are the kind of biases that prompt us to vocalize our opinions loudly during debates, influence our hiring and promotion decisions at work, and lead to the profiling of individuals by law enforcement.

Confronting Our Inner Biased Juries is not easy but doable. The first step in addressing conscious biases is acknowledging our role as both the host and the judge of these mental constructs. Unlike the rapid-fire associations our brain makes in the case of unconscious biases, conscious biases are the deliberate conclusions we draw based on partial or skewed information. They are the judgments we pass outside the courtroom, often without a complete set of evidence and without allowing the defendant (person or idea) the opportunity for a fair trial. A good example is gender bias and how there is a constant debate about how there is no gender bias when research has shown that it exists, and as a society, we must make conscious efforts to avoid it (Easterly & Ricard, 2011).

The complex part about identifying conscious biases is that they often align with our values or, at the very least, with what we perceive as being in our best interest. This alignment creates an illusion of truth; our beliefs feel valid and justified, which makes them exceedingly resilient to change. The comforting trap of confirmation bias, where we look for information that matches our beliefs, further fortifies our conscious biases. According to Cooley, Payne & Phillips (2014) at times, we are so convinced that our opinion is not bias even though it is that we start justifying our actions as valid. Unraveling the Web of Justifications is even more crucial. To untangle the web of conscious biases, we must scrutinize the string of justifications that keep them in place. Ask ourselves why we would hold these beliefs, what we stand to lose by challenging them, and what it says about us if they were to change. Human beings are pattern-seeking creatures, and our sense of self is tightly interwoven with the narratives we construct around our experiences.

We must be willing to engage in intellectual vulnerability—to be okay with the fact that we may be wrong or that our current understanding is incomplete. We can only reevaluate and, potentially, overhaul our deeply held views by challenging the validity of our conscious biases. The goal for everyone should be to recognize bias in our actions and act on it so it will not affect our personal life or put our professional career in jeopardy (Ross, 2020). Throughout this process, we must remind ourselves that doing what is right often requires adjusting what we believe to be true. Recognizing Bias Within the Collectiveness of ourselves is challenging. The pervasiveness of conscious Bias is not simply an individual challenge; it permeates and shapes the collective consciousness. Social norms, institutions, media, and legislation are all extensions of individual biases that have coalesced into societal standards. To identify conscious biases within the collective, we must critically evaluate the status quo and question whether the systems and structures we have inherited and maintained are fair or just. Conscious Bias at the systemic level often perpetuates inequality, discrimination, and the exclusion of certain groups. We can all help build an inclusive society by recognizing and addressing these institutionalized biases. It requires collective introspection, a willingness to listen to marginalized voices, and the courage to advocate for change, even when it disrupts current power dynamics.

According to Agarwal, (2020) we think that we only have bias on gender or race, and we do not realize that it expand in so many more aspects of our life. A Path to Reformation is lifelong but doable. Conscious biases are the most intransigent when reforming our thoughts and actions. They represent the summit of Bias—visible, defended, and often deeply ingrained. Nevertheless, the paradox is that because they are conscious, it is within our will and capacity to change them. To do so, we must foster an environment where critical self-reflection is encouraged, and we can challenge each other in respectful dialogue without fear of personal reprisal. Education, exposure to diverse perspectives, and empathy are the antidotes to conscious Bias. By engaging in continuous learning, broadening our horizons, and genuinely trying to understand the experiences of others, we can begin to dismantle the walls of Bias that separate us. It is a lifelong process of unlearning and relearning; we will only sometimes get it right. However, pursuing equity and respect for all demands persistent engagement with our conscious biases.

What is considered the End of the Beginning is exciting but requires constant improvement. Every time the researchers think they have found a way to prove bias, they realize that it is time to start again (Michel, 2023). Identifying and addressing conscious biases is an ongoing task, a continuous process that consists of persistent work within ourselves and societal betterment. It is not enough to understand the concept of Bias and its impact; we must look within, confront our conscious biases, and actively work to rectify the injustices they perpetuate. Ultimately, the battle against conscious Bias is a fight for our humanity—recognizing and celebrating the full spectrum of human potential stifled by the prejudices we harbor within. It is a fight for a world where our biases no longer dictate the limits of our compassion, empathy, and collective future.

The next time we feel the pull of a conscious bias, we should urge ourselves to resist the temptation to succumb to it. Even at times when we are aware of our bias and try not to act on them, some studies show that somehow, they still affect our decisions (Waroquier, Abadie & Dienes, 2020). Ask the hard questions, challenge our convictions, and be open to the discomfort of standing on the border of our known world, ready to leap into the new and unexplored territory of unbiased existence. The journey may be daunting, but the destination is true freedom and genuine understanding. Moreover, remember that the end of one Bias is only the beginning of another opportunity for growth and progress. So let us continually confront our inner biased juries to create a brighter.

Alston (2023) elaborates on the issue of when women are systematically rated with low performance compared to men, which will affect their promotion and career advances in the future. For example, an employer may think that women are less capable of excelling in technical roles than men. On the other hand, unconscious biases are unexamined attitudes or stereotypes that affect our understanding and decisions without realizing them. Regarding hiring decisions, these biases can result in discrimination against certain groups. Conscious or unconscious bias in hiring can also lead to a lack of diversity in the workplace. By favoring one group over others, organizations take advantage of the diverse perspectives and skills that a more diverse team can bring. It's essential for hiring managers and HR professionals to recognize their own biases and take steps to address them. One way is by implementing blind recruitment practices, where identifying information such as name, Gender, or age is not included in resumes or job applications. It can help eliminate conscious or unconscious biases during the initial screening process.

RQ: How do we measure conscious or unconscious bias in hiring managers?

In the labyrinthine world of professional advancement, few mazes are as fraught with contemporary controversy as the domain of hiring practices. Being mindful of our bias can help reduce discrimination (Saluja & Bryant, 2021). The specter of conscious and unconscious bias has loomed large over this space, affecting candidates from all walks of life and casting long shadows over the ideals of meritocracy and fairness.

Witnessing this from the dual vantage points of a candidate and a human resource professional, the question of how to measure bias in hiring managers is not a mere academic pondering for us —it is an existential query that demands resolution for advancing our society and workplaces. However, what tools can we forge to measure something intangible yet impactful?

Navigating through the deliberate process of selling oneself as a commodity for hire, we are no strangers to the caprices of hiring managers. Social calibration is critical to keep in mind in these cases (Hahn & Goedderz, 2020). The reality of bias revealed itself in the shock and awe of an unexpected rejection or the slight, uneasy feeling left behind by a seemingly benign comment. These experiences, which might be waved away as the isolated incidents of a sensitive applicant, seemed to repeat, ensuring a pattern too palpable to ignore. They left a personal mark that sharpened our perception of the hiring process, birthing a professional resolve to plant the seeds of equity within HR practices.

Before we begin dissecting the issue, we need to clarify the terminology. Bias, whether conscious or unconscious, is prejudice in favor of or against one thing, person, or group in comparison to another, usually in a way considered unfair. Conscious or explicit bias involves attitudes, beliefs, and behaviors where individuals know their prejudices. According to Thakral and Ribeiro (2021), unconscious or implicit bias refers to attitudes and stereotypes that, without us knowing, affect everything we do and our decisions. We are going to explain furthermore both types of biases and examples.

Unconscious Bias

One might ask, what are unconscious biases and how do I know I have them? At its core, unconscious bias refers to our quick, automatic judgments and assessments of people and situations, influenced by our background, cultural environment, and personal experiences. They are inherently human, a quirk of our cognitive machinery that was, ironically, shaped by the prejudices we now strive to outgrow. These biases are not trifling matters confined to the musings of armchair philosophers; they undeniably impact our world profoundly. From the hiring decisions made in corporate boardrooms to the split-second reactions of law enforcement officers on the street, unconscious biases can perpetuate systemic inequities and injustices. They fuel racial profiling, gender discrimination, and a litany of other societal ills, all while their architects remain blissfully unaware of the role they play. It is very hard to avoid unconscious bias even when you try to be conscious of certain believes. (González-García, Tudela, & Ruz, 2015).

Let's identify some common types of biases. The roster of unconscious biases is as diverse as the human experience itself. Whether it is the Halo Effect, which causes us to see someone as uniformly good or bad based on a single positive or negative trait, or the Affinity Bias, leading us to favor people like us, each bias has its insidious way of distorting the lens through which we view the world. Wrestling with these biases is like attempting to unravel a Gordian knot woven by society's collective psyche. In recognizing our prejudices, we must also confront the reality that these thought patterns are deeply embedded in the fabric of our cultural narratives, passed down from generation to generation. Acknowledging one's biases is an exercise in introspection and humility. It requires a willingness to interrogate the beliefs we hold not simply because we have chosen them but because they have chosen us, quietly skulking in the cavernous corridors of our subconscious. We are unveiling Unconscious Bias by Recognizing and

Addressing Prejudices. In the labyrinth of human cognition, conscious and unconscious biases act as the unseen architects of our beliefs and behaviors. Think of unconscious bias as a mask individuals hide behind it (Tsikandilakis, Bali & et. al, 2021). While the former can be identified and confronted with relative clarity, the latter poses a more enigmatic challenge. The first step in dealing with our unconscious biases is acknowledging their existence. Nevertheless, how do we know they are there, shaping our perceptions and coloring our judgment? Furthermore, how do we weed them out from the recesses of our minds, where they often operate undetected? A study performed about White American parents that try to explain race diversity to their children, at times takes the wrong turn due to the bias that already exist in them and the real purpose on explaining it to their children. By playing color blind method, they might make things worse. (Perry,Skinner, & Abaied, 2019).

We can start by reflecting on experience. On his article about the experience as a public defender, Lyon (2011) realized that prejudice and stereotyping was very common amongst attorneys, judges and prosecutors on the justice system. Each of us inherits a unique set of biases tailored to the contours of our personal story. Whether it is due to the communities we are raised in, the media we consume, or the influences of our upbringing, our biases reflect the collective imprint of our lived experiences. We are no exception. We have experienced the momentary judgment, the knee-jerk reaction, informed not by the immediate circumstances but by a lifetime of latent conditioning. To recognize these moments is to catch a glimpse of the cultural iceberg on which we sail, with only a fraction visible above the surface. There are many techniques we can use to self-discover our unconscious bias. However, self-discovery is not an exercise in futility; there are techniques we can employ to bring our biases to light.

According to (Stone & Moskowitz, 2011) training our focus on the present moment, engaging in deep self-reflection, and even seeking feedback from others can serve as a mirror, reflecting the biases we cast into the world. These moments of revelation are not indictments of our character but growth opportunities. To become aware of our biases is to peel back a layer of the subconscious, allowing light to shine on the dusty corridors rarely visited but profoundly influential. The process of addressing unconscious bias is important and needs to be consistent. Admitting our biases is one thing; acting to mitigate their impact is quite another. It requires a conscious effort to root out the weeds of prejudice that have taken hold in the fertile soil of our cognition. We can also start and Mitigate Bias in Decision-Making structurally. Our ability to make decisions free from bias is paramount in our personal and professional lives. Whether in hiring practices, project assignments, or simply the judgments we form about those around us, it is essential to adopt processes that minimize the influence of unconscious prejudices. Blind application of standardized criteria, diverse decision-making panels, and ongoing training in recognizing and addressing biases can serve as bulwarks against the influences of our subconscious. We must act with intention, grounded in the knowledge that our first instincts are not always our most authentic or just.

The role of education and dialogue is a must in the road of learning. Companies need to build strategies and training for their management and employees by testing them in unconscious bias, and pointing out the issue (Pollard, 1999). The path to a bias-free society is best traversed with the guidance of education and dialogue. By engaging with diverse perspectives, challenging our assumptions, and remaining open to the insights of others, we can begin to chip away at the monolith of prejudice that stands between us and a more equitable world. Such endeavors are not passive; they are an active participation in the betterment of our communities and a rejection of the status quo that passively perpetuates past biases. We must be willing to learn, listen, and lead by example, demonstrating through our actions a commitment to dismantling biases, whether they reside in our minds or our institutions. Recognizing and addressing unconscious biases are formidable tasks, requiring humility, dedication, and an unyielding commitment to the pursuit of equity. It is a labor of love for the future we wish to create a testament to the belief that, with effort, we can transcend the ties that would bind us to past injustices. The first step is to ask the question—how do we know if we have unconscious biases? The subsequent steps are acts of empowerment, tools with which we can dismantle the system from within. It is not a passive task, nor should it be dismissed as a mere academic exercise. The stakes are too high, the potential for growth too significant, to ignore the biases that shape our world and the work that remains to be done in erasing their influence.

Measurement Process

There are many challenges in the Measurement process. An insidious quality of bias lies in its nature—often unvoiced, frequently unrealized by the person who wields it. This invisibility cloak complicates finding a metric to gauge the level of bias in a hiring decision. Without overt actions or statements, we are left to unravel the subtler threads of human judgment.

Psychological tests and proxy measures, such as Implicit Association Tests (IATs), can illuminate implicit preferences. However, these tools have limitations and cannot capture the full spectrum of bias that might influence a hiring decision. If these biases are deeply ingrained in our way of thinking and acting, it might be very resistant to change (Tate & Page, 2020).

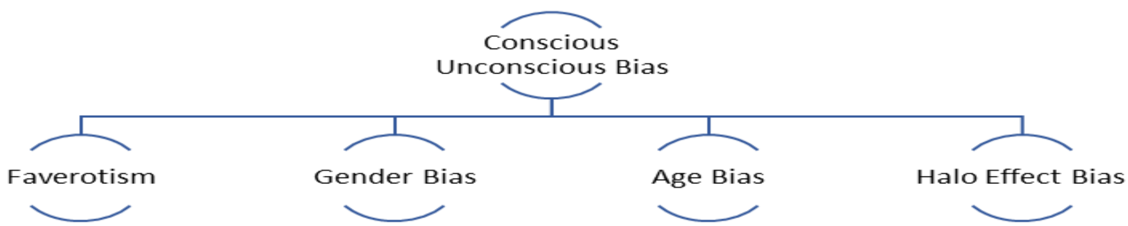

Figure 9. Examples of Bias

Hypothesis

H - Caucasian hiring managers are more likely to hide their conscious bias to justify their hiring choices.

Based on this Hypothesis, there may be a difference in the behavior of Caucasian hiring managers when concealing their conscious or unconscious biases during the hiring process. To test this hypothesis, we are going back to interview the group of Caucasian managers, precisely a group aged between 20-40 years old, from the study and drilling down more into their hiring decisions to determine if there is a difference in the likelihood of hiding conscious and unconscious bias. What is common among the

Caucasian group younger than 40 in this study is that they all selected to hire the two Caucasian candidates who were the least qualified. This study would collect data on participants' self-reported biases, their awareness of those biases, and their behaviors during the hiring process. According to Dooley (2022), how our society operates changes constantly, and that impact and blame placed on certain races builds more challenges as we go along.

Literature Review

According to Suveren's study titled "Unconscious Bias: Definition and Significance," published in the journal, the study aims to explore the concept of unconscious bias based on psychological, social psychology, and partly sociological literature. "Unconscious bias stems from a feature of the human brain that helps make quick decisions through a series of shortcuts." (Suveren, 2022, p. 424). He adds more color to the fact that we approach many situations with generalizations. Unconscious bias refers to negative biases that individuals are unaware of, which can harm interpersonal and social relationships. The study also highlights the importance of raising awareness about unconscious bias to foster more objective perspectives.

As individuals, we bring these unconscious biases to schools, healthcare, the workplace, and politics. More into his study, he noted that depending on the position someone has, their unconscious bias can affect masses if not addressed and corrected. This study touched on many issues our society faces now; however, it was heavily focused on Turkish culture. In general, we can apply and understand the importance, but in the USA, we have a more diverse population and different issues, specifically the labeling of certain races.

In the article titled "Humans' Bias Blind Spot and Its Societal Significance" by Pronin and Hazel (2023), the authors discuss the concept of the bias blind spot among human beings. "Human beings have a bias blind spot. We see bias all around us, but sometimes not in ourselves" (Pronin & Hazel, 2023, p. 1). The bias blind spot refers to our tendency to perceive biases in others but not recognize them within ourselves. This cognitive asymmetry restricts self-awareness, leading to interpersonal misunderstandings and conflicts. The bias blind spot is rooted in the mental mechanics that differentiate self-perception from social perception and in our motivations for maintaining positive self-esteem. This phenomenon extends across various domains, including social, cognitive, and behavioral biases. It emerges in childhood and appears to be present across different cultures.

The article highlights that individuals display a biased blind spot even in high-stakes situations such as investing, medicine, and human resources. This fact implies our lack of self-awareness regarding biases can have significant societal implications. Overall, Pronin and Hazel's study sheds light on the bias blind spot, emphasizing its pervasive nature and potential impact on various aspects of human life. Their study was focused on the general categorization of all races and had minimal recommendations on how to move forward with better plans and procedures for bettering the recognition of blind spot bias.

In the article by Cherry (2020) titled "How does implicit bias influence behavior: Explanations and Impacts of Unconscious Bias," the author explores the concept of implicit bias and its influence on behavior. Implicit bias refers to the unconscious attitudes or stereotypes that affect our judgments and actions, even when we are unaware. What stood out more is the behavior we all face and knowledge, such as the separation of society's influence. "In addition to the fact that we are influenced by our environment and stereotypes that already exist in the society into which we were born, it is generally impossible to separate yourself from the influence of society. " Cherry, 2020, p. 2)

Cherry explains that implicit biases can exist independently from our conscious beliefs and values. This theory means individuals may hold biases that contradict their explicit disapproval of certain attitudes or beliefs. These biases can be related to various personal characteristics such as race, Gender, religion, sexuality, and more. The article highlights that implicit biases can significantly impact behavior, influencing decision-making processes, social interactions, and even institutional practices. Understanding and addressing implicit bias is crucial for promoting equality, diversity, and inclusivity in various domains.

In the article "What implicit measures of bias can do" by Melnikoff and Kurdi (2022), the authors discuss the utility and limitations of implicit measures in studying unconscious bias. They acknowledge the importance of examining the effectiveness of commonly used implicit measures, such as sequential priming, the Implicit Association Test (IAT), and the Affect Misattribution Procedure. "The controllability of unintentional bias has major implications - moral, legal, and psychological." (Melnikoff & Kurdi, 2022, p. 2). These implicit measures have been widely employed in research on unconscious bias; there are limitations to their interpretability and predictive validity. They argue that these measures may not capture the full complexity of unconscious bias and may be influenced by factors such as familiarity with the task, cognitive processes, and context.

The authors emphasize the need for skepticism when interpreting results obtained through implicit measures and caution against overgeneralizing findings. They encourage researchers to consider alternative explanations and complementary measures to gain a more comprehensive understanding of unconscious bias. Overall, the article gives critical insights into the capabilities and limitations of implicit measures in studying bias.

Unconscious bias is essential for most to understand and recognize because they do not realize its impact on hiring. People would have lost logic over it. In their law review, Collins (2007) mentions that critics of affirmative action argue that policies like the Rooney Rule, which mandates interviews with minority candidates, perpetuate racial stigmatization and hostility. However, this stance ignores that such biases already exist and are problematic. The Rooney Rule was implemented in the NFL to address unconscious bias that led to the exclusion of qualified candidates based on race. Skeptics argued that recognizing the issue should prompt change, but recognizing does not resolve unintentional biases. The Rooney Rule combats this by enforcing interactions with African American candidates, making decision-makers confront their biases. Although not flawless, the Rooney Rule has pushed the NFL towards significant progress in diversity, acknowledging its past injustices and celebrating its strides forward. Despite the criticism, the Rooney Rule remains vital to achieving greater equality in hiring processes. Student Services is an essential resource for college and university students, providing support and assistance in various aspects of student life. From academic advising to mental health counseling, student services offer various resources to help students thrive.

Results

In addition to the above findings, what stood out in this study was the participants' behavior when asked if they noticed the names and tried to figure out the Gender and ethnicity. When we asked what made them think about Gender or ethnicity, a large group of participants said they tried to form an impression of the person through their name. They noted that many names carry certain connotations for them and that it was difficult not to make assumptions based on those associations. Goedderz & Hahn (2022) point out that most people are aware of their bias most of the time. For example, a few people mentioned that when they saw Asian-sounding names, they thought of the stereotype of Asians being great at math or technology.

Similarly, when they saw Latino names, they associated those with Spanish-speaking ability and hard workers. However, the participants quickly pointed out that these thoughts did not influence their decision to hire a candidate. They all stressed that while the name may have sparked certain conclusions in their minds, they were all conscious that this did not bear any weight in their decision-making. They universally agreed they would have hired the best-qualified candidate regardless of their name, Gender, or ethnicity.

Moreover, many participants mentioned that as employers, it was vital to remain aware of potential biases and strive to make hiring decisions based solely on merit and qualifications. Companies lose billions when Human Resources does not hire suitable candidates due to a lack of talent. (Adamovic, 2022). They felt that any preconceived notions based on a name could lead to missed opportunities and the potential for unconscious discrimination. For this reason, they took great care in reading through all resumes thoroughly and ensuring that their hiring decisions were free of bias or prejudice. Ultimately, this study highlighted the importance of awareness of potential biases during hiring. In addition to conducting thorough screening processes and focusing on the merits of each candidate, employers must also strive to remain conscious of their potential prejudices and ensure that these do not come into play when making hiring decisions. This is essential for creating an equitable workplace environment where all applicants have a fair chance of success.

When asked if they read the names, one group that stood out was Caucasians born in the USA, age 40 and below. They denied looking at names; some even became defensive even though they commented out loud. Goedderz & Hahn (2022) state that many individuals react defensively when receiving feedback about racial bias scores. During observation, we heard them mentioning Gender and ethnicity out loud. This could be due to social pressure on younger managers. Some of them even said, "I do not discriminate and do not like to be labeled as racist." We ran the numbers, and the results showed that if a manager admitted to noticing the applicant's race, they hired fewer Caucasian applicants than those who denied noticing race. There was no effect on whether the managers admitted/denied for non-Caucasian applicants. The table below provides numbers for each age group.

Variable	N	Admitted	Denied
Caucasian Group Age (20-40)	14	0	14
Caucasian Group Age (40-60)	25	25	0
Non-Caucasian Group Age (20-40)	7	7	0
Non-Caucasian Group Age (40-60)	14	14	0

Table 3. Admitted and Denied Results

Addmitted /Denied	Denied	Denied	Admitted	Admitted
Industry	Pharmaceutical	Financial Services	Technology	Financial Services
Title	Quality Manager	Senior Analyst	Principal Director	Investment Strategist
Years in Managerial Position	3	2	20	10
Age	20-30	20-30	40-50	40-50
Gender	Female	Male	Male	Male
Race	Caucasian	Caucasian	Caucasian	African American
Trust In Algorithm	20%	90%	100%	60%
Observation Notes	Names were read outloud and made comments on gender, ethnicity guessing. I asked after if she noticed names on the resumes. Immidiately denied noticing names and became defensive.	Identified ethnicity for the Asian, African and Latino candidate outloud while reviewing. Later on denied seeing names because would not want to discriminate. " I'm not a racist"	Participant read names outloud and tried guessing gender, ethnicity. When asked if names were noticed said of course I saw them. However would not affect my hiring. I want the best candidate for the job and gender and race are irrelevant.	Names were read first thing. Tried guessing gender and ethnicity. When asked if he noticed names, admiteed without hesitation. " I was just curious, but I would hire the most qualified candidate. I don't care where they come from"

Table 4. Samples of Admitted and Denied

To drill down in more details, we ran ANOVA test to see if there was an age effect on whether Caucasian or non-Caucasian applicants were hired. There was no significant difference between age groups for the rate at which they hired non-Caucasian applicants. The only effect we found was for the rates at which the Caucasian applicants were hired. Both Amanda and David were hired at different rates across age groups. Specifically, managers who fell in the 20-30 age group hired Caucasian applicants at a higher rate than those in the 40-50 age group. Below are the results:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.325[a]	.106	.090	.324998

a. Predictors: (Constant), Admitted

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.724	1	.724	6.853	.011[b]
	Residual	6.126	58	.106		
	Total	6.850	59			

a. Dependent Variable: CaucApplicants

b. Predictors: (Constant), Admitted

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	.682	.098		6.958	<.001
	Admitted	-.284	.108	-.325	-2.618	.011

a. Dependent Variable: CaucApplicants

Figure 10. <u>Anova Results Showing Caucasian Applicant Decision</u>.

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Mike	Between Groups	1.475	4	.369	1.569	.195
	Within Groups	12.925	55	.235		
	Total	14.400	59			
Amanda	Between Groups	2.550	4	.638	2.851	.032
	Within Groups	12.300	55	.224		
	Total	14.850	59			
Latisha	Between Groups	2.175	4	.544	2.381	.063
	Within Groups	12.558	55	.228		
	Total	14.733	59			
David	Between Groups	3.425	4	.856	4.122	.005
	Within Groups	11.425	55	.208		
	Total	14.850	59			
Juan	Between Groups	.333	4	.083	.905	.468
	Within Groups	5.067	55	.092		
	Total	5.400	59			

Figure 11. Anova Results Showing Caucasian Applicant Decision on Candidate Level.

Multiple Comparisons

Tukey HSD

Dependent Variable	(I) Age	(J) Age	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
NonCaucApplicants	20-30	30-40	-.21111	.132004	.505	-.58439	.16216
		40-50	-.20000	.124863	.503	-.55308	.15308
		50-60	-.25000	.143649	.419	-.65620	.15620
		60-70	-.05556	.179161	.998	-.56218	.45107
	30-40	20-30	.21111	.132004	.505	-.16216	.58439
		40-50	.01111	.074180	1.000	-.19865	.22087
		50-60	-.03889	.102697	.995	-.32929	.25151
		60-70	.15556	.148360	.831	-.26397	.57508
	40-50	20-30	.20000	.124863	.503	-.15308	.55308
		30-40	-.01111	.074180	1.000	-.22087	.19865
		50-60	-.05000	.093341	.983	-.31395	.21395
		60-70	.14444	.142044	.846	-.25722	.54611
	50-60	20-30	.25000	.143649	.419	-.15620	.65620
		30-40	.03889	.102697	.995	-.25151	.32929
		40-50	.05000	.093341	.983	-.21395	.31395
		60-70	.19444	.158810	.737	-.25463	.64352
	60-70	20-30	.05556	.179161	.998	-.45107	.56218
		30-40	-.15556	.148360	.831	-.57508	.26397
		40-50	-.14444	.142044	.846	-.54611	.25722
		50-60	-.19444	.158810	.737	-.64352	.25463
CaucApplicants	20-30	30-40	.34167	.180062	.332	-.16751	.85084
		40-50	.55833*	.170322	.015	.07670	1.03996
		50-60	.31250	.195947	.508	-.24159	.86659
		60-70	.37500	.244388	.545	-.31607	1.06607
	30-40	20-30	-.34167	.180062	.332	-.85084	.16751
		40-50	.21667	.101186	.219	-.06946	.50280
		50-60	-.02917	.140086	1.000	-.42530	.36696
		60-70	.03333	.202373	1.000	-.53893	.60559
	40-50	20-30	-.55833*	.170322	.015	-1.03996	-.07670
		30-40	-.21667	.101186	.219	-.50280	.06946
		50-60	-.24583	.127323	.315	-.60587	.11421
		60-70	-.18333	.193757	.877	-.73123	.36457
	50-60	20-30	-.31250	.195947	.508	-.86659	.24159
		30-40	.02917	.140086	1.000	-.36696	.42530
		40-50	.24583	.127323	.315	-.11421	.60587
		60-70	.06250	.216627	.998	-.55007	.67507
	60-70	20-30	-.37500	.244388	.545	-1.06607	.31607
		30-40	-.03333	.202373	1.000	-.60559	.53893
		40-50	.18333	.193757	.877	-.36457	.73123
		50-60	-.06250	.216627	.998	-.67507	.55007

Based on observed means.
The error term is Mean Square(Error) = .102.
*. The mean difference is significant at the .05 level.

Figure 12. Anova Results Showing Age Detail on Applicant Decisions

In additional to this analysis, we ran the test to see how Gender, Experience and Age impacted the fact that participants Admitted, Denied or Denied and became defensive. When ran the calculations Gender was not a significance variable (Figure 13), Experience (Figure 14) is was very small variable but age stood out (Figure 15).

A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.212[a]	.045	.029	.753

a. Predictors: (Constant), Gender

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.552	1	1.552	2.739	.103[b]
	Residual	32.848	58	.566		
	Total	34.400	59			

a. Dependent Variable: Addmitted /Denied

b. Predictors: (Constant), Gender

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	1.869	.299		6.242	<.001
	Gender	-.323	.195	-.212	-1.655	.103

a. Dependent Variable: Addmitted /Denied

Figure 13. Anova Results Showing Gender Admission or Denial. Anova results showed no significance in Admission or Denied.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.248[a]	.061	.045	.746

a. Predictors: (Constant), Years in Managerial Position

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.114	1	2.114	3.798	.056[b]
	Residual	32.286	58	.557		
	Total	34.400	59			

a. Dependent Variable: Addmitted /Denied

b. Predictors: (Constant), Years in Managerial Position

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.701	.182		9.341	<.001
	Years in Managerial Position	-.114	.058	-.248	-1.949	.056

a. Dependent Variable: Addmitted /Denied

Figure 14. Anova Results Showing Experience Admission or Denial. Anova results showed small significance in Admission or Denied

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.638[a]	.407	.397	.593

a. Predictors: (Constant), Age

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	13.994	1	13.994	39.774	<.001[b]
	Residual	20.406	58	.352		
	Total	34.400	59			

a. Dependent Variable: Addmitted /Denied

b. Predictors: (Constant), Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	2.856	.243		11.743	<.001
	Age	-.511	.081	-.638	-6.307	<.001

a. Dependent Variable: Addmitted /Denied

Figure 15. Anova Age Group Responses for Admitted / Denied. Anova results show significance in Admission or Denied.

Considering this study's findings and keeping in mind our research questions about the extent of bias in hiring managers before and after the word AI is mentioned, we found that the group of Caucasians over 40 years old and the other group (minorities) were aware of the unconscious and conscious bias however would not allow it to affect their hiring process. The younger caucasian managers, aged 20-40, might or might not be aware of their bias; however, they denied reading the names or even guessing information about the applicants. Could it be social pressure? Could it be fear of being labeled racist? The above are probably true, but they denied an observed and recorded action. We can say the hypothesis that Caucasian hiring managers are more likely to hide their conscious bias to justify their hiring choices seems to be true. R-squared adjusted =0.397, F(1.58)=39.774, P=0.001. Suveren (2022) states that unconscious bias can explain social inequality. It is an ongoing process, but with continued effort and awareness, employers hope to create a more diverse workplace environment where all candidates are given a fair opportunity to succeed.

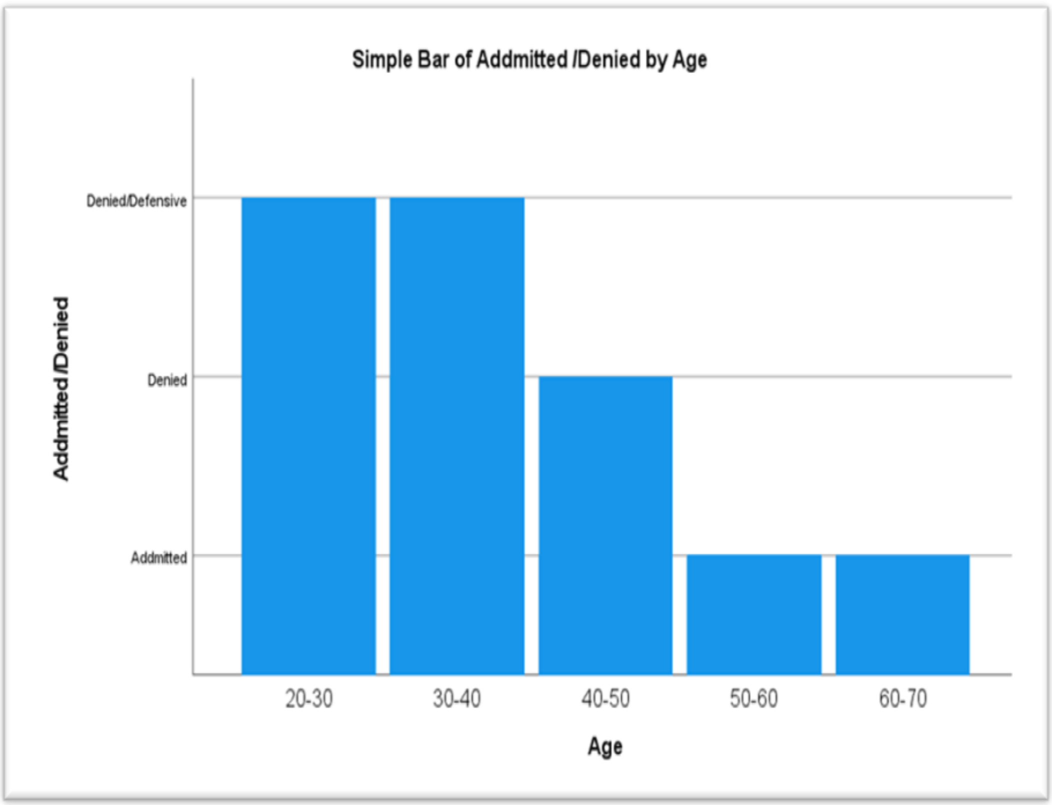

Figure 16. <u>Age Group Responses for Admitted / Denied</u>

These results show concealing bias which will promote inequality. When we consider the hidden world of unconscious bias among young Caucasian managers, the findings are disconcertingly clear. Despite the veils of workplace professionalism, it is evident that a significant portion of this managerial cohort harbors latent discriminatory tendencies. Are we facing the Age of False Progression? The concealment of bias does not just happen; it is meticulously crafted. These young managers have become adept at superficial tolerance in an age where political correctness is a watchword. They speak a different "language", attend seminars, and partake in the hiring quotas. However, beneath these gestures, the smoldering embers of bias continue to burn, waiting for oxygen to ignite into outright discrimination. Concealed masked bias create inequality (Viera & Bangdiwala, 2007).

Here are some samples of bias expressed by participants during the experiment:

- Latisha Nzeribe…hmmm this sounds like an African name for sure not African American. Also sounds like a female name, I think…
- Mike Chen… this last name sounds Chinese, oh wait he knows Chinese or is mandarin they call it? He must be good in math. Schools are better in China…. and of course, he is a hard worker.
- Juan Gonzales with a PHD ….. OH WOW…most of Spanish people I see work in restaurant business…he must speak Spanish as well…oh wait doesn't that depend if he was born here or not?! Maybe that explains his PHD if he was born here…Well…Every Hispanic I know speaks Spanish, so he is definitely bilingual. It might help with Latino clients.
- Amanda definitely a girl. Reminds me a friend of mine from high school. She came from a well-off family…I wonder where is she now …

- David Bennet such a common name. I worked in an IT department before, and we had 4 David's there and they had similar features, blond with blue eyes…talking about being confused…

- We are a nonprofit organization that is based in a poor black neighborhood. All employees are black. I would never hire a white person that does not understand what these people go through… way too privileged for this line of work. Sorry don't mean to sound like a racist but seems like you have an accent, and not sure if you are aware of all the discrimination that has happened in this country of ours.

Companies will have more comprehensive advances in hiring innovation only with the help of more studies and data analysis. (Maghsoudi, Shahri, et al., 2023). It will benefit both the employer and the employee by creating an atmosphere of fairness and equality. This study also highlights the importance of continuing to educate employers on how unconscious biases can influence decisions during the hiring process. Employers must be aware of their own potential biases and those inherent in their team members to make informed decisions without inadvertently discriminating against candidates. In this way, employers can create an equitable hiring process that considers each candidate's merits and ensures that the best person for the job is selected regardless of Gender, ethnicity, or name. By taking these steps, creating a more diverse workplace culture and ensuring everyone has an equal opportunity at success is possible. This, in turn, leads to a more robust, more productive workforce and a healthier business environment.

In conclusion, this study has shown the importance of being aware of potential biases during the hiring process and striving to make decisions based solely on merit. To perfect AI bias, we need to start with human bias acknowledgment (Hautala, 2023). By creating an equitable workplace environment, employers can ensure that all candidates are given a fair chance at success and that the best person for the job is selected regardless of Gender, ethnicity, or name. With continued effort and Education, creating a more diverse workplace culture that benefits employers and employees is possible. It ultimately leads to greater productivity and more substantial business outcomes. By actively working towards an equitable hiring process, employers can ensure all candidates are given a fair chance at success.

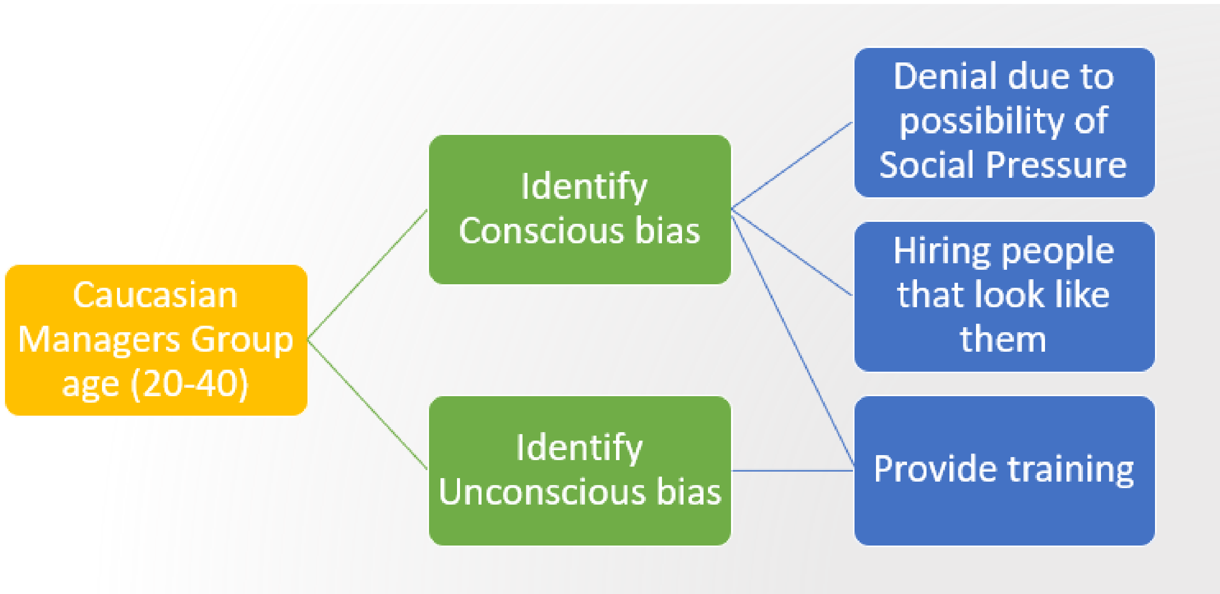

Figure 17. Future Training Suggestions for Young Hiring Managers

Chapter 5

CONCLUSION AND FUTURE RESEARCH

Many factors influenced the proposed research, but Gender, Education, and years of experience with a combination of AI knowledge are the main factors that drive the hiring manager's decision. In the initial steps of this research, we had the research questions puzzling us to what extent there is bias in hiring managers before the AI algorithm word is mentioned. During the experiment and until the end, we realized that it had no impact whatsoever. All managers were aware their companies are already using AI, and since last year, it has become THE TOPIC of every business conversation. Every company has engaged its employees in learning about the benefits of AI applications and transformed many of its processes to more innovative ways with AI. Integration of AI in HR elevates revenue and improves many layers of organizational values; however, some risks come with it. (Maghsoudi, Shahri, et al., 2023).

A larger number of participants at least 200 and more diversity in race & ethnicity.

Finding a specific experiment to identify conscious and unconscious bias in groups but more specifically focusing more on younger managers hiring behavior.

Age as a Potential Dimension

According to (Zahidi, Imam & et al., 2020), times have advanced so much that we are in a time where AI and human intelligence are working together shoulder to shoulder. Knowing that AI was involved in the process brought them more acceptance and a sense of normality. Women participants stood out with less trust in AI, and men had higher trust in AI. From this finding, we concluded that women must be more aware of their bias toward AI selections. Also, men need to be more aware of the chances that AI algorithms could have bias embedded in them. Another finding from the results brought to our attention was two separate groups identified by their differences in acceptance and awareness of their bias. In the quest for diversity and inclusion, corporate America has brandished its commitment to equality like a shining sword, ready to slay the age-old dragon of prejudice. However, what happens when the knights in shining armor, those young managers from predominantly Caucasian groups, are secretly in allegiance with the dragon? Our stance is sobering yet stark – a deeply rooted, covert bias among this demographic is more insidious than we care to admit.

What we should be avoiding is a recurring pattern of exclusion. Our findings indicated that these biases aren't random occurrences but part of a systemic pattern. Favoritism toward individuals who fit the mold of standard corporate culture is evidenced in hiring practices, promotions, and resource allocation. This selective treatment reinforces the status quo, leading to a less diverse and more homogeneous corporate landscape that stifles innovation and perpetuates inequality. Concealing one's bias is not a benign or meaningless gesture. According to a study by Bertomeu, Ma & Marinovic (2020) managers hide their bias more often than known by their superiors. It is, putting it bluntly, dangerous. By disguising their prejudices, these young managers not only compromise their leadership but also propagate the notion that hiding behind a veil of false inclusion is acceptable. The stakes become even higher when their biases mold the corporate environment into a breeding ground for discrimination, leaving marginalized groups to fight an invisible foe.

Gender Bias

In doing so, these biases betray the trust of these young leaders. The diverse employees who look up to them for mentorship and support only to find themselves held back or overlooked are left with a sense of disillusionment that erodes the fabric of the corporate community. The breach of trust is incredibly profound as these managers are often viewed as the embodiment of a progressive future, which they are, in reality, impeding. Prejudice, whether overt or covert, is a barrier that hinders the talent and potential of individuals from minority backgrounds. The nurturing environment required to foster excellence is suffocated under unchecked biases. The impact of this covert discrimination is not felt just in the corridors of the corporate world. However, it reverberates through every facet of society, curtailing advancement and contributing to the persistence of ingrained socio-economic disparities. Managers will try to mold to the environment they find due to fear of not fitting in (Tetlock, 2000), so it comes down to the HR to make sure there is progress.

The question arises – how can we address prejudice if it remains hidden? The first step is acknowledgment. We need to recognize that, despite the veneer of progressivism, there is a collective task to unearth and eradicate the covert biases within this managerial group. Only when we shed light on these prejudices can we begin dismantling them, creating a workplace culture that genuinely reflects the principles of diversity and inclusion. Organizations must create spaces for reflection and growth. By fostering self-awareness and empathy, young managers can begin to understand the implications of their unconscious biases. Interactive workshops that encourage honest conversations, role-playing scenarios, and sharing experiences can catalyze personal and collective transformation.

The Weight of the Algorithm in hiring nowadays is critical. Companies need to assure it does not affect employees negatively (Park, Ahn & et. al, 2021). One might argue that relegating such crucial decisions to lines of code is callous – that it fails to truly appreciate the nuanced qualities of an applicant that could shine through in a face-to-face interview. However, this is an antiquated perception of AI's capabilities. The algorithms used in modern recruitment match keywords on resumes, gauge the role's complexity, and incorporate metrics like job tenure, performance history, and even psychometric assessment results. The algorithm does not experience a bad day or respond under the influence of any personal circumstance. It is the epitome of consistency – treating each candidate in its digital purview the same, without fear or favor.

Transparency and Accountability

Transparency and Accountability is a must for hiring. One of the standout benefits of algorithmic recruitment is its transparency, simplification and reduction of human bias (Kambur & Yildirim, 2021). It is a binary system – whether a candidate matches or not – which is liberating in its simplicity. When a candidate is not selected, the rationale is straightforward and based on measurable criteria, not ambiguous instincts. Furthermore, algorithmic hiring can be easily audited, with the ability to track and analyze data to ensure fairness in the recruitment process. This starkly contrasts the opaque, often unchallenged decisions made in traditional hiring, which are notoriously tricky to contest on the grounds of discrimination. Companies are striving to nurture fairness with algorithms. While it is true that AI can detect and diminish certain biases, it is not a panacea. What it is, however, is a step forward. We are in the midst of an ethical transformation of our labor markets – a pivot from the whims of subjective opinion to the rigors of objective data. The conversation now should center on something other than forgoing human involvement in hiring but instead on optimizing the relationship between humans and algorithms best to serve the interests of employers and job seekers.

Companies need to be more proactive because even though they claim to want diversity, their programs are ineffective (Wynn, 2020). AI can eliminate some of the most egregious inequalities in hiring, allowing us to build a more equitable labor landscape for everyone. We should consider it an evolution and not a revolution. It is important to remember that adopting algorithmic hiring practices does not signal the end of human decision-making. When wielded responsibly, these systems can augment the capabilities of human recruiters rather than replace them. They can provide an initial vetting process free from unconscious biases, offering candidates a fighting chance to showcase their worth in person. We stand on the precipice of a new era in employment where merit and qualifications can be supreme. Algorithmic recruitment lies in maintaining a balance and ensuring that AI streamlines our hiring processes without stamping out the invaluable human touch. Without question, AI is the New Dawn for Hiring. Algorithmic recommendations may never be flawless, but their potential to rectify systemic biases and level the playing field in hiring makes them compelling. They represent an opportunity for a more just and equitable employment ecosystem, where opportunity is not just a chance occurrence but the result of a truly objective evaluation. The transformation of hiring practices will not happen overnight, nor should we rush it. It is a nuanced reality that requires careful calibration. However, as we look toward a future where organizations are increasingly held accountable for the fairness of their hiring practices, it is clear that the algorithmic vanguard offers a beacon of hope – a chance to redefine the landscape of meritocracy in our workplaces.

The consequences of biased hiring practices ripple through every fiber of an organization, from the mosaic of talent it assembles to the culture it cultivates. Biases are rooted deeply in our cultures (Okolie, 2020). A workforce should mirror the vibrant diversity of its patrons. However, the lingering consequences of unchecked bias leads to homogeneity, alienating qualified individuals who do not fit within the narrow confines of certain expectations. Consequently, diversity and inclusion initiatives must be more robust by the gatekeepers of opportunity, perpetuating cycles of inequality and underrepresentation that persist within the upper echelons of industry. A considerable onus lies upon organizations and their leaders to champion systemic change that dismantles the structures fostering bias. It can be approached through several avenues: Managers should perform more structured interviews: Steering away from open-ended questions can provide a more standardized evaluation of candidates, lessening the potential for bias to creep in. More training and education should be available and rigorous.

Mandatory training on recognizing and addressing unconscious bias should be standard practice for all hiring managers. Regular analysis of hiring data, with an eye for patterns that suggest bias, can be employed to root out systemic issues. The call to arms against bias in hiring is not just a matter of equality—it is a directive for prosperity. Fathul (2021) in his journal mentioned that studies show diverse teams outperform in their tasks compared to homogenous teams by tapping into a wellspring of innovation and fresh perspectives. By bravely confronting the reality of bias and investing in measures to mitigate it, we honor the principle of fairness and unlock the immense potential latent within our workforce. Our perspective, underscored by the encounters and insights we have accrued, ultimately echoes the sentiment that the measure of a hiring manager's character must be the conscious choice to champion diversity and inclusion over the allure of the status quo.

Practical Implications of the Studies

Companies need to navigate Bias with excellence (Douglas, 2024). Artificial intelligence has emerged in the rapidly evolving hiring landscape, promising efficiency, objectivity, and innovation. However, implementing AI algorithms in the managerial recruitment process is not a silver bullet for eliminating bias or ensuring a more equitable selection of candidates. It presents a significant stress test for hiring managers, highlighting the potential pitfalls and challenges of incorporating AI into the hiring manager's toolkit. One common misconception about AI in hiring is that it is entirely free from human influence and, therefore, unbiased. While AI can indeed mitigate certain forms of bias, particularly those related to personal characteristics, it is essential to remember that the creation and training of AI models are human endeavors. It means that AI can inadvertently introduce its own biases, often reflecting its creators' demographics and value systems. Hiring managers need to be acutely aware that the objectivity AI appears to offer is, at best, a facade. It conceals a set of programmed biases, which are not inherent and require constant vigilance and oversight to identify and correct. Identifying Algorithmic Favors: It is easy to assume that an algorithm is neutral when it consistently recommends candidates from a specific background or with a particular set of credentials.

However, managers must scrutinize the algorithms to recognize patterns that could inadvertently favor one group over another. For instance, AI might be trained on historical data that disproportionately includes successful candidates from a dominant group, perpetuating the cycle of perpetuating the cycle of one-sided recruitment.

Balancing the Digital Scale when AI flags a candidate as 'unsuitable,' what are the weighted factors, and how are they determined? These questions form the foundation for evaluating an AI system's ability to judge a candidate's diverse qualities objectively. Data collection has to be held at high standard because it is crucial to the process (Slimi & Carballido, 2023). Without clear justification, weighting specific qualifications or experiences over others can lead to biased selection criteria. Hiring managers must be skilled in understanding and questioning the logic behind these digital decisions. Realigning with Managerial Experience: Human resources professionals bring a wealth of experiential judgment and nuanced perspective to the hiring process. They can comprehend the subtleties of a candidate's body language in an interview or contextualize employment gaps within broader societal trends. AI, by contrast, lacks an appreciation for the 'gut feeling' that often underpins these managerial decisions. The Art of Interviewing where managers must be coached in the crucial art of interviewing – from formulating and asking questions that elicit authentic and spontaneous responses to interpreting possible clues hidden within those answers. It requires a deep well of emotional intelligence and contextual understanding that an AI script may be unable to replicate.

The Human Insight no algorithm can replace the insight of an experienced hiring manager who has spent years understanding the nuances of their industry and the unique needs of their organization. They are the gatekeepers against the dehumanization of the hiring process, ensuring that candidates are not reduced to mere data points but are evaluated as complex and multifaceted individuals. Building an Inclusive Ecosystem so AI in hiring can be a vital tool for building diverse candidate pools. However, without intentional oversight, it can easily lock out exceptional candidates who do not fit a pre-conceived mold. Navigating Unconscious Bias where Managers need to be equipped with the skills to recognize and address their unconscious biases, whether they are assumptions about a candidate's name, educational background, or experiences. Awareness training and structured assessments can bring these biases to light, allowing hiring managers to take corrective action. Navigating ethical dilemmas and keeping an eye on bias in AI it is essential for a diverse environment (Putri & Tran, 2023).

Going Beyond the Resume and see where diversity and inclusion extend beyond the recruitment phase; they must be woven into the very fabric of the workplace. Hiring managers should drive this effort by looking for potential and cultural fit, not just ticking off items on a list of qualifications, and by encouraging teams to reflect a variety of backgrounds and perspectives. AI alone cannot foster a culture of acceptance and support amongst employees; that responsibility falls squarely within the domain of managerial experience. In the delicate dance between AI and human intuition, the hiring manager stands as the undisputed lead, orchestrating the recruitment symphony with a keen eye on the process's science and art. The successful integration of AI is not in its ability to replace managers but in amplifying their effectiveness, challenging them to be more mindful, strategic, and, ultimately, more human. The future of hiring is not an algorithm; it is a crossroads where technology meets experience, bias battles with insight, and we can set a new standard for fairness and inclusivity with the proper training and awareness. It is the sweet spot where AI serves as an aid rather than an arbitrator, where hiring managers are paragons of a progressive and proactive approach to recruitment, instilling confidence in the process. In the end, the competitive edge will not be won by the most technologically advanced AI—it will be captured by those organizations that recognize the fusion of AI and human judgment as the new gold standard, ensuring that every hire is a testament, not just to a candidate's skill set but also to the integrity and foresight of the hiring process itself. Minorities should no longer face disadvantages in the market. The best talents should be collected no matter the race, gender or ethnicity (Kang, DeCelles et al, 2016).

In conclusion, this research has provided valuable insight into AI's use in relation to fairness and ethics in recruitment processes. It also encourages further exploration of how to reduce or eliminate such biases with the help of AI capabilities. With more research, we can strive towards fairer hiring practices that do not discriminate against any particular group. According to (Cockburn, Henderson, & Stern, 2018), AI can revolutionize the future of hiring and every process embedded in it. It can be the best and most complimentary tool hiring managers and Human Resource teams use.

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