HUMANS VERSUS MACHINES ARTIFICIAL INTELLIGENCE IN RECRUITING: BEYOND THE HYPE, UNVEILING THE REAL WORLD IMPACT

A Dissertation
Submitted to
the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree
DOCTOR OF PHILOSOPHY

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by
Bianca Picardo
May 2024

Examining Committee Members:

Min-Seok Pang, Advisory Chair, Management Information Systems
Ravi S. Kudesia, Management
Subodha Kumar, Statistics, Operations and Data Science
Matt Wray, External Reader, Sociology

ABSTRACT

Artificial Intelligence (AI) reimagined the Google search and how information is accessed daily. With vast processing times and the ability to digest large amounts of information at lightning speed, AI also can recognize patterns and commands, making information more relevant and useful for the end user. AI has a promising future when strategically placed within certain functions that may tremendously benefit from its skills, ultimately shaping business professionals to rethink approaches to solving complex business problems and determining how and where there may be strategic opportunities to reduce human capital with machines. Given the excitement of newly AI-released capabilities like ChatGPT, questions have been raised around the validity of AI and if it is ethical, especially when used in a sensitive environment like talent recruiting. The hype associated with AI has led to the assumption that it will do what it is told, and marketed as an asset that can be used anywhere. Not only does the hype of AI concern the recruiting world, but it also manifests a much bigger long-term concern for liability. This paper focuses on the use of AI in recruiting. On the surface, AI offers a lot of benefits to organizations, but many lack the knowledge and understanding of how it works. Therefore, I surveyed recruiters and managers to learn more about their dependency of AI for hiring decisions, especially when leveraging applicant tracking systems (ATS). Followed by a technical white paper, I evaluated the hype around AI in recruitment and determine best practices for companies to follow when considering implementing into this function. These technicalities include how and if AI should be used in a recruiting function.

ACKNOWLEDGMENTS

Acknowledgments: Thank you to the faculty and DBA cohort for the ongoing support, laughs, and memories over these last three years. To Precious Carter and Kevin Morgan, thank you for always going above and beyond and being there for me. The bond we have created will last a lifetime, and I am blessed that our paths have crossed. We walked into the classroom on Day 1 as complete strangers, and I can truly say you have grown to become family. Most importantly, a special thank you to my mentor Min-Seok Pang for trusting and believing in me and my ideas. You stepped in when I needed guidance the most, and I feel proud of what we have accomplished together. I firmly believe the best is still yet to come!

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CHAPTER 1

INTRODUCTION OF ARTIFICIAL INTELLIGENCE

The use of artificial intelligence (AI) has become much more prevalent in business over the past several years. AI is a disruptive technology that embodies intelligence from machines and software to mimic the thought process of a human, with much faster processing times and ability to analyze large data sets within seconds (https://www.ibm.com/topics/artificial-intelligence).

As a result, businesses have been strategically implementing AI tools within their line of work to assist with solving complex problems, alleviate manual efforts for specific tasks, and reimagining their approach to how they accomplish their work while also determining where benefits of AI may drive business impact or reduce their human capital.

As an outcome of the COVID-19 pandemic, businesses have shifted a lot of their traditional practices – For example, remote work was a major disruption for business that did not have the technology to support this level of flexibility. Businesses were also challenged to rethink their strategic approaches to how they run their business. For example, aligning their technology roadmaps to accommodate this shift, which includes their investments and budgets, resulting in the need for reorganization of employee headcounts to align to this new operating model – which at the time had no foreseeable end date.

For many businesses, these changes were challenging because they lacked the architecture, framework, and personnel to support it. However, other businesses thrived on the autonomy, which ultimately made customers more dependable on their products and services, boosting their business and revenue more than ever (i.e. Microsoft, Zoom)

The restrictions of the COVID-19 pandemic gave businesses the opportunity to reset and rethink in a way that they may have never had to do before. In a sink or swim fashion, businesses pivoted and pushed the boundaries of what could be possible to keep up with demands, or instead, struggled to survive.

As a result, AI became a lot more popular given the idea that it could assist with a lot of these challenges, making it much easier for businesses to fluently ‘get the job done’ with minimal disruption.

Historical Context of AI in Recruiting

The focus of this paper is on the use of AI in recruiting. AI in recruiting can be defined as “any organizational procedure during the recruitment and selection of job candidates that make use of AI, whereas AI itself refers to "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Hunkenschroer & Kriebitz, 2022) (Kaplan & Haenlein, 2019). In a recruiting sense, implementing AI at the front-end of the hiring process, with the use of automation, has proven to make hiring quicker and the process much more streamlined.

As previously stated, AI can process information exponentially faster than humans. In this case, a recruiter may review ten resumes in ten minutes, with a high-level understanding of the different kinds of candidates, and who may be qualified to move forward in the hiring process. However, AI can accomplish these tasks in seconds, while also parsing the resume information and aligning it to the job requirements – determining how each candidate matches up to the role and sifting out the unqualified candidates who applied without any experience. Through proactive and savvy marketing, AI companies have positioned technology as a tremendous impact tool for procuring new talent. Calling recruiting "tedious," AI has been marketed to show value for HR departments looking to reduce and synergize strenuous, time-consuming work activities.

While hiring approaches have always changed and adjusted to the market and what businesses need from the talent marketplace, AI in recruiting is not completely new. Resources, such as LinkedIn, have been exploited by job seekers looking for their next role, as well as by recruiters in search of fresh talent for businesses requiring diversified skillsets and professionals at various career levels.

However, the COVID-19 pandemic caused job seekers to rethink their careers, especially with opportunities to work remotely, increased shift flexibility, and benefit offers that more aligned to their needs. The "Great Resignation" was a tumultuous time for employers as suddenly, and previously uncharacteristically, the job seeker had increased power and the upper hand, forcing recruiters and businesses to different incentives.

Another critical factor was remote work made it possible for employees and workers to extend the geographic parameters of their location. This impacted the flux of applications coming in to each role, overwhelming recruiters and ultimately swamping the market with top talent seeking career changes or new experiences.

Attrition rates skyrocketed, and companies struggled to keep up with the application demand, and businesses were strategically challenged to adjust. . Primarily within the United States, 11.3 million jobs opened at the end of May 2020, which was the first documented year of the pandemic. This represented a substantial increase to 9.3 million from the previous month of April. (Smet et al., 2022).

While this is not the first time the economy has suffered hiring challenges; why is now the time for AI to breakthrough, especially since it certainly has not been the highest point of attrition in our history? (U.S Bureau Department of Labor Statistics, 2022). The difference between the historical quit rates and today's job market is a clear delineation between job satisfaction and flexibility. The post-pandemic world job market is booming and are being directly impacted by this shift. At the same time, HR departments are forced to monitor external demands that are more insistent than ever.

Job access has played a major role in application demand. Modern technology tools have made it much easier for job seekers to search for new roles further complicating the hiring process for recruiters. AI has been used to attract top-tier talent by leveraging its capabilities to craft descriptive and enticing job descriptions, "AI software vendors, such as Textio, use AI in the form of text-mining techniques to predict the attractiveness of a job listing based on the hiring outcomes of several millions of job posts" (Hunkenschroer & Luetge, 2022). These advancements were the infancy of AI in recruiting and have provided major "wins" to businesses by implementing cost savings. Therefore, over time, AI and its development have proven valuable to businesses in multiple areas. Particularly within recruiting, it has shown great promise by giving recruiters and HR departments an extra crutch during these difficult times. This value has shed light on the various instances where AI may be used to streamline work efforts.

Throughout this evolution, recruiting has become more complex, job seekers have become pickier, and overall, the hiring process has indisputably changed. Job seekers now have autonomy over their career development by pursuing opportunities more aligned with their passion and goals. Gone are the days when corporations dictate an employees' tenure, and businesses have struggled to keep their workforce.

On average, it costs a business six-to-nine months of an employee's salary to replace them. (Enrich, 2016). Candidates with a broad set of transferable skills and certifications have become more attractive, given the flexibility of work arrangements. However, with more remote jobs available, talent pools have expanded to target global populations making the hiring process increasingly more competitive. The job seeker is no longer required to be in a physical workspace or reside within a certain geographic radius of a business location, opening remote opportunities worldwide. These new realities post-pandemic have resulted in a number of new questions with solutions yet undetermined.

CHAPTER 2

LITERATURE REVIEW

The impact and seemingly limitless possibilities of AI has generated research, case studies, and experiments, as well as hypotheses, legitimate conclusions, and rampant speculation. This research paper focuses on the promotion of use of AI in recruiting by businesses and stakeholders, as well as the general understanding amongst managers and recruiters, particularly during the recruitment process.

Within this dissertation's literature research, the focus was on Fortune 500 companies, seeking to understand the fundamental use of AI in recruiting, and the impact it has on the overall hiring process.

AI comes in the form of different algorithm models that are tested and challenged to ensure validity, efficiency, and effectiveness. Different aspects of AI are used for varying cases. For example, machine learning (ML) is another intelligence compartment in this model. ML has two distinct forms: supervised and unsupervised learning (Klingler, 2022).

AI Models

For learning to be supervised, the data and content are pre-populated into the algorithm to learn from ground truth data, often seen in historical data sets for credit approvals and statistical or financial data (Klingler, 2022). Ground truth is evaluating the machine's output and testing the results with a real-world data set (Techopedia, 2022). Keeping these AI tools honest is vital to ensuring competence and accuracy as they become more popular.

In addition, unsupervised learning is when the algorithm is given raw data without annotations, often seen in financial analysis and fraud detection industries (Klingler, 2022). This example is another form of teaching the algorithm to learn independently without any pre-adjusted bias or phrases to scan.

Through these differing forms of intelligence, models can be created for various needs, preconditioning the rules to adjust the algorithms decision behavior:

- **AI Models:** Analyze existing data and make informed predictions, often used in business environments to drive efficiencies.
- **ML Models:** Often leverages a mathematical approach to making predictions on future events, which includes regression and classification models. (Viso, 2022)

While the infrastructure of the models remains consistent across different products, when used in recruiting, companies can inform the algorithm of critical words, rephrasing, qualifications, skills, and information they would like it to scan resumes for.

In a global survey by Mckinsey, participants were asked what drove them to want to stay, leave, or return to their jobs. Of those who quit between 2020 and 2022, 17% did not return to work, 48% changed industries, and 35% took a new job in the same industry (Smet et al., 2022). Given these changes, the literature fails to explain how algorithms are compensating for these employment changes. In other words, for those changing industries, how does the algorithm adjust biases and develop the ability to learn to deviate from previously preferred candidates? Alluding that, without evidence of the ability to recognize these permutations, how can we be sure that all of the best and qualified candidate are being put into the advanced into the proper pool for consideration for a position?

Furthermore, this algorithm's decision criteria is just as important as how the results are interpreted by the end user. For the example presented in this case, the recruiter, making it clear why job seekers were presented as qualifiers over others that did not meet expectations of the job description.. In the case of recruitment, recruiters must understand how recommendations are made by the algorithm. "Recruiters must be able to understand and explain how and why an algorithm arrived at its decision" (Guerra et al., 2022). Without full disclosure of the intellectual property of the algorithm, and proper training for staff to understand how to recognize when the results are off or if there are any red flags, the dependency and trust on these recommendations cannot and should not be fully trusted. What type of trust or hesitations, if any, do recruiters place in the hands of these algorithms to deliver the accurate information they need to inform their recruiting process

Bias

One area AI has helped address in hiring processes is the elimination of human biases. In addition, the use of AI in recruiting has become more prevalent as businesses further developed their diversity, equity, and inclusion strategies. Similar to what we previously discussed regarding the use of AI to assist with crafting unique and enticing job descriptions to attract top talent, AI has been granted the trust to reduce human bias during the selection process. Whether this is removing race, gender, age, to any other demographic criteria that may cause bias, This has been a strong marketing tactic for businesses driving more use of AI in recruiting, by eliminating recruiters who have a specific perception of the “type” of person they want to hire. In other cases, humans lack the ability to think differently or consider candidates from different backgrounds or experiences that may lead to an untraditional type of hire. The truth is, how can we know for sure whether AI is reducing this bias when we are still unclear as to how the algorithm arrives at its decisions?

In addition, given what we know about the complexity of AI, specifically when used in tools like Applicant Tracking Systems (ATS), the knowledge and understanding of how the tool works is required for personnel to interact with it. Businesses have recognized these shortcomings and structured their IT teams to perform IT Risk and Privacy assessments to test the algorithms as much as possible to gauge their level of trust.

Feedback Loops

As we consider the massive trust instilled in AI, and further dive into the process of how to maintain honest algorithms, a critical step is to continually learn, test, and engage with an algorithm’s feedback loop. A feedback loop informs the algorithm whether a decision is right or wrong. This data enables data scientists or whomever is managing the tool to adjust an algorithms parameters to perform better in the future, ultimately ensuring the intelligence is continually evolving to produce more refined recommendations (C3.ai, 2021). Feedback loops are the nucleus of AI’s recommendation engine, and even though it has an ability to learn over time, it still requires human involvement to test, alter, and ensure they are generating accurate, honest, and useful outputs.

There is an existing misconception that these activities can be performed on their own, but proper governance must be established to ensure businesses are using AI properly. Since we still do not understand why or how an algorithm arrives at its decision, it is not ethical to remain overly dependent on AI to provide feedback between algorithms or fully trust the output (Pal, 2019). This is not to say that algorithms may not be able to achieve this level of intelligence and precision in the future, but today we are not there yet. For an algorithm to be effective, the interactions with it are critical. Throughout the literature, we discovered a gap in the experience of recruiters and managers when it comes to understanding how and why ATS tools work the way they do. The involvement of algorithms is filtered through an ATS software, which is commonly used in the hiring process to gather resumes and candidate profiles for assessment

Even if AI is leveraged somewhere during the hiring process, machines have far superior capabilities to humans. Further, if we assumed humans could fully understand how AI operates, humans could not keep up in speed with their intelligence to process large sums of information at a rapid speed and storage capacity. Engagement does not always mean it is positive, negative feedback loops can also create more of a bias for applicants. Naturally, bias will always be present and rooted in our human behavior, which can be passed in code to predictive hiring algorithms (Raub, 2018). And even then, we still may never determine the root cause of how and why it has arrived at its decision, making its promise to deliver in an efficient way, inefficient and unreliable.

Given these insights, algorithms are conditioned to learn from an existing data set or bundle of information. The goal is to tell the algorithm what you want it to know, allowing it to organize the information into categories and provide answers. As an example, if the algorithms were to ingest historical hiring data from a period with gender or racial inequities, the algorithm would make suggestions based on pre-existing patterns. Or, if the algorithm ingested data that was discriminatory against people of color, it would conclude that a Caucasian male was the preferred race and ethnicity for hire because historical data shows that the Caucasian white male was hired more frequently between a period in history where racism was highly prevalent. In this scenario, the algorithm would identify an African American man or woman lower than that of a white Caucasian counterpart. From a humanistic perspective, when determining how hiring decisions align to diversity and inclusion efforts, emotional intelligence would be used to deem an algorithm discriminatory against African American candidates given their race and ethnicity. However, the algorithm would not know any better.

With further testing and enhancements, we can surmise the algorithm could learn about types of discrimination, and therefore no longer negate African American descent and weigh them lesser on the qualification scale. In an updated scenario, an African American man and a Caucasian woman would both be deemed a qualified overall fit for Company X. As a recruiter, one may look at these results and determine the algorithm was successful in reducing discrimination, since two women of different ethnicity and background were ranked the highest out of the candidate pool. However, how do we know for certain that this is true? How can one determine that the algorithm weighs men and women the same? Better yet, should they always be weighted the same? While yes, it is illegal to hire an individual based on their gender, race, religion, or sexual orientation or identity, there may be positions that are better suited or more male-dominant, making algorithms more bias toward a specific hire.

Unfortunately, there may also be a use case where too much refinement in an algorithm causes an issue. Over time, when the refinements are too specific with requirements, perfect becomes impossible, making it challenging for the AI to determine which candidates have a higher weight than the others.

In 2017, Amazon, one of the world's largest e-commerce retailers, experimented with AI in their recruiting process and suffered many challenges that impacted their brand and overall business. Amazon was one of the first to explore using AI for this function and developed an internal model to mirror the 1-to-5 star rating formats for candidates, who were also used in their customer service product feedback for their site products (Lauret, 2019). Since the algorithm was new, the learning curve featured potential challenges businesses may face and the discrepancies that may arise from the data.

Over time, Amazon started to recognize an inconsistency with the output of the candidate pool, raising concern regarding whether the algorithm was working properly. Amazon learned that the historical hiring data taught the algorithm to prefer more male candidates. In addition, the algorithm started to recognize a pattern and followed it thinking it was getting smarter, and that its predictability was getting more accurate. This skewed the validity of parsing the results, "It penalized resumes that included the word "women's," as in "women's chess club captain," in addition to downgrading graduates of two all-women's colleges" (Hamilton, 2018). As a result, recruiters were able to flag this concern given that the male-dominance was obvious, however Amazon quickly learned the importance of the ground truth data, and ensuring their hiring algorithm adequately monitored to reduce detrimental hiring issues.

In other circumstances, AI showed to work better in specific industries than others, and even with frequent feedback loops and engagement, it can sometimes hurt AI models based on how they are built and informed, as well as their ability to reduce bias properly. “In many high-stakes applications, like hiring and lending, these decision-making systems may reshape the underlying populations. When the system is retrained on future data, it may become not less but more detrimental to historically disadvantaged groups” (Liu, 2020).

For example, in a real-world use case provided by Microsoft, a “university made admissions decisions based on SAT scores. SAT scores are an imperfect indicator of academic qualification” (Liu, 2020). The differing scoring ranges changed the qualifying applicants’ threshold, making those applicants who may have been on the cusp of qualification, no longer considered for admission due to the high-performance ranges and outliers throwing off the average (Liu, 2020). The algorithm learned to increase the threshold based on these results, and it impacted the incentive and likelihood for the lower-level applicants to apply to university or even have a chance at being accepted, especially since their SAT score was explicitly noted to be subjective. Algorithms historically have lacked the emotional intelligence required to make these types of decisions; they do not have a threshold where it can communicate that a decision is required beyond the scope of their capabilities. However, as humans and within business especially, society has instilled a specific amount of trust that it will deliver its promises, rather than being skeptical on the quality and ethics associated with the results. AI has not evolved and matured to meet these demands — these interpretations would be better informed by a human who can properly gauge the outliers.

Continuing, historically AI has also been used in field experiments studying labor market discrimination. Name discrimination also played a major part into candidates getting selected for an interview. Within each resume, the names were altered to represent less traditional and common names, and replaced with more ethnic and non-ethnic names that are commonly used amongst different races. Name discrimination was present in the results, and showed significant discrimination against mostly African American names, "White names received 50 percent more callbacks for interviews" (Mann & O'Niel, 2017). A quality as simple as name bias can deter a candidate from receiving an opportunity, even if they have equivalent skills and qualifications to a counterpart of a different race or culture (Mann & O'Niel, 2017). Sometimes testing the algorithm can only identify obvious and drastic results that are easily determined to be inaccurate, however this type of bias may take years for a business to recognize. There is so much that we do not know about the potential risks of AI in recruiting that have yet to be discovered.

In many cases, historical data does not always provide a complete picture of what fair representation may look like in an organization, especially since they are constantly evolving in nature and continuing to break barriers of financial, race, and gender inequities. Businesses thrive on insight-driven decision making and prioritize it in many other areas to make strategic choices, however the literature fails to represent a standard on how AI should be governed in this type of environment to ensure equal opportunity employment and that employees are well trained on how and when AI should be trusted and used.

At a high level, the impact of AI in recruiting is major, considering that 72% of resumes are skimmed from the candidate pool before a human ever sees them (Mann & O'Neil, 2017), alluding that bias may exist well before the evaluation process by the recruiter ever begins (Kim, Bodie, 2021). In addition, it may be more difficult for a recruiter to catch inaccuracies if they are not reviewing the 72% that never reached their desk. Furthermore, taking these additional steps may slow the process and take away the value-add of implementing this tool this in the first place to save time and speed the hiring process.

Research further suggests that the input and ground truth of the fundamental aspects of AI play a critical part in their success and ability to deliver on their promise. The technical aspects of how AI in recruiting works significantly impacts the end users or individuals who are engaging and making strategic choices based on the outcome of the algorithm. AI should be carefully considered for these nuances before ever implementing this type of tool into a recruiting function.

Applicant Tracking Systems

Recruiters must stay ahead of the curve and find ways to be more efficient wherever possible. An Applicant Tracking System (ATS) is a software that uses AI to automate administrative tasks in recruitment and hiring (Team, 2022). They are commonly used to track and review applications but have several functions for autogenerated recruitment. Ninety-nine percent of Fortune 500 companies use an ATS, typically due to company size and corresponding demand of job interest and applications (Hu, 2022).

While ATS tools do not completely replace the HR function, there are requirements needed from the technology for recruiters:

- Simplicity – They must have a seamless user experience, requiring minimal IT support, while being cost-effective and affordable.
- Data Analysis & Reporting – To evaluate a large number of submissions, the need to generate valuable insights, benefitting the recruiter.
- Social – Job postings and descriptions are deployed to a target market, visible on social media and career platforms.
- Safety – Meet compliance policies and regulations.
- Easily Integrated – Seamless integration into other HCM tools utilized by the company. (Halutzy, 2016)

Table 4 AI applications per recruiting stage

Stage	Outreach	Screening	Assessment	Facilitation
Objective	Identify possible candidates & persuade them to apply	Derive shortlist of most promising candidates	Identify which candidate is most appropriate for the job	Coordinate with applicants throughout the process
AI applications	Formulation of job ads (e.g., gender-neutral wording) Targeted advertisement of open positions (e.g., via social media) Notification of job seekers Identification of active or passive candidates (e.g., via LinkedIn or ATS[a])	Scanning of resumes (beyond keywords) to score or rank candidates Matching of candidates & job openings to identify best fit	Analysis of video interviews with AI technology (voice/face recognition) Simulation/games/tests to assess certain skills, capabilities and traits Scraping & analytics of social media postings for psychological profiles Linguistic analysis of writing samples & web activity	Use of NLP[b] to parse CVs & extract relevant information to fill-in application forms automatically Transparency on where applicants stand in the process & elucidation of next steps Scheduling of interviews & sending of job offers Communication with applicants & answering of questions by chatbot

[a]Automated tracking system
[b]Natural language processing

Figure 1. AI Applications in Recruiting

Hunkenschroer & Luetge, 2022)

According to Figure 1, AI applications are common during differing phases of the hiring process. ATS tools, such as Workday, LinkedIn Talent Hub, and Indeed Apply, have remained cutting-edge for years and implemented AI into their product offerings. Specifically, the AI in these hiring tools opens significant areas of opportunity for both parties:

1. Companies receive incredible insights and recommendations on candidates whose skills align with the posted job description. In addition, the AI is sifting through applicants who have already applied and recommending the most qualified to the recruiter.
2. As a job seeker, the hiring process has become more manageable. AI scans their resumes and profiles to recommend jobs matching their skill set, ultimately suggesting where they should apply.

However, as complexities in recruiting and AI evolve, the tool is only as beneficial as the process supporting it. Many professionals question the use of AI in hiring by wondering if recruiters are even using them to begin with – Hiring inefficiencies still exist, but where is the root cause? Are HR departments and employers in the way of the process, or are other conditions that must be true for AI to work efficiently and appropriately?

Research Question and Motivation

To address the gap in the literature, this research focuses specifically on the perception of AI in recruiting and whether it will ever replace human users entirely, while also considering the influence it has on the recruiting process and overall hiring structure.

While we understand the flux of candidate applications has become difficult for HR departments to manage and sustain, and therefore implementing AI into recruiting is intended to improve this process, we are not convinced it works. When interpreting the literature, we have discovered a clear relationship between driving value and efficiency when implementing AI. However, there are gaps when comprehending how AI delivers, specifically from the perspective of the recruiter and manager. Some apparent gaps and dependencies question whether AI should ever be used in hiring or if the tools need to be more mature or developed enough to compensate for its shortcomings.

RQ: How Does AI Deliver on Its Promise for Talent Sourcing?

Companies are jumping at any opportunity to adopt the latest technology to make their business more attractive. However, there are significant gaps when it comes to understanding how AI works in recruiting and the trust that recruiters and managers place on the technology.

Thus, the growing need to govern AI in recruiting and setting boundaries on its uses is an ongoing challenge. With candidate pools continuing to increase, having enough manpower readily available to parse through hundreds of resumes is only one subset of the overall problem: How can recruiters and companies ensure the most qualified candidates get representation through the hiring algorithm?

Implementing AI in recruiting has become a desirable and deliberate choice for strategic leaders who see it as a “quick win” for their organization. However, the same leaders may lack the knowledge and information to make an informed choice, by also weighing the risks, vulnerability, and liability they place on their HR departments. Of course, the main goal is to ensure that the right person is hired for the job — the existing literature shows the benefits AI can provide also cautions the validity of how it connects the dots from an emotional intelligence perspective that human evaluation perspective provides and adds. Value comes in many forms depending on the nature of the industry and its culture, and in this case, the value is defined as the ability to make decisions based on the characteristics of a candidate's profile, and not their specific skills or qualifications that require checking off the standard employment boxes.

RQ: Can AI Capabilities and HR Functions Coexist?

Given what we know about feedback loops, it is unclear if the education and awareness of how AI works within ATS tools to understand if users are properly informing the algorithm with information. Other insights have been shared to validate the quality of the hire and whether the analytics are being captured by the managers around performance (record of skills, qualifications, and qualities of individuals deemed an excellent fit for the company culture).

A significant gap has been discovered between recruiters and managers, who lack overall comprehension of AI technology in ATS tools, and how this dynamic impacts the hiring process. For example, suppose managers do not circle back to HR with feedback on their new hire and overall satisfaction. In that case, no historical data is shared with the algorithm to show whether its decision making was positive or negative, which in turn improves the selection criteria for future roles. If these assumptions are indeed proven accurate, then the growth of talent management and a company's DE&I efforts are solely absorbed by the recruiter's thoughts and opinions. Therefore, AI in recruiting is not actually delivering on its promise of driving value to a business, rather it is rendered a marketing tactic to represent the business as modernized and innovative, when in reality it is causing harm to the process. This has resulted in conversations around whether the unconscious bias in recruiting is solely from the algorithm or the interpretation of a recruiter and their lack of knowledge on how AI in recruiting works. If hiring processes to not compensate for these conditions, businesses will end up with the same candidates they have always preferred to hire, and in effect, missing potentially attracting top-tier talent that is not getting weighted accurately against the algorithm.

Methodology

The scope of this study includes a survey for recruiters and managers working at a Fortune 500 company, including companies with 6,000 or more employees in size. The study's intent will be to determine if and how AI delivers on identifying talent sourcing, by surveying two populations, hiring managers, and recruiters to better understand their relationship and how AI extends throughout the hiring process.

In this study, two surveys will be distributed to two different populations: Recruiters – S1 **(See Appendix A)** and Managers – S2 **(See Appendix B).**

In S1, the study intends to:

- Dive into the experience and perspective of recruiters;
- Better understand their interaction and understanding of AI;
- Ascertain how AI is currently used within their company to supplement recruiting constraints;
- Assist them with refining candidate pools.

By focusing on larger companies, (Fortune 500,) the application demand is much higher, and therefore ATS tools are acquired to assist with manual resume parsing.

However, given the complexities of ATS tools and company culture, some recruiters may not find these tools useful. This survey will help determine how impactful ATS tools are to recruiters and their ability to perform their jobs at a high level; or conversely if they are not interested in using them By implementing open text fields, we strive to gain recruiter feedback to understand potential nuances and draw out high level themes for their perspective.

Determining how often recruiters depend on output or internal processes to refine candidate pools will illuminate whether AI is helpful in this business function. In other words, are job seekers fairly evaluated based on their skill set and ability, or is there an underlying bias?

Part two of this study will focus on surveying managers who are a critical piece of the recruiting process. S2 will be centralized around managers with a recent new hire, defined as a manager who hired someone on their team within the past 6-12 months. Questions will be targeted to better understand their knowledge of AI, interactions with recruiters, and the overall hiring experience at their company.

If AI in recruiting is intended to drive proficiency and attract stronger candidate pools, then it will be important to understand if managers feel they are receiving high-quality prospects. Questions are tailored around their experience and feedback will be requested regarding areas of opportunities to improve the recruiting process to determine if AI in recruiting has a potential impact to improve the process or make it more challenging. This approach will help us determine whether AI is delivering on its intended promise, from a managerial perspective. These managers are included in this study due to the impact candidate pools have on their team's future success. Managerial input and satisfaction with recent hires will help us home in on that promise and further assess AI's impact on recruiting.

In addition, it will be necessary for this study to evaluate and uncover whether these managers felt they received a qualified candidate, especially by determining if the candidate indeed possessed the appropriate skills needed from the original job description. This will help us determine if AI in ATS tools are able to accurately parse resumes to see past the finessers, ultimately weeding through the candidates to account for a wider scale of skills and experience. As part of this study, managers will be asked to determine the quality of their recent new hire. Questions will focus on the new hire's performance, skillset, relevancy to the job requirements, and ability to add immediate value to their team or department.

For participation in this study, recruiters and managers were targeted through personal and professional networks, such as LinkedIn and Facebook. The goal was to reach 1,500 participants with an expected response rate of 20%. In the event the response rate is low, colleagues and senior leaders will be encouraging to share the survey in a broader communication to their staff and organization. Lastly, if needed, a third-party agency will be leveraged to identify additional participants. Each survey should take 5-10 minutes to complete.

Upon completing this study, the results will be analyzed and married to draw high level conclusions regarding the use of AI in recruiting via ATS tools. In addition, we strive to gain insights on the overall recruiting experience and process. We will determine if our findings disclose any significance to success of AI in recruiting with regards to company size, culture, or industry. The consistency in how AI is leveraged from one corporation to another may open other areas for concerns or opportunities related to business technology architecture.

For Study 1, our hypotheses that we will test will cover the following:

- **H1:** AI improves candidate hiring accuracy with a focus on high-quality acquisition.
- **H2:** AI improves the quality of hires, with a focus on increased diversity.
- **H3:** AI-driven talent sourcing sets clear hiring expectations and enhances strategic decision-making in recruitment.

Contributions

This research spans multiple disciplines, primarily at the Fortune 500 level. This research intends to bring awareness of AI, how it works and should be used to further explore if it should be implemented as part of a recruiting function. When leveraging it for recruiting, companies have instilled far too much trust in AI's promise to deliver the same quality of a hiring experience as a human-recruiter. Businesses much align to the risks and nuances of AI and thoroughly validate its ethics and integrity against their internal hiring standards. The future of a company's success and growth depends on its ability to hire well and diversify its workforce. In addition, this research will bring more awareness to equal opportunity employment policies across HR departments that establish ethics, policies, and best practices for businesses engaging with AI or relevant hiring tools in recruiting.

CHAPTER 3

STUDY 1 DATA COLLECTION

A quantitative research approach was utilized by distributing surveys to two populations: recruiters and managers. *Recruiters* are the primary contact responsible for sourcing candidates for a business. *Managers* are considered the direct points of contact for HR to collaborate to fill open positions.

Given the specific participant subjects, a third-party survey company was consulted for this research to ensure the study could target a broad enough sample size featuring in large corporations. A *large corporation* is defined as a business with more than 6,000 employees. Targeting larger corporations was critical given that companies of this size most likely have a higher application demand and have adopted ATS tools to support hiring.

The surveys were structured to capture:

- Background information on the role and company,
- Knowledge and understanding of AI, and
- The overall experience with the hiring process.

The questions included Likert scales, multiple choice, and open-ended text fields.

Both surveys were designed to ascertain how deep AI extends into the recruitment process. In addition, we aim study the dependency level recruiters have on ATS tools. Since recruiters work closely with managers, managers were consulted to further understand the entire dynamic between both parties, ultimately to determine if AI in recruiting is driving efficiency, or if the people and processes are hindering the effectiveness.

While the business community debates if AI is suitable for recruiting, we focused on investigating the accusations that AI tools improve hiring, to further understand its intended promise, particularly given the hype and marketing campaign promises surrounding limitless possibilities. We aim to discover the root cause of why managers and companies feel the need to implement a tool like AI in hiring and if there are any other underlying conditions or concerns that help frame why their existing processes are broken, or businesses feel their candidates' pools are not satisfactory.

Data Analysis

The data was collected via Qualtrics, and responses were evaluated to determine if participants were eligible to remain in the study:

Approval Criteria:
▪ Legitimate Company name ▪ A completed survey consisting of appropriate and respectful responses ▪ The participant was in the correct role (Hiring manager or HR professional) based on each respective survey ▪ Not a test user

In S1, we received a total of 384 responses. After evaluation, 181 were disregarded, and 203 respondents remained part of the study, ranging from several different industries **(See Figure 2)**

Response	%	Count
Pharmaceutical	4.17%	8
Finance	7.29%	14
Food & Beverage Services	4.69%	9
Retail & E-Commerce	18.23%	35
Technology & Software	14.06%	27
Health & Insurance	19.79%	38
Other (Please specify)	31.77%	61

Figure 2. Study 1: Recruiter Responses by Industry

Additional Industries listed in Other: Agricultural, Airline & Transportation, Business Services, Construction, Customer Service, Education, Energy & Consumption, Entertainment, Government & Military, Hospitality & Tourism, Manufacturing, Medical. Non-profit, Public Administration, Real Estate, Recruiting, Utility

The sample size captured respondents from within an HR community and exemplified a diversified set of roles. The roles are defined by the following:

- **Recruiter:** Responsible for finding talent for entry and mid-level positions
- **Executive Recruiter:** Responsible for finding talent for high-level C-suite positions
- **Talent Acquisition:** Focused on workforce planning – "Deals with the strategies, tactics, and processes for identifying, recruiting, and retaining the human resources a company needs" (SHRMs)

- **Other:** A role within HR but not directly involved in the hiring process (Chief of Talent, Director of HR, HRIS, GR Generalist, HRBP, CEO, HR Onboarding)

In S2, 292 responses were received, 55 were screened out, and 237 remained a part of the study. The results from the open-text field questions were imported into Excel, where analysis was identified to pull high-level themes from respondents.

Findings

The results shared several significant findings regarding AI in recruiting, and, in some cases, forced companies to have seemingly uncomfortable conversations about the approach they are employing . After scoring, reviewing, and aggregating the data, this paper decided to focus on four themes:

- **T1**: Discrepancies between how both parties feel about the use of AI
- **T2**: Both parties claim the hiring experience is great but are critical and complain about shortcomings
- **T3**: For AI in hiring to work, it needs a cohesive ecosystem for implementation from a people, process, and technology perspective

The data showed significant differences between recruiters' and managers' thoughts regarding using AI in a hiring function.

Company	# of Employees	Company	# of Employees	Company	# of Employees
1. Sam's Club	2,300,000	11. Dollar General	164,000	21. Exxon	62,000
2. Walmart	1,600,000	12. Google	156,500	22. McDonalds	50,000
3. Amazon	1,541,000	13. Johnson & Johnson	150,000	23. Waste Management	49,500
4. Target	440,000	14. Chick Fil A	140,000	24. Weis	23,000
5. CVS	300,000	15. Verizon	104,219	25. Wells Fargo	22,000
6. Lowes	300,000	16. Nike	83,700	26. Regions	20,073
7. Chase	256,981	17. AstraZeneca	83,500	27. Key Bank	18,000
8. Microsoft	221,000	18. Meta	71,970	28. Expedia	16,500
9. Bank of America	165,773	19. Merck	69,000	29. Acrisure	16,000
10. Apple	164,000	20. ADP	63,000	30. Organon	10,000

Figure 3. Top Companies by Size

Given what we know about AI, we assumed recruiters would support and use it, mainly since it is intended to streamline resume parsing to be easier and faster. Recruiters expressed how in some cases, AI is practical and extremely valuable when placed at the front end of the process since it can quickly ELIMINATE front-line candidates, who are not qualified or aligned to the job description .

Based on the results of this study, we aligned these outcomes to the recruiter's overall satisfaction with the quality of resumes generated from the AI **(See Figure 4).**

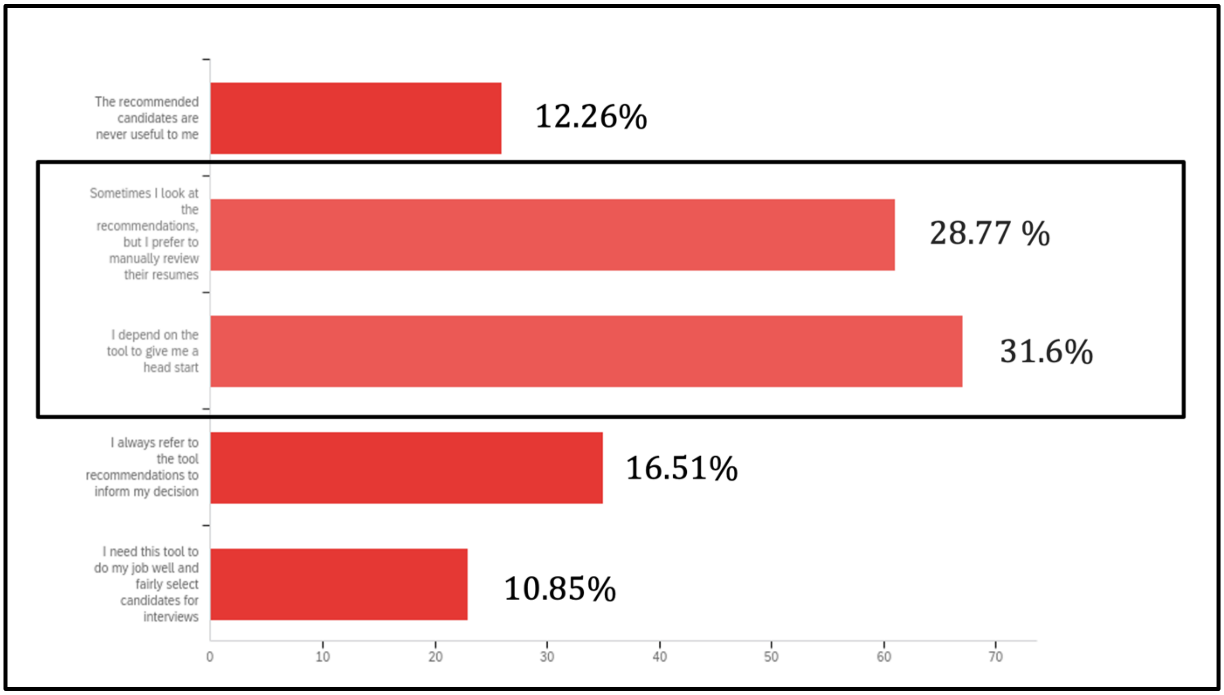


Figure 4. Satisfaction of Resume Quality from AI

The data disclosed that over 60% of recruiters leverage an ATS tool during their process, indicating they were satisfied with the resumes. An additional 11% felt highly dependent on it to do their job well and reasonably select candidates for interviews. These results indicate that using AI is purposeful for an initial scanning process, but it still has not adopted fully by the majority. However, the resumes that may be individually selected by the recruiters may not be as accurate as the tool that claims to parse from an unbiased point of view by focusing on the basic job posting qualifications.

In S1, we discovered that 85% of recruiters were familiar with ATS tools and their use. However, 74% felt indifferent to AI and needed little to no dependency to perform their job tasks (See Figure 5) adequately.

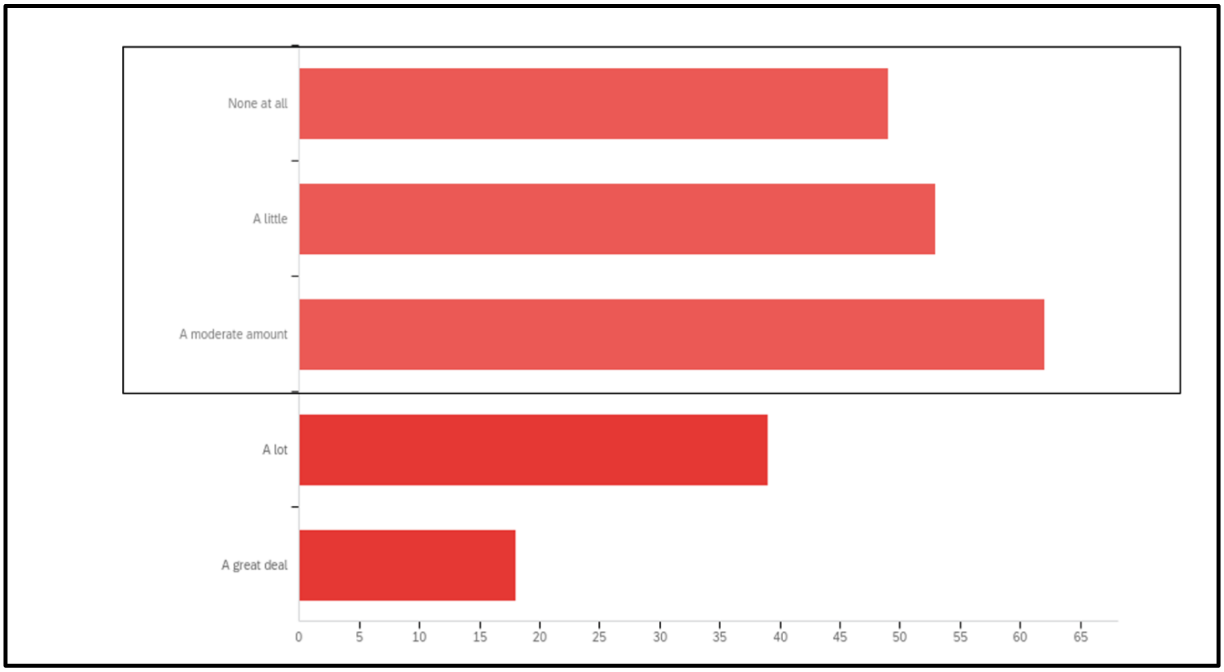


Figure 5. Level of Dependency on AI

Recruiters compliment Ai and its potential, , but a large number are not dependent on it. . When it comes down to their parsing preference, we learned that instead of handling the process manually.

In S2, we compared the results from S1 and recognized that overall, 94% of managers disclosed that they felt they hired their top choice. However, a small amount of concern was raised when 33% of managers suggested that they would change their hiring decision if given the opportunity. To put this in perspective, a large company with over 70,000 employees would reconsider 33% of its workforce (23,100 employees) if completely hired based on AI recommendations.

Similarly, managers feel recruiters are not the best people to decide whether candidates would succeed in the role or fully know when someone would accurately qualify to advance in the process. Frankly, as this is the recruiter's role, when managers were adamant about these decisions needing to be more cohesive, it indicates a disconnect. Managers want to be a part of informing the process, and recruiters are setting boundaries on how much they are willing to involve them.

In some cases, managers also wanted to know why initial resumes from the recruiter's review were held back. Managers felt they should be provided with a summary rationale of these candidates since they are the subject matter experts, and their opinion might differ from the recruiters, who may not be able to catch hiring mistakes due to a lack of understanding of the area of business or the role itself. This theme was prevalent in feedback from both parties. Our analysis continues to draw connections to the misalignments between managers and recruiters and their preferences. The process is two-fold: Managers recognize that the resumes they receive are from the recruiter's analysis. However, they are blind to the complete talent pool without a line of sight into resumes that were eliminated in initial scanning by AI. If recruiters are not leveraging AI, hiring decisions are being determined by their perceptions and potential biases based on their internalized interpretation of resumes and how they align them with job descriptions. Recruiters deem discussing candidates with managers a much more productive use of their time, but managers need more capacity to manage their daily responsibilities while also being embedded of this process. We have discovered that there is a distinct disconnect and an unwillingness to compromise.

Another clear development in our analysis was the false sense of security around AI's ability to be less biased, and that job seekers have resumes that accurately represent their skills and experience**.**

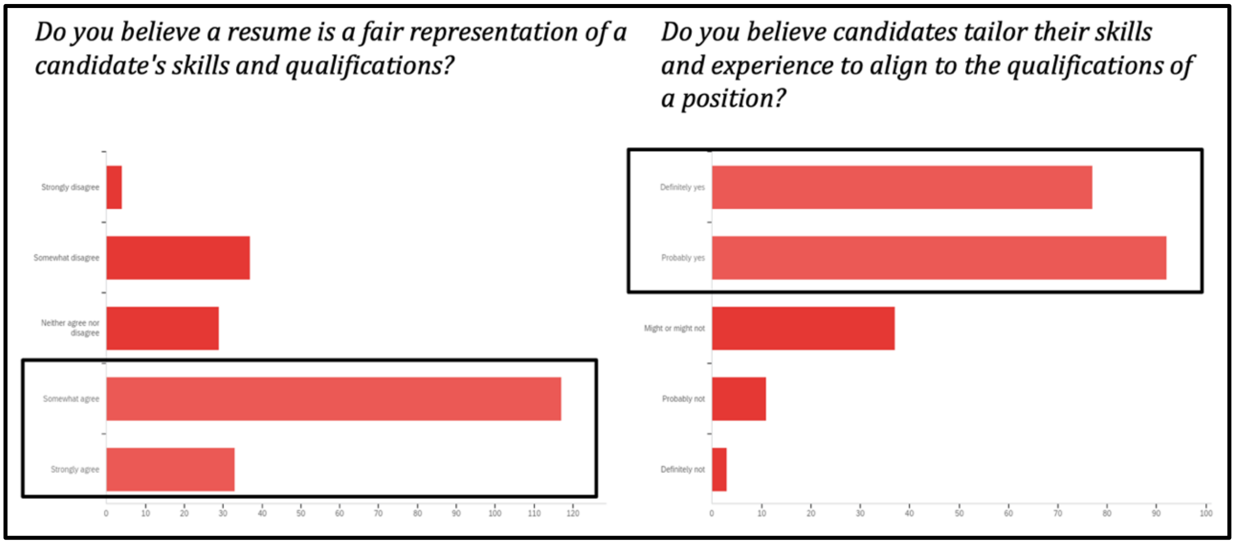


Figure 6. Candidate Evaluation based on Skills and Expertise

Recruiters were asked if they felt resumes were a fair representation of a candidate's skills and qualifications **(See Figure 6).** In our responses, 68% of recruiters agreed it was a fair representation. However, when asked if they felt resumes were tailored to align with a job description, 77% felt confident this was happening. So, in some cases, a resume is a fair representation, and in other cases, candidates are lying their qualifications through the resume parser, and recruiters are seemingly aware. This misalignment between recruiters and how they engage with these tools shows the need for improved training. Knowledge and awareness of AI, how impactful it is for recruiters to be appropriately educated on how it works and should be used, is contributing to its success or failure.

As a result, is the reliance on AI causing more problems for companies? Significant amounts of media and so called "experts" would have us believe recruitment is all automated, but we know that is false. There is a significant amount of time and energy from an individual recruiter, and our data supports that a human often reads every resume. Managers feel they are finding good people, but the good people need more longevity and fit within the culture.

T2: Both parties claim the hiring experience is effective, but still have concerns and issues.

Throughout this study, we recognized that there is much potential for both parties to adapt to AI and all it offers, but what is still being determined is if they will ever be able to adapt to each other.

Managers expressed having both an overall great experience working with their recruiters; while also voicing significant concerns regarding their hiring experience with recruiters. These include:

- Recruiting has a high turnover causing hiring delays, and managers are infrequently working with the same recruiter.
- The existing hiring process is outdated and too slow.
- Interview questions are bland and need to be adjusted to maximize the candidates' time to truly get to know if they would be a good hire.
- Talent pools need to be more diversified by posting positions on different platforms for widespread visibility.
- Recruiters need a better understanding in writing job descriptions, especially regarding the managers' perspective.
- Consultations of 30-to-60minutes are challenging to fully understand the needs and expectations comprehensively.

In comparison, recruiters felt the hiring process is genuinely a good experience, but over 52% stated that sometimes managers are challenging to work with. Recruiters generally felt the following:

- If the process is not going well, they are willing to start over to ensure managers are pleased with candidate pools
- Candidates are being sourced in a reasonable time frame **(See Figure 7).**

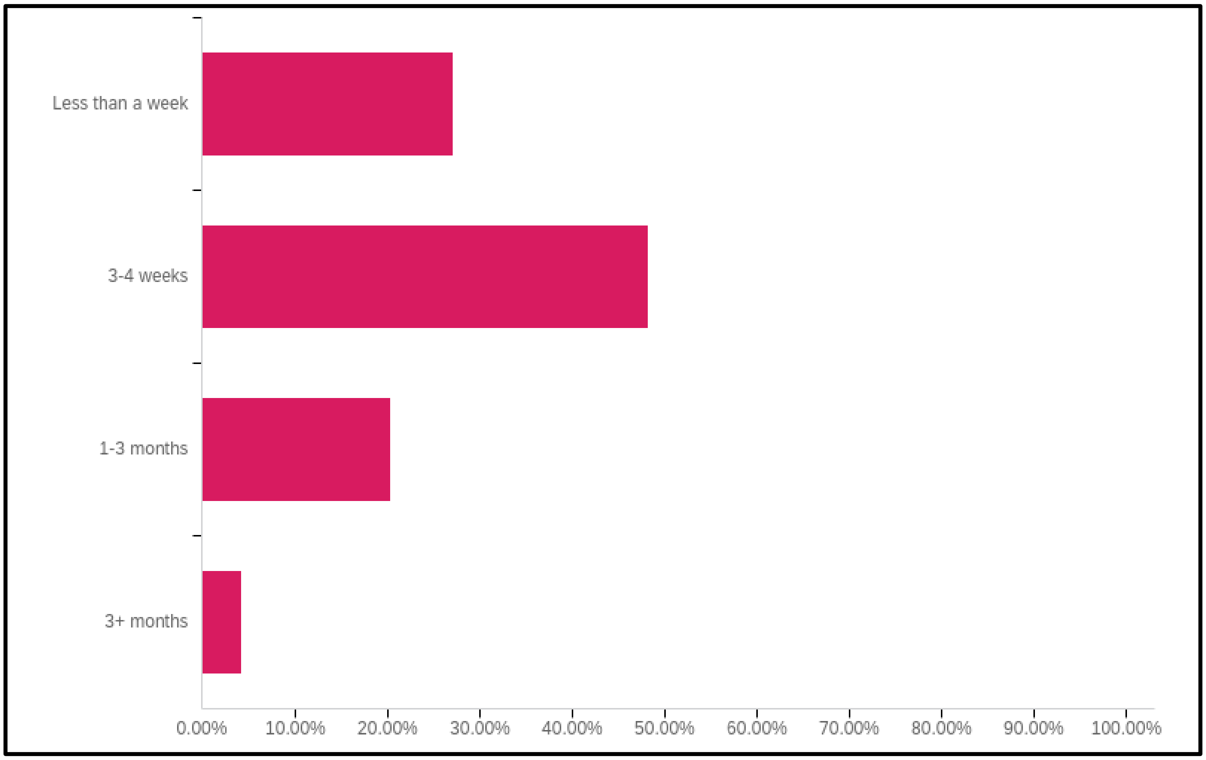


Figure 7. Timeline for Sourcing Candidates

Amongst both parties, we recognized the additional external factors impact the experience throughout this process:

- Both roles work differently based on their own career experiences
- The timing of hiring depends on the ability to efficiently work together by aligning schedules for interviews to fill a role quickly.

- Once a candidate is selected, delays in HR paperwork leads to delays official starts.

In some cases, recruiters are inaccurately blamed for the speed of the process.

T3: For AI in hiring to work, it needs to be a part of a cohesive ecosystem for implementation from a people, process, and technology perspective

It became clear that both groups generally felt that AI should not be evaluated as an isolated capability, requiring cohesiveness across the company's people, processes, and technology. **(See Figure 8)**

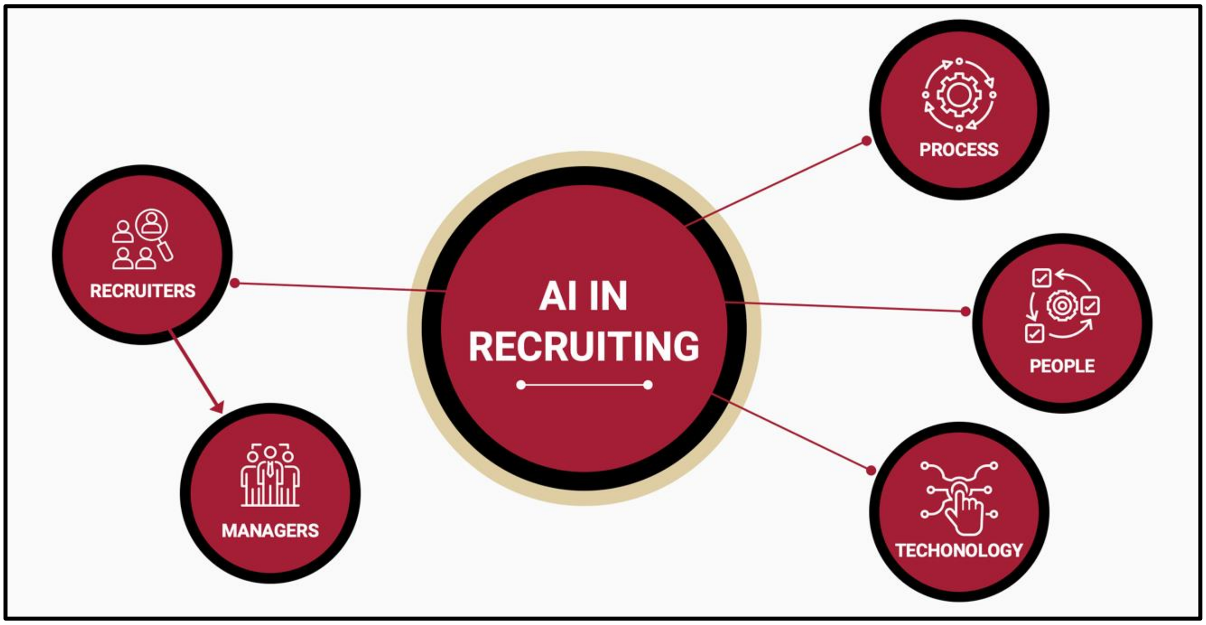


Figure 8. Conceptual Model

An important outcome of our data was acknowledging the uniqueness of AI technology in hiring while recognizing it works in other functions that the public is most familiar with. The perception of AI and how it has been marketed infers that it is intended to translate well to other functions. This thought process adds to AI's hiring hype, convincing people to believe it should have the capacity and capability to take on processing automation in this field. As a result of our study, we learned that most capabilities within an ATS are manual. Currently, the tool interacts with recruiters. Managers suggested the ATS tools should be more inclusive to include them and their hiring panels, if applicable, so that they can gather routine information and feedback on candidates and the AI can learn directly from the source.

Recruiters and managers may think AI is helping them move quicker and more efficiently, but they are not on the same page. However, the reality is that when making a hiring decision, both parties need to focus on the details important to their team and company to evaluate resumes properly.

In addition, recruiters were asked about the essential qualities they consider for moving a potential candidate forward to the interview process **(See Figure 9).**

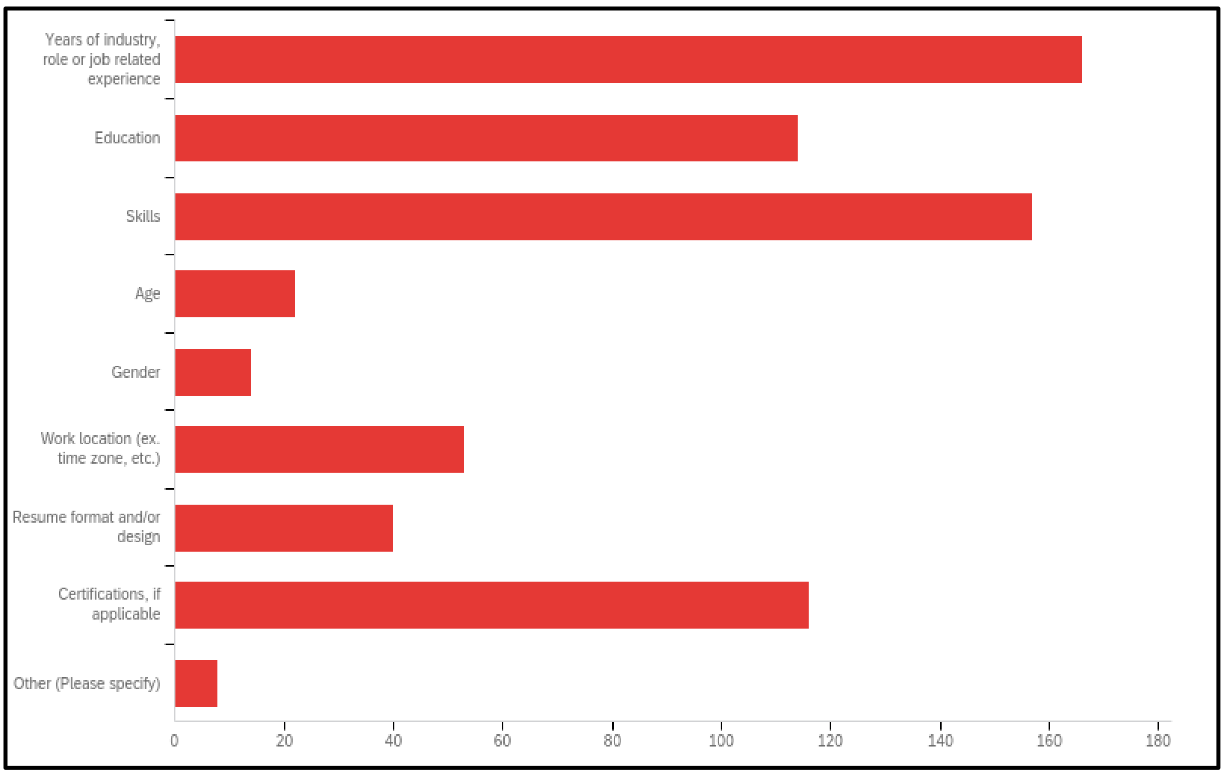


Figure 9. Resume ATS Candidate Selection Criteria

In **Figure 9**, the results indicated, unsurprisingly, that relevant industry-related experience, skills, certifications, and education were critical for evaluating a qualified resumes. From a people perspective, recruiters judge based on these qualities, but is AI thinking similarly? As an outcome of this study, we conclude there needs to be a formal resume design standard. However, relative best practices showcase experience and qualifications, so everything must be aligned for the tool to understand what it is supposed to focus on. For instance,

a. Skills are commonly written differently with similar definitions. How does AI account for these nuances?
b. How does a candidate manipulate AI to survive the ATS scanner?
c. How does AI account for transferrable skills?

In addition, our study discovered that over 80% of resumes were reviewed in the ATS on a rolling basis or within the first two weeks. The data leads us to infer that the quality of the candidate can also be based on the timing of when the applicant applied, highlighting a potential biases. Therefore, candidates are not evaluated across all that applied but rather on a rolling basis, and if a candidate applies later, then the ATS will not rate them higher or flag the system to bring them to the top of the list. In addition, some recruiters recognize the shortcomings in AI and expressed a lack of faith it can perform in this function. In a large cross-functional corporate environment, processes move slowly, whereas technology updates move and change rapidly, raising the concern of whether people can keep up.

In addition, considering the tool is new and exciting, it has yet to mature into a reliable product. The hype surrounding the of adaptation to this capability has caused hesitation for managers who expressed passionately that it should only be used in this function once it can disclose how and why it arrived at its parsing decisions. Companies should be able to disclose to candidates who were not qualified or selected. Currently, AI cannot disclose this information to a human, who then can determine whether its criteria were honest and reliable, or if it was influenced by predictive biases. We must reach this point in product maturity before job seekers suggest they have been discriminated against, making it impossible for any company to defend the tools' decision criteria in any court of law.

Statistical Methods

In each survey, six questions that were asked of both HR recruiters and Managers were merged into one database and recoded into a Likert-type scale. These six distributions of Likert-type scales were checked for the assumption of normality using Shapiro-Wilk tests. If the assumption of normality was violated, then non-parametric Mann-Whitney *U* tests were used to compare the HR recruiter and Manager groups on the respective six questions. Medians (*Mdn*) and interquartile ranges (IQR) were reported and interpreted for each group. Statistical significance was assumed at an alpha value of 0.05 and all analyses were performed using SPSS Version 29 (Armonk, NY: IBM Corp.).

Research Limitations

There were several significant research limitations noted in Study 1. Each survey had a different design, resulting in only 6 questions in S1 and S2 that could be analyzed where both parties were asked similar questions. As a result, these six questions were analyzed to determine the relationship between both recruiters and managers and the impact AI has on the recruiting process to deliver on its promise for talent sourcing.

In addition, due to economic challenges, there were thousands of layoffs in the technology industry in 2022 and early 2023, making it challenging to reach companies like Amazon, Google, Twitter, and Meta, among the top companies implementing AI across their organizations.

Furthermore, this survey design limited our ability to capture accurate information at the right level to support our research question.

Conclusion

AI is a new, exciting, and promising tool that is being embraced worldwide. With recent disruptive technologies, like ChatGPT, the world is becoming more familiar with the capabilities and benefits that AI can offer in a matter of seconds.

This study indicates there is a sense of "excitement" regarding AI in hiring. As a result, we have learned the relationship between recruiters and managers needs major improvement. Throughout these themes, we recognize the work that must be done to improve the hiring process, which falls within people, process, and technology standards and best practices to ensure a smooth, quick, and efficient end-to-end hiring process. There are gaps throughout this system that companies disregard by suggesting tools to fix an issue with their overall culture and business processes. Often, technology is presented as the solution for these challenges when there are other underlying concerns and areas of opportunity. AI is adapting as part of an existing ecosystem, but everything is not working together efficiently.

In addition, there is an underlying belief that AI will significantly impact HR departments and the long-term job security of recruiters. Will AI ever get to a place where it can fully automate the hiring function? If the development continues, will companies improve at drawing the line and formulating proper governance? With how fast AI is evolving and the general speed technology consistently changes, coupled with how slowly corporations move with technology integrations and adoptions, the trifecta ecosystem required for success seems further away than it does attainable at this time. Without the consistent commitment from companies to strategically implement this tool into their working methods. All employees, not just recruiters and managers, need to understand the implications of AI on a fundamental level.

Moreover, any company headed in this direction needs to be positioned in a framework that can quickly adapt to rapid change to keep up with the ongoing external demands. In some cases, it may require companies to hire and assign more human capital to oversee these efforts to maintain consistency across their organization with frequent evaluations and feedback from employees and new hires on their hiring experiences. Otherwise, the promises of AI in hiring is positioning itself as a Corporate America equal opportunity employment disaster. Future research will inform what conditions need to be true for AI to excel in this space, and despite the hype, AI's role in hiring might still be limited.

CHAPTER 4

AI LIMITATIONS AND BENEFITS IN RECRUITING

Leveraging Lilliefors Significance Correction, all six of the questions that were similar between the HR recruiters and Managers were not normally distributed, so we will have to use non-parametric statistics for the comparisons. We know this violation occurred using the Shapiro-Wilk tests (See Figure 10)

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
RespondedPromptly	.279	391	<.001	.807	391	<.001
Strategic	.258	392	<.001	.853	392	<.001
ClearExpectations	.230	391	<.001	.838	391	<.001
HighQualityCandidates	.262	392	<.001	.835	392	<.001
SatisfiedWithQualityTalent	.236	390	<.001	.838	390	<.001
DiverseSelections	.238	392	<.001	.827	392	<.001

Figure 10. Tests of Normality

By grouping these variables, there were statistically significant differences between the HR Recruiters and Managers for Responding promptly, $p = 0.003$; high-quality candidates, $p = 0.044$; and diverse selections, $p = 0.005$.

No differences were detected between strategic, $p = 0.32$; clear expectations, $p = 0.62$; or satisfied with quality talent, $p = 0.12$. Further analysis was done to gather the medians and interquartile ranges for these findings (See Figure 11).

			Percentiles		
		Group	25th	Median	75th
Tukey's Hinges	RespondedPromptly	HR Recruiter	4.00	4.00	5.00
		Manager	4.00	4.00	5.00
	Strategic	HR Recruiter	3.00	4.00	5.00
		Manager	3.00	4.00	5.00
	ClearExpectations	HR Recruiter	3.00	4.00	5.00
		Manager	3.00	4.00	5.00
	HighQualityCandidates	HR Recruiter	3.00	4.00	5.00
		Manager	4.00	4.00	5.00
	SatisfiedWithQualityTalent	HR Recruiter	3.00	4.00	5.00
		Manager	4.00	4.00	5.00
	DiverseSelections	HR Recruiter	3.00	4.00	5.00
		Manager	4.00	4.00	5.00

Figure 11. Percentile Median Ranges

The assumption of normality was violated for all six questions, $p < 0.001$. Non-parametric Mann-Whitney *U* tests were used for the comparisons. It was found that there were statistically significant differences between the HR recruiter and Manager groups for job candidates responding promptly to queries, $U = 16045.0$; $p = 0.003$, high quality candidates being found; $U = 17073.0$, $p = 0.044$; and a diverse selection of candidates being yielded from the process, $U = 16192.0$, $p = 0.005$. In each instance, Managers rated significantly higher than HR recruiters. No significant differences were detected between the groups for making strategic suggestions, $U = 18120.5$; $p = 0.32$, setting clear expectations; $U = 18562.5$, $p = 0.62$; or satisfaction with the quality of talent, $U = 17388.0$, $p = 0.12$. See the medians and interquartile ranges for the six comparisons in Figure 12.

Comparisons

Questions	HR Recruiter	Manager	*p*-value
Responded Promptly	4.0 (4.0 – 5.0)	4.0 (4.0 – 5.0)	0.003
Strategic	4.0 (3.0 – 5.0)	4.0 (3.0 – 5.0)	0.32
Clear Expectations	4.0 (3.0 – 5.0)	4.0 (3.0 – 5.0)	0.62
High-Quality Candidates	4.0 (3.0 – 5.0)	4.0 (4.0 – 5.0)	0.044
Satisfaction with Quality of Talent	4.0 (3.0 – 5.0)	4.0 (4.0 – 5.0)	0.12
Diversity in Selections	4.0 (3.0 – 5.0)	4.0 (4.0 – 5.0)	0.005

Figure 12. Statistical Comparisons of Survey Questions between HR Recruiters & Managers

(Picardo, 2023)

The findings in Figure 13 reveal a statistical distinction between HR recruiters and managers. Both groups are aligned on the influence of AI in recruiting, resulting in heightened responsiveness and receiving a high-quality and diverse talent pool. While this verifies the validity of our hypotheses (H1 and H2) from a strategic standpoint, examining overall satisfaction among managers and HR recruiters with their recent hires are insignificant. This leads to the conclusion that AI indeed has an impact, yet there still needs to be more robust work to provide overall satisfaction and success despite accruing benefits in various aspects.

Furthermore, HR practitioners seem to have several concerns when leveraging AI in a recruiting function:

- **Satisfaction Discrepancy:** The data suggests a significant distinction in satisfaction levels between HR recruiters and managers. HR practitioners may be concerned about the potential implications of this discrepancy, such as its impact on collaboration and overall organizational harmony.

- **Effectiveness of AI Implementation & User Experience:** HR practitioners may potentially be concerned about the effectiveness of AI implementation. Questions may arise about whether the anticipated benefits are fully realized or if these challenges hinder the user experience or optimal daily use. These concerns may also arise with on-the-job training and ensuring all employees are supported with subject matter experts and consultants available to answer questions and gather feedback. The overall user experience may cause comprehension and time-saving concerns. Appropriate enhancements cannot be made to refine ATS tools and standardize best practices without effectively gathering this user feedback.
- **Job Security:** The alignment on the impact of AI in certain aspects of recruiting may raise concerns about job security. HR practitioners may feel less inclined to suggest adopting this tool within an organization in fear and threat it may impact their job security. Specifically, with a tool like AI, it has the ability to make suggestions and give feedback that may be priorly analyzed by an external consultant.

Addressing these concerns may involve further investigation, communication, and strategic adjustments that will be required to ultimately satisfy managers, recruiters, HR practitioners, and strategic leaders before implementation. HR practitioners may need to be embedded deeper into the hiring process to fully understand these challenges and differing perspectives, while also identifying areas for improvement, to ensure AI technologies are effectively contributing to organizational goals.

As a result, our hypotheses were tested, and our results showed the following:

- H1: AI-driven talent sourcing significantly improves candidate matching accuracy for high-quality candidates compared to traditional methods.
- H2: AI-driven talent sourcing leads to higher-quality hires, demonstrating a significant increase in diversity compared to traditional methods.
- H0: The strategic decision-making capabilities of recruitment processes are similar between AI-driven talent sourcing and traditional methods.

These results show the need for a second study focused on targeting a population of subject matter experts (SMEs) in AI to dive deeper systematically to understand the automatability of hiring tasks. By focusing on SMEs at this level, we will further comprehend how AI fulfills its promise in recruiting and whether the impact extends well beyond the recruiting process itself, influencing the job security of HR professionals. By doing so, we will continue to explore if there are hiring tasks more conducive to AI or if it will eventually become a one-size fits all solution in recruiting.

AI Limitations and Benefits in Recruiting

While we continue exploring AI's capabilities, we remain challenged with fundamental concerns of how it works. Our first study showed discrepancies between two significant groups of managers and recruiters; their dependency and knowledge of AI; and how it is currently leveraged in their organizations. The use of AI in a recruiting function comes with complexities. We have, as shown in our original research question focused on the "promise" AI intends to deliver from a people, process, and technology perspective. However, we quickly realized our findings exemplified a bigger question focused on when AI works and when it does not. To determine if a suitable function in recruiting, it is important to understand the limitations and benefits of the tool.

The impact of AI's original "promise" did not stem directly from the marketing strategies performance, but rather the "hype" of this new and exciting capability that is accessible to the public. Not to mention, every company and their employees jumping at the opportunity to incorporate it into their daily business lives, hoping to do their jobs faster.

With recent news around the evolution of ChatGPT, an AI tool trained to follow instructions in a prompt and provide detailed responses (OpenAI, 2023), companies recognize AI's benefits and how users can lean on them to get more detailed information than a normal Google search. This has been misleading for technical users with limited knowledge and experience in the fundamentals of how AI works. The most interesting aspect of ChatGPT and its adoption was the ease of use, which allowed the tool to spread like wildfire. Simply by requiring users to sign up on a waitlist, once granted access, they could immediately ask the AI tool any question to produce content, with results generating immediately. Given these considerations, we cannot blame anyone for being excited about AI and its seemingly limitless offerings; as it has changed the traditional way we have accessed information in the past, ultimately leading to more innovation.

However, with limited governance, it has also found itself in functions where it does not belong. The adoption has been tremendous, but when embedded into recruiting, there appears to be less exciting. Our findings concluded that while the AI is new and exciting, it is forcing itself into a function where recruiters do not like it and are not seeing the expansive value like the public. While Study 1 shed light on recruiters and managers knowledge and dependency of the tool to hire new talent, it leads us to believe the benefits of AI in recruiting are falsely represented. It appears the excitement of this tool is convincing the c-suite; those responsible for adopting these tools in-house; are transforming their talent pools when it is not achieving those results.

Literature Review

When you hear of AI, you automatically think of automation – In the simplest of equations: If I place AI here, then it will process the information I want faster than a human, and will happen automatically. While this may be true in some cases, the most common misconception is that it is intended to replace the need for human involvement. Will AI ever automate a recruiting function? Throughout this research, I have not yet been convinced it will be possible, given that it always lacks the emotional intelligence required to evaluate a person beyond what is on paper. Sometimes, we want to work with people because we have a good feeling about them, or maybe we can see their potential based on what they offer from a professional lens, regardless of their skills profile or previous experience.

Despite this, based on the model used, AI is more than capable of replicating processes and behaviors that are consistent and continuous with minimal deviations, which is like what we experience at the grocery store self-checkout or within a factory processing line.

However, different AI methods are intended for different functions, meaning they are developed to replicate a specific behavior or output. Deep learning, for example, is "a method in AI that teaches computers to process data in a way that is inspired by the human brain" (AWS, 2023). Even if inspired, it may not be able to give us an accurate result, especially since all human brains process information differently.

In a circumstance like hiring, AI would need to model human-like thinking with coded brain mapping to mimic these behaviors. It would still require the diversity of thought and the question is if algorithms can be coded to model this thinking and compensate for a recruiter and ultimately reimagine their role and engagement with hiring talent. Within the literature, we have learned that recruiters, which are referred to as users (See Figure 13), need to be a part of the perception, cognition, and execution of the hiring process, essentially "closing the loop" on human-AI interaction (Chen, 2022). By leaning on humans to improve the overall "service capability," technology can only continue to grow and expand over time, making it more dependable and fluent, but never fully automated. This process will still require a combination of AI tools in a decision-making framework, such as leaning on machine learning algorithms to meet "users' expectations of the intelligent robots" (Chen, 2022).

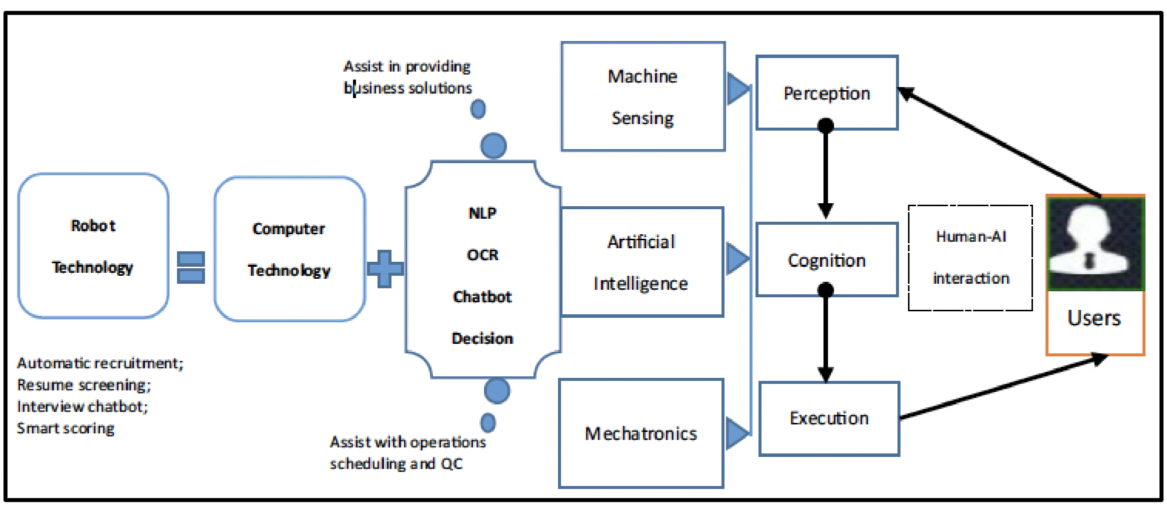


Figure 13. Human–AI Interaction Process and Usefulness

(Chen, 2022)

AI is built on deep-learning models, which recognize complex patterns in pictures, text, sounds, and other data to produce accurate insights and predictions to answer questions or generate accurate results (AWS, 2023).

In recruitment, when discussing resume parsing, a similar technique is used to evaluate a candidate by identifying the quality of their education, experience, previous employment, and potential. Depending on the complexity of the algorithm, it may also use natural language processing (NLP) to learn more about the applicant's personality or skills while also understanding their employment patterns. The algorithm may also project how long a candidate may spend within a specific role before asking for a promotion or leave the company. These judgments are based on their interpretation of the AI, which are information-based assumptions that can be unjust and sometimes may breach a job seeker's privacy.

The complexities of deep learning can become complicated, especially since there are multiple hidden hierarchal layers throughout processing that assist AI with pattern matching and making decisions (See Figure 14) (Waldrop, 2019).

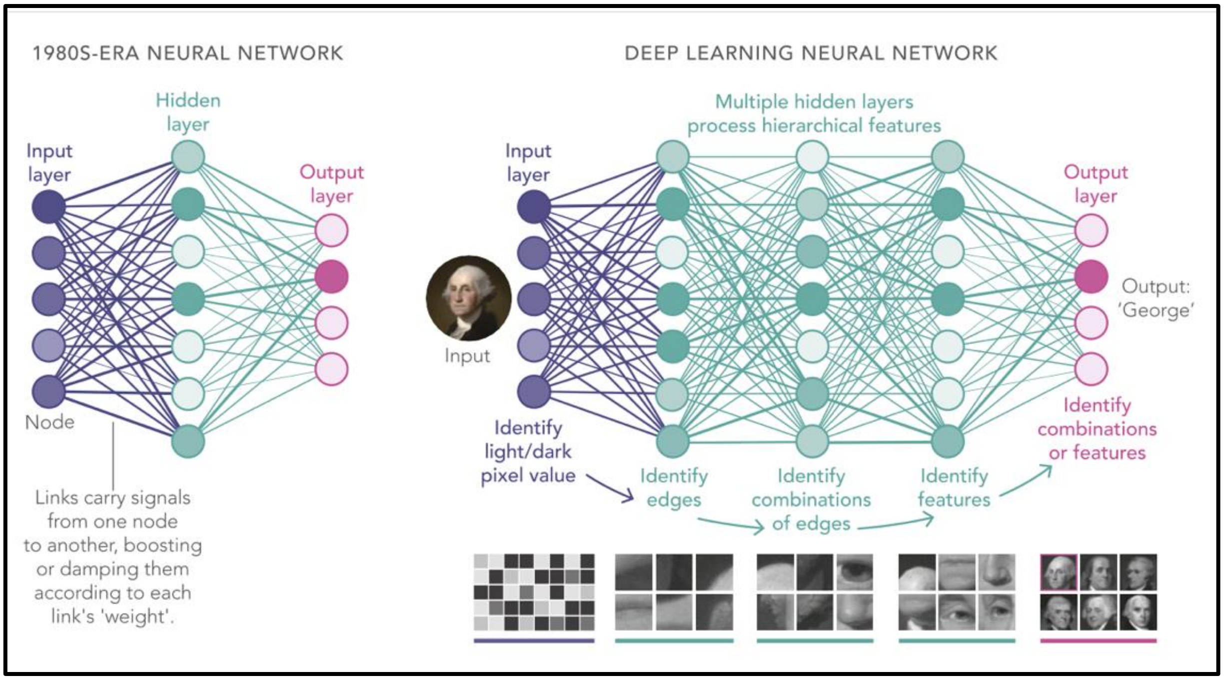


Figure 14. Deep Learning Neural Network

(Waldrop, 2019)

The three layers of a deep-neural network consist of an input, hidden, and output layer (See Figure 15).

Input Layer	Nodes that input data for processing
Hidden Layer	Processes and passes data through to the neural network
Output Layer	Notes that output the data

Figure 15. Deep Learning Functional Processing Layers

(AWS, 2023)

These layers cohesively work together to intake and digest and pattern match different combinations of information. Most algorithms are trained with databases consisting of large sums of data for it to sift through, so essentially you can tell it what you want it to learn and then it will continuously grow by processing new knowledge and comparing it to what it already knows.

For example, if we were trying to identify an image of George Washington, deep learning would do it as follows? The image of George Washington would be placed within the input layer via a node, also known as a neuron (See Figure). Within these neurons, the deep learning processing of information occurs. The neurons interact with the algorithms hidden layers, which hold their own bias (Reyes, 2023). These biases are needed to form weights in the decision-making process, determining if the information is aligned back to the search for the original image in the input layer.

At the same time, within each of these hidden layers, the algorithm also determines if the image is new information or if it has never been given. These biases are important, for without them, then the activation function will not be applied – An activation function is often “added into an artificial neural network in order to help the network learn complex patterns in the data” (Jain, 2019). In other words, it must process the information to effectively communicate to the next neuron, further advancing the process of solving for whatever it is looking for from the input layer (Jain, 2019). Each of these hidden layers has a different goal and, in this case, would dissect the visual of George Washington to understand its elements from a physical, visual, and technical perspective.

Within each of the hidden layers, AI will begin pattern-matching the graphic, looking at coloring, facial recognition of physical features, and overall appearance. The details are then compared with images and information in its existing library, sifting through each node to determine if it fits the respective criteria, answering yes or no, and then moving from one layer to the next before landing at an output (Waldrop, 2019). Once determined, the information is sent to the output layer, which is consumed by the end user and it will identify the image is in fact George Washington, the first President of the United States.

To achieve these results, within the development or progression over time, AI must be given a large data set of information including all previous presidents or famous public figures, or humans that were stored in a facial recognition database.

Nevertheless, if we follow the same structure as we did with the George Washington example, and decided to input a fictional character into the input layer – What would happen? For example, we chose an image of Simba from The Lion King and asked AI to determine who this person was. Given that Simba is a fictional character, the backend of the algorithm would need to be trained to identify Simba as a person, even if they did not resemble human-like features. In this scenario, the output layer may suggest that Simba is Drake, a famous rapper and hip-hop singer, which does not make any sense at all, given there are no clear physical resemblances of both people other than the fact that they are both iconic. This is a way to conclude that AI was never trained to learn about animated characters and the information was never introduced into a data set.

Still, an information repository can lead to deep learning's downfall. If not properly managed, governed, and continuously trained, AI may never be able to process an accurate output, even if it consumes large amounts of data that may be simply irrelevant.

When we translate these fundamentals to a hiring function, we quickly ask ourselves how AI impacts a job seeker's ability to be recognized appropriately. “Many popular job posting websites such as LinkedIn and Indeed use AI-powered ATS algorithms to filter out or sort candidates and streamline the hiring process” (Lauret, 2019). No one may know where discrimination occurs, but while a candidate may not be an animated character, what if they were disabled and had different skills and qualifications leading to a diverse set of work experience? AI would lack the emotional intelligence formulate and judge the candidate the same way a human would. One could argue that if applying for a role that required physical endurance or activities, a candidate who is disabled or handicapped would not be qualified for the position. However, candidates do not have “disabled” written on their resume.

RQ2: When Does AI Work in Hiring and When Does it Not?

Despite promises, the role of AI in recruiting may be limited. As an outcome of our initial study, we recognized misunderstandings of AI in recruiting, particularly in determining when and how it may work well in hiring. To answer the research question, the focus of our dissertation will be on what AI can and cannot accomplish. From there, we will be able to determine if AI has the means and potential to properly embed itself into a recruiting function.

Limitations of AI

The challenge with recruitment automation is there is no way to ensure with confidence that talent is fairly assessed and pre-selected without bias. In the previously proposed example of George Washington, even if he has a unique skillset, background experience, and received a strong education, he may be removed from contention because at one point in his lifetime he was the President of the United States, making him overqualified.

So, when discussing the use of AI in recruiting, what aspects of it am I particularly referring to within its limitations?

Recruiters	
Focus Area	Limitations
[People] Reducing Bias	Bias may still exist in the data used within the algorithm
	Algorithms may also be biased if not properly trained or frequently tested. Staff need to be in place to support this
	Algorithms lack the emotional intelligence that humans possess, and are unable to recognize unique or uncommon differences in potential talent
	Lack of overall transparency (decision making, assessment criteria)
[Process] Efficiency	Lacks emotional intelligence to evaluate a candidate holistically
	Does not account for transferable or soft skills for talent coming from different roles and with a variety of experience
	Algorithm design may be biased and unable to determine how it navigates through its selection process
[Technology] Compliance and Policies	Data privacy and storing PII data from candidates can be difficult to secure
	Can be costly; ensuring staff and personnel are equipped with the skills and knowledge required to ensure proper governance
	The "unknown" makes companies vulnerable to legal challenges
Hiring Experience	Impersonal interactions between recruiters and candidates throughout the process, making them feel less important or special

Figure 16. Limitations of AI

(Picardo, 2023)

At a high level, AI is understood to be the overarching capability, "a technique in a machine used to mimic human-like behavior" (Reyes, 2023). Deep learning is embedded within AI to further enhance the emotional intelligence and human-like behavior. This is like the experience of engaging with a customer service chatbot online. Chatbots leverage natural language understanding (NLU) to understand the words from a user and what they are trying to accomplish. Chatbots, “rely on machine learning and deep learning—elements of AI, with some nuanced differences—to develop an increasingly granular knowledge base of questions and responses that are based on user interactions” (IBM, 2023). When you have a question about a product, or a service, customers can message the chatbot online to contact a representative (Reyes, 2023).

Well, most times, when speaking to a chatbot it may feel like speaking to a real human being, but customers are speaking to a robot, which has been trained to present itself with that human-like feel, without a customer knowing the difference. This need for a human-like experience has evolved greatly during the past decade because it is the only way for humans to allow tools to take their jobs away from them. And when embedded into business areas like this, it does in fact save a lot of time and get customers where they need to go quicker and more efficiently than speaking to a live human being.

In recruiting, algorithms and ATS tools lack the emotional intelligence and empathy to properly make an educated decision. In this case, I suggest AI to never be used in recruiting at all. Recruiters are not willing to let AI take their jobs away from them, and even if there was a possibility they could, I do not believe they would let them.

Furthermore, another aspect of AI is machine learning, which is achieved through trained data, and requires human intervention to tell the machine what the user is intended to learn. For example, asking the machine to determine the difference between lamented and hardwood flooring. The human may start sharing qualities of the look, feel, and design features of a lamented flooring, and the machine will interpret this information, and begin to understand and learn the difference between the quality and differing models. These attributes are critical in machine learning to know how to guide its intelligence.

Deep Learning

Deep learning, however, is also a subset of AI and differs from machine learning in that the features are picked out by the neural network, with limited human intervention (Reyes, 2023). As a result, deep learning is more complicated to manage and sustain because it requires continuous training of data sets so that it has enough knowledge to make its own decisions. With deep learning relying on its neural networks for processing, it has to be able to see what a human can see, recognizing digital aspects of data that may resolve in the root of human common sense.

How do we define common sense? Common sense is the accumulation of background knowledge of how the world works (Bengio et al., 2021). As humans, we look at something and we inherently know. How and why do we know? We may have seen something once and without someone telling us or teaching us, we just know this information internally. When we think about what deep learning and algorithms are unable to do, it is simply that – They do not have the ability to just know. They lack common sense. They need to be told, they need to be trained, and over time they can automate the brain function of differing variables leading them to a solution or output. But sometimes, as humans, we do not always arrive at a solution or defined output, rather a theory or a thought may later bridge a gap in our understanding. Until deep learning has decision criteria that is at a level to compensate for its lack of emotional and human intelligence and common sense, then it is hard to justify or support its involvement where the livelihood and careers of people are at risk. It is both nonsensical and unrealistic.

Researchers are confident that deep learning will eventually evolve to where it acquires common sense (Bengio et al., 2021). But until then, there are researchers who believe deep learning will never solve certain problems and humans will always resort back to a symbolic and standard AI approach.

Sustainability

There are additional limitations residing in the need for constant improvement and training proper predictions and capabilities. Sometimes, it is not sustainable for humans to have the capacity to maintain the algorithms, resulting in months of time and an intense amount of man hours to train and grow these algorithms (Reyes, 2023). In addition, from a technological perspective, the computational power required to run these machines, while enhancing them, is no small feat. Aside from the human and resource issue, the vast and growing need to build and maintain databases renders innovation and sustainment difficult (Reyes, 2023). Researchers and data scientists are challenged physically, mentally, and financially, then make it difficult for companies to maintain their investments and funding with limited or no return, in the hope of finding a breakthrough. This is different than medicine and vaccines, where without continued innovation and belief it would be impossible to further advance medicine, which requires trial and error. AI does not share the same weight and sense of urgency because it is preventing disease that kill people, rather it is a tool when used improperly in functions like recruiting, are killing people's careers instead.

Benefits of AI in Recruiting

Most times, when there is a business problem, it is easy to apply new technology for possible results. Instead, identifying the root cause of what may not be working only helps all parties involved work better together. While it seems reasonable that managers and recruiters could improve collaboration, the data shows managers want to be more involved in the process because they feel they hold more knowledge about skills and qualifications that are relevant to the role than a recruiter can determine on their own. This leads us to believe that poorly written job descriptions may lead to hiring inaccuracies – Companies are not targeting the right talent because they are unclear in their job descriptions.

As a result, this issue has made managers feel the need to get closer to the process by micromanaging recruiters. AI does have the potential to generate thorough, detailed, and accurate job descriptions, from an unbiased perspective and can include a well-rounded set of skills and qualifications needed to perform at a high level and meet the manager's expectations. Ultimately, streamlining the recruiting process by attracting relevant qualified talent, and improving the relationship between recruiters and managers.

A recent study exploring the benefits of AI in recruitment. suggested it is an innovative way to work, driving "a sustainable competitive advantage that can be achieved through dependability, time savings, cost-effectiveness, and a better candidate experience" (Gusain et al., 2023). However, while we are aware of the proposed benefits of AI in recruitment, there are some nuances that raise concern about its marketed value-adds. **(See Figure 17).**

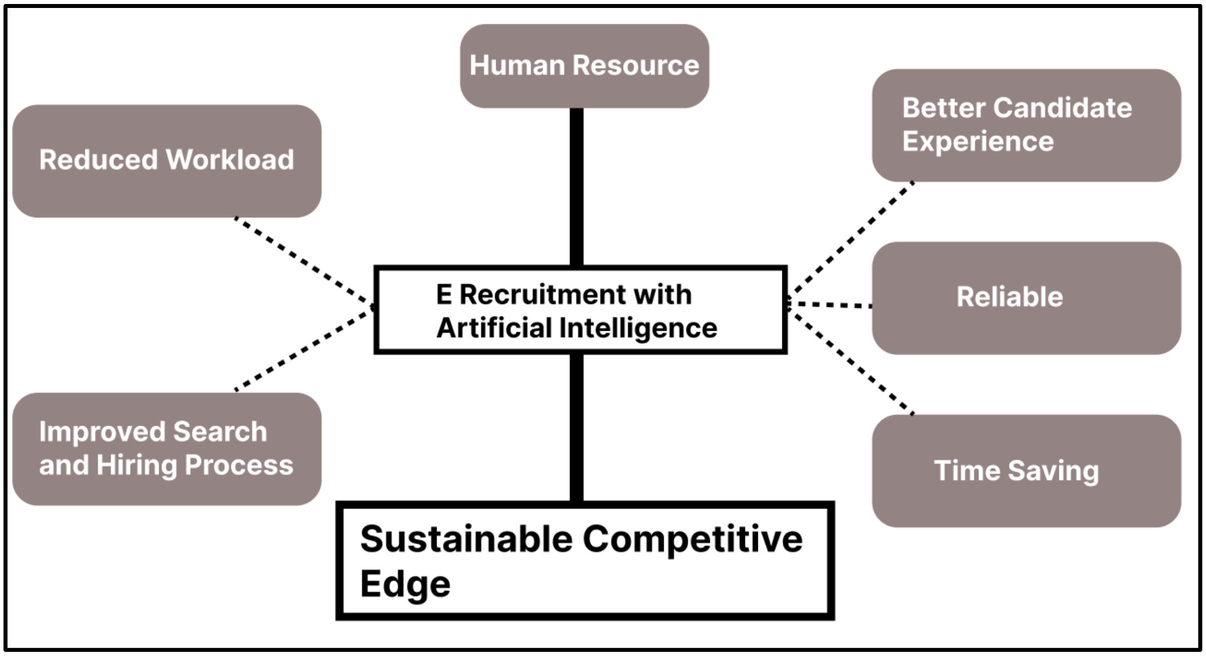


Figure 17. Benefits of Using AI in E-recruitment
(Gusain et al., 2023)

In the case of job descriptions, there appear to be several significant issues and the most common is the writing. Job descriptions areare not written in a way where a candidate can conceptually understand the true requirements of the role and their responsibilities, especially when they are company culture dependent. Job descriptions are sometimes written to appease HR departments, with the goal of gaining approval to post. With good reason, HR may be sensitive in approving and opening new roles, preventing over-hiring and competing with existing roles that share responsibilities. Therefore, job descriptions are altered to meet the requirements, but in doing so, the wrong type of talent is targeted. This makes the process longer and more convoluted. Job seekers will apply for a role because they believe it aligns with their career development and aspirations. Then they discover their job entails responsibilities well beyond what was communicated, resulting in companies hiring a strong candidate for the wrong role.

From the job seeker's perspective, job description concerns immediately position them at a disadvantage. AI can be used to identify what companies are seeking, which benefits both parties, ultimately saving time in the process. If job descriptions are clearer and more accurate, then seekers are more inclined to apply for roles they can advance to the interview stage.

However, while there may be spillover of applicants not meeting the requirements and are outliers, at least companies will now attract the right talent in a more accurate pool.

A potential benefit for companies is finding a candidate they never thought to consider hiring, which establishes a mindset for managers and recruiters to think outside the box and embrace an approach of attracting new talent and stop limiting the overall candidate potential.

Diversity & Inclusion

The idea of algorithmic inclusion supports the notion of diversity, ensuring the backend is strategically designed to predict a better outcome for candidates. By breaking down an algorithm into three focus areas of data, design, and decisions: the algorithm has the potential to be shaped to properly meet expectations. Doing so, would alleviate most concerns related to poorly written job descriptions, age discrimination, and gender bias, which returns us to the original theory and promise AI intends to deliver.

However, even when strategically positioned to identify the gaps in AI, we are still determining if they can be completely fixed and automated without continuous interjection from humans. From a data perspective, "data feeds into algorithms and are weighed and statistically analyzed to make predictions about job performance." The responsibility only partially falls on the tool, and this responsibility is shared amongst the people engaging with it and making these strategic decisions.

While we have been focusing on AI in a recruitment function, the responsibility may also fall on the managers within specific roles that are more AI-process focused, or not familiar at all. Depending on AI in the ATS may be driven by a group of data scientists or programmers that trust the AI in their daily business practices and want to procure talent that meets a strict set of qualifications (Tippins et al., 2021; Vassilopoulou et al., 2022). Therefore, depending on AI's relevancy, knowledge, and dependency on a specific department may also influence how the tool is designed (Kelan, 2023). Taking it high level, the process would need to be consistent across the enterprise, confirming that hiring best practices are aligned to a set of fundamentals and not a specific division or role. This will ensure equal opportunity for all candidates, internal and external, and reduce discrimination.

Ongoing Technology Innovation

As technology rapidly evolves and changes, so do approaches to hiring and job opportunities. Job seekers and their experience span many different levels, especially when considering the digital tools and resources more readily available for upskilling, training, and certifications. Many companies have done away with the four-year college degree requirement and recognize the importance of having a strong skills profile.

Considering this evolution, AI has a great opportunity to adjust its algorithm and nodes to focus on the core skills sought in an ideal candidate, leading to more diversity. Instead, the AI in ATS tools categorizes job seekers based on scanning for relevant keywords or, in other cases, using advanced neural networks trained to refine the most successful candidate in a specific field or position (Campbell, 2023).

However, AI scanning and parsing may be best suited at a different phase of the hiring process. For example, how does an internal referral match with an external job seeker? While a company may want to develop an existing employee and give them a career-advancing opportunity, due diligence is still required if external candidates are allowed to apply. For example, recruiters and managers may finalize an interview process and recognize that a few internal and external candidates exhibit unique skills. They all have strong qualifications making them a great fit for the role, but they need help deciding whom to extend an offer to. In this scenario, AI can be leveraged to review the resumes to determine the following:

- How do the candidate's skills match with the other applicants?
- Does AI recommend one over the other by reducing the bias from personality?
  a. Does personality matter?
- Is there a candidate more qualified on "paper" than perception from the in-person interviews?

Leaning on AI in these scenarios only ensures job seekers are vetted from a corporate culture perspective, but it is an honest and valid third-party review that states, and with reason, why a candidate was or was not selected, which today is one of the biggest limitations of AI in recruiting.

Today, since AI is unable to articulate how it arrived at its hiring decision, this positions the tool in a part of the process where recruiters can defend their decision, as well as protect their company. By doing so, the due diligence builds a strong business case for future accusations or lawsuits from job seekers, which is also backed by logical reasoning that defends their decision. These insights also help flag potential biases from leadership on the interpersonal connection and relationships that may be formed during the interview process and potentially sway their hiring decisions.

There are multiple methods on how AI could be beneficial and add value to recruiting. As stated, AI is still evolving with valid concerns related to its accuracy, biases, and ability to think like a human, even within sophisticated, deep-learning neural networks.

AI Process in Recruiting

Today, AI is embedded at the front end of the hiring and candidate screening process. The deep learning algorithms are trained to recognize certain patterns and evaluate a resume based on specific qualities. Whether this is the quality of candidate's education, or their years of experience, AI is looking for talent to fit within certain parameters. Job seekers may be screened out because they did not properly format their resume to fit the parsing requirements. This does not stop job seekers from hiring resume writers to help "trick" the algorithmic bots NLP so they can get triggered for an interview with the recruiter.

However, even with the intent to embed this capability at the front end of the process to weed out outliers or talent deemed unfit for the role, the workarounds and risk for large corporations may be much worse. Aligning the perspective back to the previous approach to skills, AI is not serving recruiting process by selling a false sense of confidence to recruiters who are sold on trusting a tool to perform properly.

AI Ethics

The literature acknowledges shortcomings of AI in recruiting from a human rights and ethics perspective. Once source states, "hiring companies have a moral duty to safeguard applicants' rights not only in the hiring decisions they make but also in how they treat applicants during the selection process (Hunkenschroer & Kriebitz, 2022) (Köchling & Wehner, 2020). A job seeker's right to privacy is required by employers to ensure they are safeguarding them, which they cannot ensure when using AI-powered tools for screening. Whether this is through AI facial recognition that is used to determine behaviors or personality traits, or name discrimination from the parsing their resumes or cover letters, there is no way to ensure the safety of a candidate's privacy because AI does not have the emotional intelligence to accurately depose them (Hunkenschroer & Kriebitz, 2022).

Considering a job seeker's human rights and privacy, regardless of whether a candidate is deemed qualified, the deep learning neural networks are biased toward job seekers who appear overqualified. If a candidate falls within the parameters, they are triggered as top talent; however, they may also quickly fall out of the parameters if their skills and experience exceed the job posting's requirements. The AI fails to measure true potential because again, it lacks the emotional intelligence to recognize job seekers have random career changes, and sometimes for no legitimate reason at. The reasoning also does not need to be disclosed on their resume or to any employer; it is their right to privacy. Sometimes, these factors are out of their control, and without any reason, job seekers should not be denied an opportunity because they have experience well beyond the intended pay grade.

Given this, companies are chasing an idea or expectation, but really, they are missing out on, what one could argue, is companies using AI are cold-hearted in their approach to building out their teams and developing their workforce because they want to save the time and money. Gone are the days when an interviewer blown away and an immediate connection is made, giving an incentive to go the “extra mile” and offer the position. AI removes all those opportunities and personal connections. While the counter argument may state this lack of interpersonal connection is a good thing in terms of bias, once the AI is done with its job, two people still must engage and work well together. Companies are willing to stand strong on business ethics, but have not taken similar stances that blurs the lines of ethics if it may be more cost-effective.

In another example, while career changes are common and often happen in the workplace, deep-learning algorithms fail concerning age discrimination and transparency. When we learned about the future of talent and the value of having a strong and diverse skills profile, we also learned that career advancement opportunities have a slower runway for job seekers nit in a specific age criterion. Literature does ask the question: Does transparency inherently conflict with AI recruiting? Moreover, it is not one-sided by asking, "Does the right to transparency mean understanding how the algorithm generally operates (e.g., how the algorithm uses data and weighs specific criteria)? Alternatively, does transparency imply disclosing the conditions and explanations for each algorithmic decision?” (Hunkenschroer & Kriebitz, 2022).

Benefits of AI

AI is complicated and still premature in the sense that we have only scratched the surface of its capabilities. AI has its limitations, but its benefits to the world are much greater when looking at it from the lens of time and cost savings.

Recruiters	
Focus Area	Benefits
[People] Reducing Bias	Reduces unconscious bias in candidate evaluations
	AI knows exactly what it is looking for - Consistent Application Criteria (Applicant Tracking Systems)
	Skills and qualifications are the focus of the assessment, avoids the "foot in the door" approach, less about personality and networks
[Process] Efficiency	Speeds up candidate screening process to hire talent quicker
	Reduces administrative tasks
	Automates resume parsing based on job descriptions and desired hiring qualities
	Can keep up with high application demand, specifically for popular roles in larger companies
[Technology] Compliance and Policies	Compliance with labor laws and regulation to ensure equal opportunity employment
	Makes the process much easier to follow and track over time, including using a database of candidates to circle back for future roles (Applicant Tracking Systems)
Hiring Experience	Objective evaluation without human involvement

Figure 18. Benefits of AI

(Picardo, 2023)

With lightning-speed processing times, and rain man level knowledge, humanity has never had access to this type of information as quickly, thoroughly, and accurately as we have had in the past. The strides have been significant, especially when thinking about where we started in the library with the Dewey Decimal System and 400-page encyclopedias. With the evolution of the internet and prevalence of the iPhone, we are spoiled with Google searches, but AI still managed to go a step further. You can feed AI information, and not only does it immediately respond , but you can also give it actions and tell it what you need help with. I do not want to undermine the algorithm's ability to change the way we think about processing data, because the advances we have seen are remarkable.

For example, AI has shown great benefits in the healthcare industry when making predictions for cancer patients, interpreting MRIs, or medical data. These advancements have shown humanity how powerful AI can be when leaning on its intelligence to pattern match and project potential illnesses or issues the human eye may have not seen. So as much as I have argued that AI is detrimental to hiring, AI has the ability to show me something I am not able to see for myself.

In the support of reducing bias, and name discrimination, if we uncover how an algorithm recognizes a candidate's name, it may end up being determining factor as to how their application was weighted. For example, let us take the name Nishant, which is normally given to a male of Hindu descent. When a resume is parsed, an algorithm may recognize the name Nishant and determine his ethnicity. To the algorithm, this could impact the job seeker in two ways:

- **Scenario 1:** The algorithm recognizes that Nishant is of Indian descent, and determines they are not the preferred candidate for the position based on historical data or context provided by the employer.
- **Scenario 2:** The algorithm determines Nishant is a great fit for the position and weighs their application higher than an applicant named Anthony, a commonly used name for a Caucasian white male.

When I explored the idea of AI lacking common sense, I previously mentioned its ability to recognize information and piece together without being instructed. In this case, the benefits of using it in this function remove the unconscious bias an employer may have against employing people from outside of their region or from diverse backgrounds. While an employer may never actually admit the reasoning behind why they may have overlooked Nishant's application, I hope that algorithms remain fair and just in their point of view, like it did within Scenario 2.

One conclusion we can draw is companies that are striving to be more diverse, may lean on a tool like AI in recruiting to remove biases of their recruiters and managers to break down silos and historical racial barriers. This is a great way to lean on a third-party tool to keep recruiters and managers honest, while also building a more diverse and inclusive workforce. All in all, we have learned the recruiting process and hiring technicalities need more consistency. All companies have their internal ATS tools with differing algorithms. Standardization for screening is going to be required. Similar to how HR policies are consistent across the globe and within respective countries concerning termination and equal opportunity employment efforts, recruiting best practices must be included in this governance and hold the same weight for liability and potential lawsuits. For example, figuring out how to templatize resumes across ATS tools can benefit everyone. Currently, there is a general standard for crafting a perfect resume by including your education, skills and background, certifications, and employer referrals to move past the ATS scanners. Depending on the algorithm used, the AI may be unable to parse the resumes when compared to another ATS tool. This may result in the algorithm missing key information that could be a determining factor for a job seeker.

If resume parsing improves, it benefits both parties. Ultimately, making it much easier for applicants to apply to multiple jobs without manually plugging in their resume details each time. In addition, they will not have to deal with knowing what skills or qualifications are unfairly being held against them.

Conclusion

From what we have discovered about algorithms and neural networks consuming large datasets and processing information at vast speeds, humans will always need help keeping up. There may not be a right answer about whether AI can truly perform in an environment co-existing with recruiters, but we know that what and how we use AI today is an Achilles heel. Algorithms are consistent with how they work, but we as humans are not consistent in how we are using them. At this rate, from a human rights and ethical point of view, companies are putting themselves at risk until we can correct the blurred lines of AI in recruiting and begin enforcing our hiring practices and policies to align to our hiring technology.

While the literature states that the tool is more than capable of performing certain tasks, the better question is if it *should*. If trained properly, AI in recruiting can help alleviate many hiring challenges, ultimately refining talent pools to the best of the best while also modernizing the workforce, keeping them relevant, and, in some cases, eliminating means for potential discrimination. At this moment in time, I still believe significant work needs doing before it can ever be implemented into hiring technology.

As quickly as technology advances, companies must continue to invest in building their digital acumen, ensuring their processes maintain pace with external trends and demands of innovation and technology changes. In doing so, when new tools like AI succumb to reality, then companies will feel more prepared and ready to embrace and adopt them. Right now, society is moving backwards by trusting it to handle tasks it is unsuitable too. This is not to say AI will not get there, but companies are exposing their weaknesses. Job seekers are in the driver's seat and ultimately holding the power to determine what happens next.

Innovation drives a different level of persistence and commitment to rethinking the way things may have been done in the past to improve better results. This proposal to standardize the resume may raise issues of concern and only add to the increase in application demand. AI's external influence and marketing push have sent mixed signals to companies by overpromising and underdelivering. Researchers continue figuring out how to measure the success of AI in these different functions. Even when evaluating AI alongside workplace outcomes, there are significant literature gaps related to impacting the following areas: recruitment and selection, employee and labor relations, performance management, health, safety, and well-being, as well as human resource planning (Pereira et al., 2023).

The future of this research will continue to explore the technicalities of ATS tools, their algorithms, potential impacts to job seekers, and overall well-being of companies. We will propose a general standard for implementation of AI in a recruiting function and determine when and where it should appropriately be used. This is not to say that, as a technology-dependent world, we cannot still find a way to make lemonade. However, with the right ingredients and approach, we can innovate AI in a recruiting function to ensure it is driving value, is honest, and fair by ensuring the right people, with the right skills, land in the right jobs, to not only innovate, but essentially change the world.

CHAPTER 5

RESEARCH QUESTION AND MOTIVATION

AI has presented an ongoing challenge for companies as they grapple with the task of incorporating its best practices into their operations to automate, streamline, and enhance existing tasks and processes. In 2021, a study employed a structured keyboard-based approach to analyzing AI in recruiting articles in Business Source Complete. The findings of this study showed that AI articles published from 2016 to 2020 broke down AI into three different yet critical topics: a theoretical perspective on the ethics of AI, the legal perspective on its risks, and the technical aspect of implementation (Hunkenschroer & Luetge, 2022).

In Study 1, the data revealed certain limitations, particularly in the field of AI in recruiting, which has led to a hesitancy in adopting AI technology and a lack of confidence in its ability to drive more efficient recruiting practices. To delve into this issue, a qualitative study was conducted by Malin et al. involving HR professionals. The study focused on their perceptions of AI-based chatbots and decision support tools for candidate pre-selection. The companies under investigation varied in size, ranging from 10 to 18,000 employees, and operated in the automotive and media sectors. Furthermore, the study encompassed professionals with diverse levels of experience in the recruitment field. Additional details about the demographics of the study participants can be found in the Table below (Malin et al., 2023).

Table 1. Demographic details of interviewees.

ID	Industry	Experience in Recruiting
E0	HR consulting	22 years
E1	Research and development	3 years
E2	Media	2 years
E3	Construction, procurement, printing centre, facility management and cleaning, and IT	5 years
E4	Financial services	1 year
E5_1	Automotive industry	3 years
E5_2	Automotive industry	12 years
E5_3	Automotive industry	7 years
E6	Audit, consulting, financial advisory, risk advisory, and tax	10 years
E7	Electrical and electronics industry	5 years
E8	Intralogistics	22 years
E9	Paper industry, corrugated board industry, and packaging industry	4 years
E10	Automotive industry	10 years
E11	Metal industry, machine, and plant engineering	12 years
E12	Healthcare	12 years
E13_1	Public service and representation of interests	10 years
E13_2	Public service and representation of interests	20 years
E13_3	Public service and representation of interests	5 years
E14	Telecommunications, IT, and mobile communications	10 years
E15	Research	30 years
E16	Food production and trade	12 years
E17	Management and technology consulting	1 year
E18	Staffing service	4 years
E19	IT	7 years
E20	Insurance	n.a.

Table 1. Demographic Details of Interviewees

(Malin et al., 2023)

The findings of this study closely align with the results of Study 1 in terms of the comprehension of AI and its functioning, as well as the level of experience in working with it. These discoveries can be categorized into two primary themes: (1) The Scope of AI and (2) the definition of instruction (Malin et al., 2023). Moreover, the interviewees expressed the belief that AI remains limited and is primarily rule-based. They perceive its scope to be centered around four key recruiting tasks: (1) providing information, (2) data gathering, (3) candidate exploration, and (4) matching and (pre)-selection (Malin et al., 2023)

	USE CASES OF AI	
	narrow	**broad**
Providing information	• Provision of information about the open job position and company • Status quo of the application • Appointment arrangement	• Employer branding • Consulting
Gathering of data	• Upload application documents • Completeness check of the application documents • Inquiry about personality types (personality test)	• Analysis of personality
	• Pre-interviews	• Job interviews
Candidate exploration	• Passive candidate exploration in internal and external databases	• Automated creation and posting of job advertisements • Job rotation
(Pre-)selection and matching	• Visualisation for filtering • Matching including creation of short and long lists • Creation of proposals for rejection and invitations for the further application process • Sending of interim messages to applicants • Generation of reports/ basis for statistics	• Matching personal fit and company • Automated rejections

Figure 1. Use cases associated with a narrow and broad scope of AI grouped by recruiting tasks.

(Malin et al., 2023)

Furthermore, with AI rapidly gaining traction and continuously evolving, the enthusiasm surrounding its potential benefits for employees is justified. However, there continues to be significant resistance from recruiters towards embracing change. In another study conducted by Suseno, HR professionals were the focus, and the investigation centered on two distinct aspects: beliefs and anxiety regarding AI, as well as change readiness (Suseno et al., 2021). The research findings pertaining to these dimensions can be visualized in the conceptual model (Suseno et al., 2021).

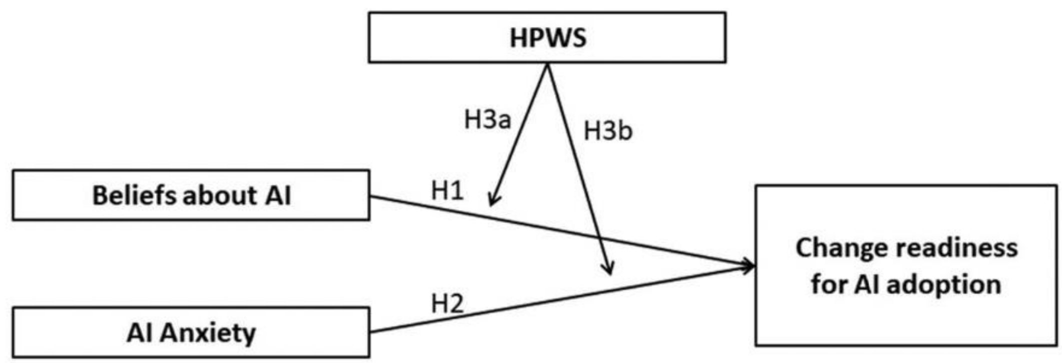


Figure 1. The conceptual model.

(Suseno et al., 2021)

What made these findings unique was the emphasis placed on the organization's readiness for change rather than solely focusing on whether AI could fulfill its intended purpose. The study by Suseno et al. specifically explored how well companies prepared and trained their employees to minimize anxiety related to the incorporation of AI into their job roles. According to Suseno et al., "Individuals with positive beliefs were more likely to accept the change to adopt AI, while individuals who experienced higher anxiety over AI were less ready to adopt AI" (Suseno et al., 2021).

As we continue to identify gaps in the existing literature, it becomes evident that the motivation for automating hiring tasks through AI is driven by two key factors: cost reduction and time-savings (AMZILE et al., 2023). By continuously demonstrating how

AI automation can enhance efficiency and cost-effectiveness in these hiring functions, we can make a compelling argument for its potential success if users are willing to adopt it.

To address concerns around bias and ensure the proper testing of tools used in workplace hiring, companies and even states like New York and the United Kingdom have implemented stricter laws (Friedman, 2022). Risk assessments are performed to evaluate algorithms used in "automated employment decision tools" (Friedman, 2022). The United Kingdom has taken a strong approach by establishing "lead AI Ministers across all departments to bring together work on risks and opportunities driven by AI in their sectors and to oversee implementation of frameworks and guidelines for public sector usage of AI" (Donelan, 2024). Such governance ensures that each functional area adopting AI technology pays close attention to algorithmic processes to mitigate potential challenges that may arise as AI continues to evolve on its own.

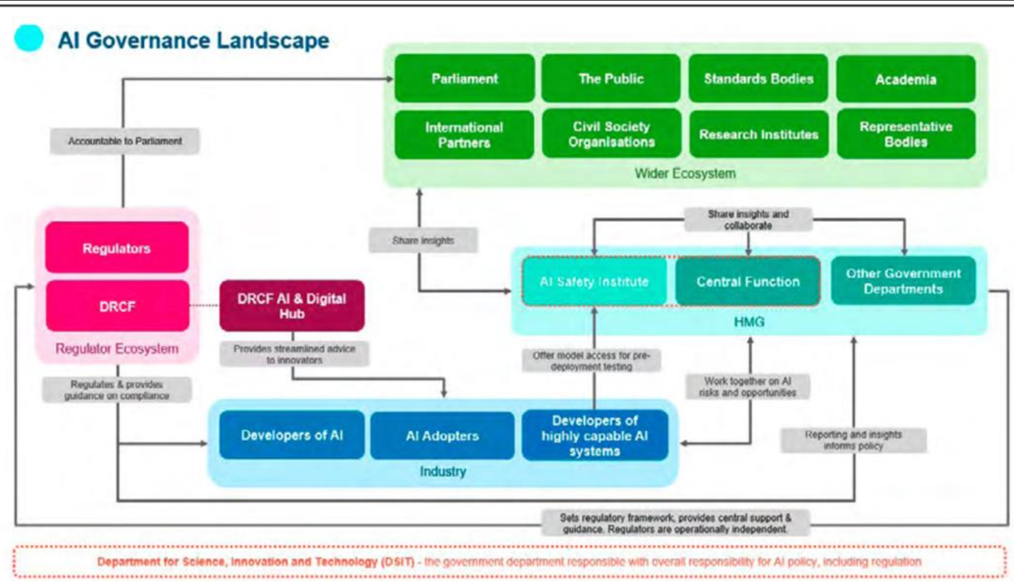
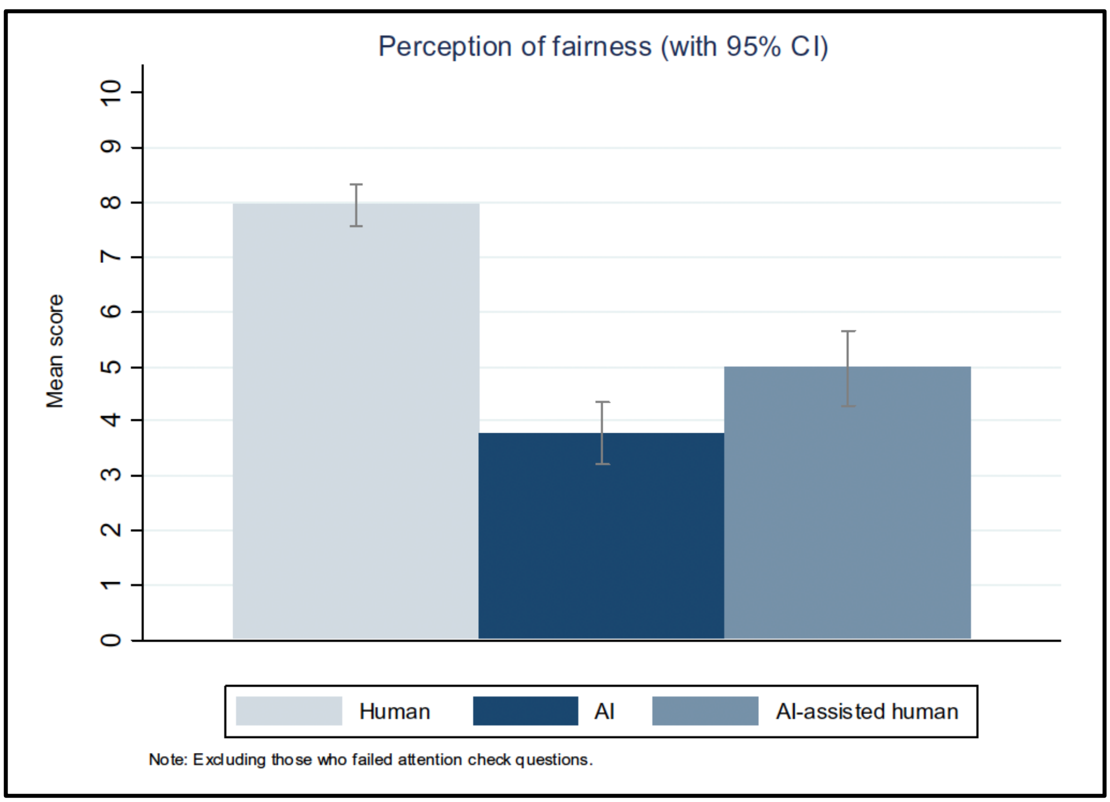


Image 1: A diagram of the AI regulation landscape showing the relationships between the government, regulators, industry, and the wider ecosystem.

(Donelan, 2024)

Lastly, the ethics of algorithms are not solely from the perspective of the business; rather, they also concern job seekers. Job seekers are skeptical about how hiring algorithms work and their overall fairness, specifically because the selection criteria is not disclosed to them at the front-end of the process. Job seekers are not clear on how they are being assessed. "A potential mechanism underlying algorithm resistance is the belief that algorithms will not be able to recognize their uniqueness as a candidate," ultimately questioning if their skills and qualifications measure up to the ATS scanners (Lavanchy et al., 2023). With this perspective in mind, companies often forget that the hiring process is a two-way street. While job seekers are in the front seat by applying to positions aligned with their passion and career goals, the interview process, or lack thereof, speaks volumes about the company, its culture, and whether or not it would be a good fit to work there.



(Lavanchy et al., 2023)

From this study, the perception of fairness of AI shows that the majority of job seekers felt more confident in a human-based approach to the recruiting process as opposed to an AI or even an AI-assisted human approach (Lavanchy et al., 2023).

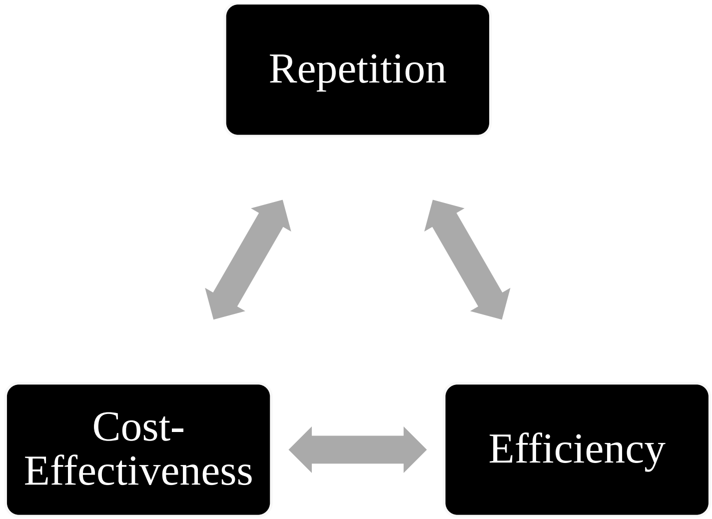
Furthermore, algorithm bias may dramatically impact the recruiting experience. For example, it may lead to job seekers not hearing back about jobs they have applied to, or in some cases, hearing back within minutes of applying – alluding that they have been rejected by the algorithm before a human being even saw their application. From the company's perspective, they may not even be fully aware that this is the job seeker's experience, also knowing that they are potentially missing highly qualified talent since the algorithm decided they were not qualified for a position without considering other hiring factors.

Validation of Hiring Task Automatability

Building on the findings from the initial survey and existing research, the second study aims to further explore the potential for automating different hiring tasks using AI. Recruiters were surveyed to gather their perspectives on the feasibility of automating specific tasks in the hiring process. The data collected was analyzed using correlation statistics to uncover possible links between AI adoption and the perceived ability to automate various hiring tasks.

In this study, hiring automatability refers to the degree to which tasks and processes in the hiring process can be efficiently and effectively automated using AI technologies (Chui et al., 2015).

Dimensions of Hiring Task Automatability Y



MEASUREMENT OF HIRING TASKS

Research Question #1: How does the repetition of hiring tasks affect the efficiency of the hiring process?

H1: Higher levels of task repetition are associated with lower efficiency in the hiring process.

This research question aims to investigate the relationship between the repetition of hiring tasks and the overall efficiency of the hiring process. The independent variable is "repetition," which refers to the frequency or recurrence of performing specific tasks in the hiring process. The dependent variable is "efficiency," which evaluates how well and quickly the hiring process achieves its objectives. The hypothesis (H1) suggests that as the level of task repetition increases, the efficiency of the hiring process decreases.

Research Question #2: How does the repetition of hiring tasks impact the cost of the hiring process?

H2: Higher levels of task repetition are associated with increased costs in the hiring process.

This research question explores the connection between the repetition of hiring tasks and the associated costs of the hiring process. The independent variable remains "repetition," representing the frequency or recurrence of performing specific tasks in hiring. The dependent variable is "cost," which measures the financial resources expended during the hiring process. The hypothesis (H2) suggests that as the level of task repetition rises, the costs incurred in the hiring process also increase.

Research Question #3: How does AI's ability to identify skill qualifications influence the efficiency of the hiring process?

H3: Improved AI skill identification leads to higher efficiency in the hiring process.

This research question focuses on examining the impact of AI's ability to identify skill qualifications on the overall efficiency of the hiring process. The independent variable is "skill qualifications," referring to the AI system's capability to accurately identify and assess candidate skills. The dependent variable is "efficiency," which evaluates how well and quickly the hiring process achieves its objectives. The hypothesis (H3) proposes that improved AI skill identification positively affects the efficiency of the hiring process.

Research Question #4: How does AI's ability to identify skill qualifications affect the costs of the hiring process?

H4: Enhanced AI skill identification leads to reduced costs in the hiring process.

This research question investigates the relationship between AI's ability to identify skill qualifications and the resulting costs in the hiring process. The independent variable remains "skill qualifications," representing the AI system's effectiveness in accurately identifying and assessing candidate skills. The dependent variable is "cost," measuring the financial resources expended during the hiring process. The hypothesis (H4) suggests that as AI skill identification improves, the costs associated with the hiring process decrease.

Data Collection, Analysis, and Statistical Methods

A quantitative survey was distributed to subject matter experts in recruiting by a third party, Cint. According to Zippia (2024), there are approximately 264,000 recruiters employed in the United States, therefore according to Survey Monkey, we were able to determine that a target sample size of 389 participants was required to effectively measure the impact.

Frequency and percentage statistics were used to describe the demographic characteristics of the sample. Spearman correlations were used to test for significant associations between survey items that used Likert-type response sets. Non-parametric Kruskal-Wallis (three or more groups) and Mann-Whitney *U* tests (two groups) were used to compare the responses to survey items using categorical response sets to other survey items that used Likert-type response sets. When a significant main effect was detected using Kruskal-Wallis tests, post hoc comparisons were performed using Dunn's test. Medians and interquartile ranges were reported and interpreted for the comparisons of categorical responses on survey items using Likert-type response sets. All analyses were performed using SPSS Version 29 (Armonk, NY: IBM Corp.) and statistical significance was assumed at a two-sided alpha value of 0.05.

The following questions from the survey have been labeled to streamline the data analysis:

Repetition

R1	How often are repetitive tasks encountered in the recruiting process?
R2	How often are you performing resume screening in the recruiting process?
R3	How often are you updating candidate profiles in the Applicant Tracking System (ATS)?
R4	How often are you scheduling interviews?

Efficiency

RE1	How does the repetition of hiring tasks impact the overall efficiency of the hiring process?
RE2	In your experience, what specific tasks in the hiring process become more efficient with repetition?
RE3	Are there any challenges or bottlenecks that arise due to the repetition of certain hiring tasks? (Select all that apply)
RR4	In your experience, which of the following strategies or technologies have you observed to improve the efficiency of repetitive hiring tasks?

Cost-Effectiveness

RC1	How does the repetition of hiring tasks affect the overall cost of the hiring process?
RC2	Are there specific areas within the hiring process where cost savings can be achieved through task automation?
RC3	What are some potential cost drivers that arise from the repetition of hiring tasks?
RC4	Have you encountered any cost-saving measures or best practices related to repetitive hiring tasks?

Statistical Results

In Section 1, Spearman correlations were employed to analyze the relationship between subject matter experts' perceptions and the frequency of repetitive tasks in the recruiting process. The analysis revealed statistically significant positive correlations between subject matter experts' perceptions (RE1) and the frequency of repetitive tasks (R1, R2, R3, and R4) (rs ranging from 0.20 to 0.32, $p < 0.001$). However, no significant correlations were found between subject matter experts' perceptions of the cost of hiring tasks (RC1) and the frequency of these tasks (R1, R2, R3, or R4) ($p > 0.05$).

Variables	R1	R2	R3	R4
RE1	0.32*	0.20*	0.30*	0.30*
RC1	0.04	0.07	0.04	0.02

Statistically significant correlation, $p < 0.05$

Table 2. Spearman Correlations for Repetition of Hiring Tasks

Furthermore, Kruskal-Wallis tests were conducted to compare categorical responses regarding the efficiency of specific hiring tasks (RE2) against Likert-type items representing the frequency of these tasks (R1, R2, R3, and R4). Significant main effects were detected for the frequency of resume screening (R2) ($p = 0.02$). However, no significant main effects were found for the frequency of other tasks (R1, R3, and R4) ($p > 0.05$).

Outcome	Question	1st choice	2nd choice	3rd choice	4th choice	5th choice	p-value
RE2		Resume screening	Use of ATS	Reference Checks	Scheduling interviews	Other	
	R1	3 (2 – 4)	4 (2 – 4)	3 (2 – 4)	4 (3 – 4)	4 (4 – 4)	0.19
	R2	4 (3 – 4)	4 (3 – 5)	3 (2 – 4)	4 (3 – 4)	4 (3 – 5)	0.02*
	R3	3 (2 – 4)	4 (3 – 5)	3 (2 – 4)	4 (3 – 4)	3.5 (2 – 5)	0.06
	R4	3 (2 – 4)	3 (3 – 4)	3 (2 – 4)	3 (3 – 5)	2 (1 – 3)	0.08
RE3		Repetition does not crate challenges or bottlenecks	No challenges or bottlenecks arise from repetition	Increases the risk of errors or inconsistencies	Leads to delays in hiring process	Other	

Table 3. (continued).

	R1	4 (2 – 4)	3 (2 – 4)	3 (3 – 4)	4 (2 – 4)	4 (3 – 5)	0.38
	R2	4 (2 – 4)	4 (3 – 5)	4 (3 – 4)	4 (3 – 5)	3 (3 – 5)	0.61
	R3	4 (2.5 – 4.5)	3 (2 – 4)	4 (3 – 4)	4 (2 – 4)	3 (2 – 5)	1.0
	R4	3 (2 – 4)	3 (2 – 4)	3 (3 – 4)	3 (3 – 5)	3 (2 – 4)	0.33
RE4		Standardized interview templates	Using ATS	Resume Screening Software	Leveraging chatbots or AI-powered virtual assistants for candidate communication	-	
	R1	3 (2 – 4)	3 (2.5 – 4)	3 (2 – 4)	4 (3 – 4)	-	0.04*
	R2	4 (3 – 5)	4 (3 – 5)	3 (3 – 4)	4 (3 – 5)	-	0.008*
	R3	4 (2 – 4)	4 (3 – 5)	3 (2 – 4)	4 (3 – 5)	-	0.001*
	R4	3 (2 – 4)	3 (3 – 4)	3 (2 – 4)	3 (3 – 4)	-	0.003*
RC2		No specific Areas for cost savings	Resume Screening	Interview coordination and scheduling	Onboarding and new employee paperwork		
	R1	3 (2 – 4)	3 (2 – 4)	3 (2 – 4)	4 (2.5 – 4)	-	0.42
	R2	3 (2 – 5)	4 (3 – 4)	4 (3 – 4.5)	4 (3 – 5)	-	0.21
	R3	4 (2 – 4)	3 (2 – 4)	4 (3 – 4)	4 (3 – 5)	-	0.04*
	R4	3 (2 – 3)	3 (2 – 4)	3 (3 – 4)	3 (3 – 5)	-	0.009*
RC3		Increased manual effort and time required	Higher recruitment agency fees or advertising costs	Duplication of administrative tasks	Communication gaps between employee and job seeker		

Table 3. (continued).

	R1	4 (3 – 4)	3 (2 – 4)	3 (2 – 4)	3 (3 – 4)	-	0.12
	R2	4 (3 – 5)	3 (3 – 4)	3.5 (3 – 4)	4 (3 – 5)	-	0.009*
	R3	4 (2.5 – 4)	3 (2 – 4)	4 (2 – 4)	4 (3 – 4)	-	0.91
	R4	3 (3 – 4)	3 (2 – 4)	3 (2 – 4)	3 (3 – 5)	-	0.38
RC4		Implementing recruiting strategies to better target talent	Utilizing video interview software/assessments for initial candidate screening	Leveraging employee referral program to reduce third-party recruitment costs	Streamlining onboarding tasks by making them more digital and easily accessible	Other	
	R1	3.5 (3 – 4)	3 (2 – 4)	3 (2 – 4)	4 (3 – 4)	3 (2 – 4)	0.06
	R2	4 (3 – 5)	3 (3 – 4)	4 (3 – 4)	4 (3 – 5)	2.5 (2 – 3)	0.02*
	R3	4 (2 – 4)	4 (2 – 4)	3 (2.5 – 4)	4 (3 – 4)	3 (2.5 – 3.5)	0.87
	R4	3 (2 – 4)	3 (3 – 5)	3 (3 – 4)	3 (3 – 4)	2.5 (1.5 – 3.5)	0.04*

Findings: Values are median (interquartile range), * statistically significant correlation, $p < 0.05$

Table 3. Kruskal-Wallis Tests for Specific Tasks

Additionally, categorical responses regarding challenges or bottlenecks arising from repetition (RE3) were compared against Likert-type items representing the frequency of hiring tasks (R1, R2, R3, and R4) using Kruskal-Wallis tests. No significant main effects were found (p-values range from 0.33 to 1.00).

Finally, Mann-Whitney U tests were conducted to analyze responses regarding strategies or technologies to improve efficiency (RE4) against Likert-type items representing the frequency of hiring tasks (R1, R2, R3, and R4). Significant main effects were found for R1, R2, R3, and R4 ($p < 0.05$), indicating perceived differences in the effectiveness of various strategies or technologies across different hiring tasks.

In Section 2, Spearman correlations were utilized to analyze the relationship between subject matter experts' perceptions and the effectiveness of specific hiring strategies. The analysis revealed statistically significant positive correlations between subject matter experts' perceptions (SR1 and SR2) and the effectiveness of hiring strategies (SRE1, SRE2, SRE3, SRE4, SRC1, SRC2, SRC3, and SRC4) (rs ranging from 0.26 to 0.41, $p < 0.001$).

Variables	SRE1	SRE2	SRE3	SRE4	SRC1	SRC2	SRC3	SRC4
SR1	0.33*	0.36*	0.41*	0.41*	0.38*	0.31*	0.38*	0.35*
SR2	0.26*	0.32*	0.34*	0.33*	0.28*	0.24*	0.31*	0.29*

Findings: Statistically significant, $p < 0.001$

Table 4. Spearman Correlations

Furthermore, Mann-Whitney U tests were conducted to compare categorical responses regarding specific hiring strategies (SR3_1 to SR3_5) against Likert-type items representing the effectiveness of these strategies (SRE1, SRE2, SRE3, SRE4, SRC1, SRC2, SRC3, and SRC4). Significant differences were found for certain strategies, indicating perceived variations in effectiveness across different strategies.

Outcome	Question	1st choice	2nd choice	p-value
SR3_1		Did not choose	Resume Screening	
	SRE1	3 (3 – 4)	3 (3 – 4)	0.002*
	SRE2	3 (3 – 4)	4 (3 – 4.5)	0.03*
	SRE3	3 (3 – 4)	4 (3 – 5)	0.007*
	SRE4	3 (3 – 4)	4 (3 – 4)	0.03*
	SRC1	3 (3 – 4)	3 (3 – 4)	0.19
	SRC2	3 (3 – 4)	4 (3 – 4)	0.07
	SRC3	3 (3 – 4)	4 (3 – 5)	< 0.001*
	SRC4	3 (3 – 4)	4 (3 – 4)	0.008*
SR3_2		Did not choose	Skill-based Assessments	
	SRE1	3 (3 – 4)	3 (3 – 4)	0.04*
	SRE2	3 (3 – 4)	4 (3 – 4)	0.03*
	SRE3	3 (3 – 4)	4 (3 – 4)	0.01*
	SRE4	4 (3 – 4)	4 (3 – 4)	0.31
	SRC1	3 (3 – 4)	3 (3 – 4)	0.78
	SRC2	4 (3 – 4)	4 (3 – 4)	0.90
	SRC3	3 (3 – 4)	4 (3 – 4)	0.05
	SRC4	3 (3 – 4)	4 (3 – 4)	0.42
SR3_3		Did not choose	Phone or Video Interviews	
	SRE1	3 (3 – 4)	3 (3 – 4)	0.30
	SRE2	3 (3 – 4)	4 (3 – 4)	0.07
	SRE3	3 (3 – 4)	4 (3 – 5)	0.07
	SRE4	4 (3 – 4)	4 (3 – 4)	0.22
	SRC1	3 (3 – 4)	3 (3 – 4)	0.21
	SRC2	3 (3 – 4)	4 (3 – 4)	0.63
	SRC3	3 (3 – 4)	4 (3 – 4)	0.45
	SRC4	3 (3 – 4)	4 (3 – 4)	0.13
SR3_4		Did not choose	Reference Checks	
	SRE1	3 (3 – 4)	3 (3 – 4)	0.04*
	SRE2	4 (3 – 4)	4 (3 – 4)	0.42
	SRE3	4 (3 – 4)	4 (3 – 4)	0.50
	SRE4	4 (3 – 4)	4 (3 – 4)	0.65
	SRC1	3.5 (3 – 4)	3 (3 – 4)	0.44
	SRC2	4 (3 – 4)	3 (3 – 4)	0.93
	SRC3	4 (3 – 4)	4 (3 – 4)	0.77
	SRC4	3 (3 – 4)	4 (3 – 4)	0.43

Table 5. (continued).

SR3_5		Did not choose	Portfolio Reviews	
	SRE1	3 (3 – 4)	4 (3 – 5)	< 0.001*
	SRE2	4 (3 – 4)	4 (3 – 5)	0.005*
	SRE3	4 (3 – 4)	4 (3 – 5)	0.03*
	SRE4	4 (3 – 4)	4 (3 – 5)	0.003*
	SRC1	3 (3 – 4)	3.5 (3 – 4)	0.08
	SRC2	3 (3 – 4)	4 (3 – 4)	0.03*
	SRC3	4 (3 – 4)	4 (3 – 5)	< 0.001*
	SRC4	3 (3 – 4)	4 (3 – 4)	0.06

Findings: Values are median (interquartile range), * statistically significant correlation, $p < 0.05$

Table 5. Mann-Whitney U

Overall, the findings from Sections 1 and 2 provide insights into subject matter experts' perceptions of the relationship between repetition, efficiency, and cost-effectiveness in the recruiting process, shedding light on potential areas for improvement and optimization.

Industry Heterogeneity

The demographic characteristics of the sample are presented in Table 6. There was a wide range of industries represented in the sample. The majority of participants had a bachelor's degree or higher, were below the age of 45, and gender was relatively evenly dispersed between men and women. Almost 30% of the sample had missing data for the demographic characteristics.

Variable/Level	Frequency (%)
Industry	
Pharmaceutical	6 (1.0%)
Finance	41 (7.0%)
Food and Beverage Services	21 (3.6%)
Retail and E-Commerce	39 (6.6%)
Technology and Software	69 (11.7%)
Health and Insurance	42 (7.1%)
Medical	26 (4.4%)
Education	26 (4.4%)
Manufacturing	46 (7.8%)
Transportation	13 (2.2%)
Real Estate and Hospitality	17 (2.9%)
Government	11 (1.9%)
Other	60 (10.2%)
Missing	171 (29.1%)
Education	
High school diploma or equivalent	66 (11.2%)
No degree	20 (3.4%)
Bachelor's degree	226 (38.4%)
Master's degree	74 (12.6%)
Professional degree	29 (4.9%)
Missing	173 (29.4%)
Age	
18-25	55 (9.4%)
25-35	136 (23.1%)
35-45	140 (23.8%)
45-55	56 (9.5%)
55+	30 (5.1%)
Missing	171 (29.1%)
Gender	
Male	223 (37.9%)
Female	191 (32.5%)
Non-binary/third gender	2 (0.3%)
Prefer not to say	1 (0.2%)
Missing	171 (29.1%)

Table 6. Demographics

When delving deeper into industry heterogeneity with AI, a recent study at MIT revealed that AI adoption in the U.S. is uneven, with its use predominantly clustered in large companies and industries such as manufacturing and healthcare (Eastwood, 2024). Additionally, according to a November 2024 Census Bureau survey, fewer than 4% of companies are utilizing AI to produce goods and services (Dinlersoz, 2023) (See Table 7).

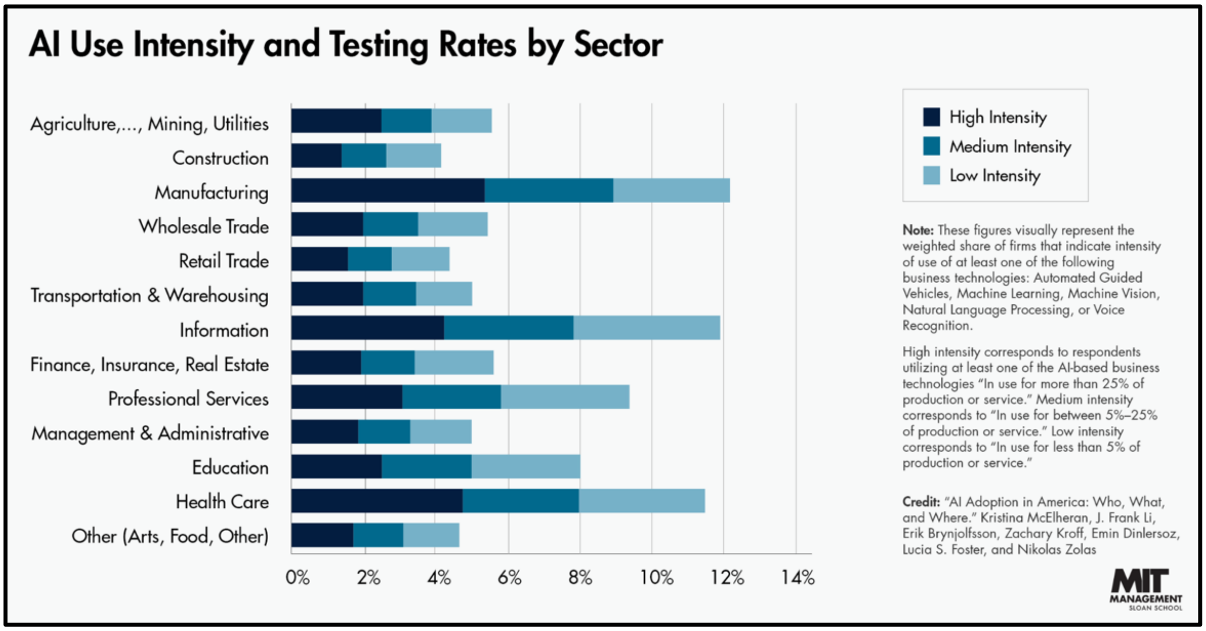


Table 7. AI Use Intensity and Testing Rates by Sector

(Dinlersoz, 2023)

These findings raise questions about AI adoption within these industries and whether or not demographics play a part in its adoption. Within the MIT survey, they discovered that "startups using AI were more likely to have younger, more highly educated, and more highly experienced leaders than startups that were not using AI. Venture capital backing and a focus on process innovation were also associated with AI adoption" (Eastwood, 2024). Comparing this data to our findings (See Table 3), technology & software, manufacturing, and finance ranked high frequency for the use of

AI within their industry (26.5%). Meanwhile, the majority of respondents were between the ages of 25 and 45 years old (46.9%), with a bachelor's degree (38.4%).

Confirming this, the adoption of AI in specific industries may lead to a significant impact at the C-suite level. Technology innovators who are pioneering this new way of working, particularly those in leadership positions, are more committed to enhancing AI capabilities within their companies and across relevant sectors. With such adoption in healthcare and manufacturing industries, they are much closer to machine usage and may find it far less shocking to their business to incorporate AI-like changes.

Research Question	Data Results
RQ1: How does the repetition of hiring tasks affect the efficiency of the hiring process?	Significant positive correlations between subject matter experts' perceptions and the frequency of repetitive tasks
RQ2: How does the repetition of hiring tasks impact the cost of the hiring process?	No significant correlations were found between subject matter experts' perceptions of the cost of hiring tasks and their frequency
RQ3: How does AI's ability to identify skill qualifications influence the efficiency of the hiring process?	No data to support this question
RQ4: How does AI's ability to identify skill qualifications affect the costs of the hiring process?	Not enough data to accurately answer this research question

(Picardo, 2024)

Research Limitations

This research focused on the utilization of AI in recruiting, specifically from the perspective of recruiters. Initially, our study intended to capture insights from hiring managers; however, we quickly learned that the voice of the "customer" was emerging at the recruitment level. Therefore, our second study was primarily focused on obtaining data from the subject matter expert level. With that being said, AI in recruiting is not strictly a recruiter issue, and whether or not they are adapting AI’s capabilities, extends well beyond their HR role. Future research should continue to explore the impacts of AI in recruiting at the strategic and executive levels. By doing so, we can further understand the influence AI has within this function and learn more about the overall expectations senior leaders hold regarding its use within their own corporations, as well as their awareness of its capability to pose harm or risk to their organization. This includes properly training their staff on its use, and providing ongoing guidance and support as it evolves as a tool.

Furthermore, this research does not test AI at the algorithmic level. While ATS tools are frequently used in recruiting, testing these algorithms for bias is necessary to ensure fair operation. However, although all ATS tools are similar, they do differ. Future research should continue to explore whether certain algorithms are better at detecting job seekers fairly and accurately compared to a human. For example, there may be some algorithms that are able to detect key skills or experience that are not easily interpreted from a resume, assuming a candidate in one industry could translate their experience to another and still perform at a high level – similar to the thought-work done by a human, but with the emotional intelligence to differentiate them for the other candidates as a job seeker with great potential.

Finally, this research concentrated on companies with 6,000 employees or more that have embraced AI in their recruiting processes. As we delve deeper into the exploration of industry heterogeneity, it becomes pertinent to ascertain whether AI performs more effectively within smaller companies, typically with 100 to 1500 employees ranging from 1 to 100 million in revenue (Hait, 2022). Alternatively, if AI is employed for broader candidate selection and screening, it becomes essential to assess fundamental skill sets that may not directly correlate with the job itself, such as college education, background, location, and primary skills required.

Finally, incorporating additional screening questions could potentially lead to a less evenly distributed response rate across genders. Within Qualtrics, the demographic information was not mandatory, resulting in some data reflecting conclusions that may only pertain to half to three-fourths of the overall sample size when considering age or gender.

By expanding this research within this domain, researchers can establish standards based on precedence to demonstrate that if AI is to be used within a recruiting function, proper governance of the algorithms is necessary to ensure they meet specific guidelines and regulations for equal opportunity employment. This will contribute to AI's benefits in recruiting and also help companies advance their recruiting practices to meet external demands.

Future Research

Given the nature of this research, it would benefit from a qualitative approach, specifically in the form of semi-structured interviews. Within the data, Recruiters and Managers demonstrated alignment across several concrete issues in the hiring process. To facilitate the identification of necessary process improvements, conducting semi-structured interviews and employing causal theme-coding analysis may unveil new themes that warrant attention at the Executive level.

Subsequently, researchers would be equipped to delve into the root cause of the relationship between recruiters and hiring managers, thus determining if AI is effectively and appropriately supporting them. In the original conceptual model, the three main elements affected by AI in recruiting were people, process, and technology, and their synergy in functioning together. Future research endeavors will persist in uncovering this dynamic to further enhance the hiring process.

Conclusion

In conclusion, AI in recruiting is continuously evolving, with new features and challenges emerging daily. Given the global challenges brought by COVID-19, in a post-pandemic world, companies are more determined than ever to stay ahead of the technology curve. However, while vetting and understanding the tools and capabilities they pursue is essential, it's equally crucial to grasp the potential disruption these tools may bring to employees and the company's overall well-being.

Ethically, there are numerous concerns surrounding AI in recruiting, particularly regarding its ability to provide a fair representation of a job seeker and their skills. On the other hand, AI is also streamlining and accelerating the hiring process in unprecedented ways – though this presents its own set of dilemmas. As a society, we must continually question whether we're adopting AI merely for the sake of it or if there's genuine value to be gained.

Utilizing AI in recruiting isn't inherently difficult, but the real quandary lies in whether we should. Do we truly want machines to be the primary arbiters of talent in our workforce? And if so, can we confidently assert that AI is ethically equipped to make such judgments? While some may argue in favor, there are still numerous loopholes that must be addressed and thoroughly researched before we can assert that AI will indeed succeed in revolutionizing the recruitment process.

REFERENCES

Amzile, K., Beraich, M., Amouri, I., & Malainine, C. (2023). Towards a digital enterprise: The impact of artificial intelligence on the hiring process. *Journal of Intelligence Studies in Business*, *12*(3), 18–26. https://doi.org/10.37380/jisib.v12i3.894

Author, iGrad. (2016, January 15). *The cost of replacing an employee and the role of Financial Wellness*. Enrich Financial Wellness. https://www.enrich.org/blog/The-true-cost-of-employee-turnover-financial-wellness-enrich

Barnes, P. (2019, November 11). *Artificial intelligence poses new threat to equal employment opportunity*. Forbes. https://www.forbes.com/sites/patriciagbarnes/2019/11/10/artificial-intelligence-poses-new-threat-to-equal-employment-opportunity/?sh=35bcbcb36488

Bengio, Y., Lecun, Y., & Hinton, G. (2021). Deep learning for AI. *Communications of the ACM*, *64*(7), 58–65. https://doi.org/10.1145/3448250

Bertrand, M., & Mullainathan, S. (2003, July 28). *Are Emily and Greg more employable than lakisha and Jamal? A field experiment on labor market discrimination*. NBER. https://www.nber.org/papers/w9873

Campbell, K. (2023, May 11). *How job websites use artificial intelligence to filter resumes (2023)*. Medium. https://medium.com/geekculture/how-job-websites-use-artificial-intelligence-to-filter-resumes-2023-8982efaaf2b4#:~:text=Many%20popular%20job%20posting%20websites,and%20streamline%20the%20hiring%20process.

Chen, Z. (2022). Collaboration among recruiters and Artificial Intelligence: Removing human prejudices in employment. *Cognition, Technology & Work*, *25*(1), 135–149. https://doi.org/10.1007/s10111-022-00716-0

Chui, M., Manyika, J., & Miremadi, M. (2015, November 1). *Four fundamentals of Workplace Automation*. McKinsey & Company. https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/four-fundamentals-of-workplace-automation

Dinlersoz, C. B. and E. (2023, December 21). *Only 3.8% of businesses use AI to produce goods and services, highest use in information sector*. Census.gov. https://www.census.gov/library/stories/2023/11/businesses-use-ai.html

Donelan, M. (2024, February). A pro-innovation approach to AI regulation. GOV.UK. https://www.gov.uk/government/publications/ai-regulation-a-pro-innovation-approach/white-paper

Eastwood, B. (2024, February 7). *The who, what, and where of ai adoption in America*. MIT Sloan. https://mitsloan.mit.edu/ideas-made-to-matter/who-what-and-where-ai-adoption-america#:~:text=Use%20varied%20among%20sectors.,clustered%20in%20some%20unlikely%20places.

Feedback loop. C3 AI. (2021, July 21). https://c3.ai/glossary/features/feedback-loop/#:~:text=Feedback%20loops%20allow%20AI%20systems%20to%20know%20what,to%20help%20the%20system%20do%20better%20next%20time.

Friedman, G. D. (2022). New York City Imposes Stringent Requirements on Use of Artificial Intelligence in Workplace Hiring and Promotions. *Employee Relations Law Journal*, *48*(1).

Glass, G., Fadel, R., & Peterson, K. (2022, May 5). *Empowering employees to learn in the flow of work*. Training Industry. https://trainingindustry.com/articles/strategy-alignment-and-planning/empowering-employees-to-learn-in-the-flow-of-work/

Guerra, R. (2023, March 27). *What is Ai Transparency & Why is it critical to your recruiting strategy?*. Resource Hub. https://learn.credly.com/blog/what-is-ai-transparency-why-is-it-critical-to-your-recruiting-strategy

Gusain, A., Singh, T., Pandey, S., Pachourui, V., Singh, R., & Kumar, A. (2023). E-recruitment using artificial intelligence as preventive measures. *2023 International Conference on Sustainable Computing and Data Communication Systems (ICSCDS)*. https://doi.org/10.1109/icscds56580.2023.10105102

Hait, A. W. (2022, March 30). *The majority of U.S. businesses have fewer than five employees*. Census.gov. https://www.census.gov/library/stories/2021/01/what-is-a-small-business.html#:~:text=SBA's%20Table%20of%20Size%20Standards,100%20to%20over%201%2C500%20employees).

Hamilton, I. A. (n.d.). *Amazon built an AI tool to hire people but had to shut it down because it was discriminating against women*. Business Insider. https://www.businessinsider.com/amazon-built-ai-to-hire-people-discriminated-against-women-2018-10

Heaven, W. D. (2021, June 17). *Bias isn't the only problem with credit scores-and no, ai can't help*. MIT Technology Review. https://www.technologyreview.com/2021/06/17/1026519/racial-bias-noisy-data-credit-scores-mortgage-loans-fairness-machine-learning/

Hiring algorithms are not neutral. Harvard Business Review. (2017, February 22). https://hbr.org/2016/12/hiring-algorithms-are-not-neutral

Hu, J. (2023, June 25). *Report: 99% of fortune 500 companies use Applicant Tracking Systems*. Jobscan. https://www.jobscan.co/blog/99-percent-fortune-500-ats/

Hunkenschroer, A. L., & Kriebitz, A. (2022). Is ai recruiting (UN)ethical? A human rights perspective on the use of AI for hiring. *AI and Ethics*, *3*(1), 199–213. https://doi.org/10.1007/s43681-022-00166-4

Hunkenschroer, A. L., & Luetge, C. (2022). Ethics of ai-enabled recruiting and selection: A review and research agenda. *Journal of Business Ethics*, *178*(4), 977–1007. https://doi.org/10.1007/s10551-022-05049-6
Introducing chatgpt. Introducing ChatGPT. (2023). https://openai.com/blog/chatgpt

Islam, M. T., & Tamzid, M. (2023). Artificial intelligence in human resource management. *Management Education for Achieving Sustainable Development Goals in the Context of Bangladesh*, 61–80. https://doi.org/10.57240/dujmbk04

Jain, V. (2019, December 30). *Everything you need to know about "activation functions" in Deep learning models*. Medium. https://towardsdatascience.com/everything-you-need-to-know-about-activation-functions-in-deep-learning-models-84ba9f82c253

Johar, V. (2022, June 13). *Council post: Artificial Intelligence in hiring: A tool for recruiters*. Forbes. https://www.forbes.com/sites/forbesbusinesscouncil/2022/06/10/artificial-intelligence-in-hiring-a-tool-for-recruiters/?sh=4a8b289d3200

Kaplan, A., & Haenlein, M. (2019). Siri, Siri, in my hand: Who's the fairest in the land? on the interpretations, illustrations, and implications of Artificial Intelligence. *Business Horizons*, *62*(1), 15–25. https://doi.org/10.1016/j.bushor.2018.08.004

Kelan, E. K. (2023). Algorithmic inclusion: Shaping the predictive algorithms of artificial intelligence in hiring. *Human Resource Management Journal*. https://doi.org/10.1111/1748-8583.12511

Kim, P. T., & Bodie, M. T. (2021, September). Artificial Intelligence and the Challenges of Workplace Discrimination and Privacy. https://ssrn.com/abstract=3929066

Klingler, N. (2023, February 28). *The ultimate guide to understanding and using AI models (2023)*. viso.ai. https://viso.ai/deep-learning/ml-ai-models/

L, M., & Mathi, Dr. M. S. (2023). Efficacy of Artificial Intelligence in Human Resource Management. *International Journal of Research and Analysis in Commerce and Management*, *2*(2). https://doi.org/https://www.iarj.in/index.php/ijracm/issue/archive

Lauret, J. (2019, August 16). *Amazon's sexist AI recruiting tool: How did it go so wrong?* Medium. https://becominghuman.ai/amazons-sexist-ai-recruiting-tool-how-did-it-go-so-wrong-e3d14816d98e

Lavanchy, M., Reichert, P., Narayanan, J., & Savani, K. (2023). Applicants' fairness perceptions of algorithm-driven hiring procedures. *Journal of Business Ethics*, *188*(1), 125–150. https://doi.org/10.1007/s10551-022-05320-w

Liu, L. T. (2020, January 21). *Negative feedback loops: Using an economic model to inspect bias in AI*. Microsoft Research. https://www.microsoft.com/en-us/research/blog/when-bias-begets-bias-a-source-of-negative-feedback-loops-in-ai-systems/

Malin, C., Kupfer, C., Fleiß, J., Kubicek, B., & Thalmann, S. (2023). In the AI of the beholder—a qualitative study of HR professionals' beliefs about AI-based Chatbots and decision support in candidate pre-selection. Administrative Sciences, 13(11), 231. https://doi.org/10.3390/admsci13110231

Maurer, R. (2024, February 16). *Ai adoption in HR is growing*. Welcome to SHRM. https://www.shrm.org/topics-tools/news/technology/ai-adoption-hr-is-growing#:~:text=The%20study%20also%20found%20that,technology%2C%20finance%20and%20information%20industries.

Margaret Rouse, Margaret Rouse is an award-winning technical writer and teacher known for her ability to explain complex technical subjects simply to a non-technical, Rouse, M., Margaret Rouse is an award-winning technical writer and teacher known for her ability to explain complex technical subjects simply to a non-technical, May, L. updated: 9, & updated:, L. (1970, May 9). *Ground truth*. Techopedia. https://www.techopedia.com/definition/32514/ground-truth

Mugge, P., Abbu, H., Michaelis, T. L., Kwiatkowski, A., & Gudergan, G. (2020). Patterns of digitization. *Research-Technology Management*, *63*(2), 27–35. https://doi.org/10.1080/08956308.2020.1707003

Pereira, V., Hadjielias, E., Christofi, M., & Vrontis, D. (2023). A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review*, *33*(1), 100857. https://doi.org/10.1016/j.hrmr.2021.100857

Raub, M. (n.d.). *Bots, bias, and BIG DATA: Artificial Intelligence, algorithmic bias, and disparate impact liability in hiring practices*. ScholarWorks@UARK. https://scholarworks.uark.edu/alr/vol71/iss2/7/

Resources for Employers: The 12 best applicant tracking systems. Recruiting Resources: How to Recruit and Hire Better. (2023, July 4). https://resources.workable.com/tutorial/best-applicant-tracking-systems

Reyes, K. (2023, February 12). *What is deep learning and how does it work [updated]*. Simplilearn.com. https://www.simplilearn.com/tutorials/deep-learning-tutorial/what-is-deep-learning

Robert Henderson, C. (2023, May 30). *The top 500 ATS resume keywords of 2023*. Jobscan. https://www.jobscan.co/blog/top-resume-keywords-boost-resume/#how-do-you-find-the-right-keywords-to-use

Rustagi, G. S. & I., Smith, G., Rustagi, I., & Genevieve Smith is the associate director at the Center for Equity. (n.d.). *When good algorithms go sexist: Why and how to advance AI Gender Equity (SSIR)*. Stanford Social Innovation Review: Informing and Inspiring Leaders of Social Change. https://ssir.org/articles/entry/when_good_algorithms_go_sexist_why_and_how_to_advance_ai_gender_equity

Smet, A. D., Dowling, B., Hancock, B., & Schaninger, B. (2022, July 13). *The great attrition is making hiring harder. are you searching the right talent pools?*. McKinsey & Company. https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/the-great-attrition-is-making-hiring-harder-are-you-searching-the-right-talent-pools

Suseno, Y., Chang, C., Hudik, M., & Fang, E. S. (2021). Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: The moderating role of high-performance work systems. *The International Journal of Human Resource Management*, *33*(6), 1209–1236. https://doi.org/10.1080/09585192.2021.1931408

Team, Zippia, (2023, July 21). *Recruiter demographics and statistics [2024]: Number of recruiters in the US*. Recruiter Demographics and Statistics [2024]: Number Of Recruiters In The US. https://www.zippia.com/recruiter-jobs/demographics/#

Zippia Team, C. (2023, July 4). *The 12 best applicant tracking systems*. Recruiting Resources: How to Recruit and Hire Better. https://resources.workable.com/tutorial/best-applicant-tracking-systems

The true costs of firing an employee. Paychex. (N.d.). https://www.paychex.com/articles/human-resources/the-true-cost-of-terminating-an-employee

U.S. Bureau of Labor Statistics. (n.d.). *The "great resignation" In perspective : Monthly labor review*. U.S. Bureau of Labor Statistics. https://www.bls.gov/opub/mlr/2022/article/the-great-resignation-in-perspective.htm

The University. (2023). *What is Deep Learning*. Amazon Web Services. https://aws.amazon.com/what-is/deep-learning/

Waldrop, M. M. (2019). What are the limits of deep learning? *Proceedings of the National Academy of Sciences*, *116*(4), 1074–1077. https://doi.org/10.1073/pnas.1821594116

What is a chatbot?. IBM. (2023). https://www.ibm.com/topics/chatbots

What is ground truth in machine learning?: Domino Data Lab. What is Ground Truth in Machine Learning? | Domino Data Lab. (n.d.). https://www.dominodatalab.com/data-science-dictionary/ground-truth

APPENDIX 1

RECRUITER SURVEY

Section l – AI in the Hiring Process

1. What is the name of the company you work for? (Open text)
2. Select your role type (Multiple choice)
3. Which hiring (ATS) tool does your company use for resume submissions? (Multiple choice)
4. How familiar are you with AI used in hiring? (Not familiar at all/Extremely Familiar)
5. What is your dependency on an ATS Tool to find qualified candidates to interview for a position? (Select dependency)
6. How often are you satisfied with the quality of resumes from the ATS? (Multiple choice)
7. Do you believe a resume is a fair representation of a candidate's skills and qualifications? (Yes/No/Sometimes
8. Do you believe candidates alter their resume (add critical words, years of XP, etc. to outsmart ATS tools to believe they are qualified? (Yes/No/Sometimes)
9. Do you believe artificial intelligence recommendations work well in hiring tools?
10. How likely are you to agree with the following statements regarding ATS Tools? (Likert)
    a. ATS tools drive efficiencies for recruiters in the hiring process
    b. ATS tools eliminate bias associated with selecting qualified candidates for a position

c. ATS tools are accurate with their resume parsing and scanning capabilities
d. ATS tools extract a candidate pool that is a fair representation of their qualifications and skills for the position
e. I trust ATS tools and their ability to recommend great candidates

Section ll – Hiring Process with Managers

1. Please describe the selection criteria for determining which candidates should be moved forward for an interview.
2. When reviewing resumes, what are the most important qualities to consider? (Select all that apply)
3. How often do hiring managers give you the autonomy to refine candidate pools and recommend whom to interview? (Likert scale)
4. What would be your next steps if the manager is unsatisfied with the recommendations? (Open text)
5. Please briefly describe the process of working with the hiring manager to determine job requirements. (Open text)
6. Once the position has been posted, what is the average lead time before you begin evaluating candidate submissions? (Multiple choice)
7. Are hiring managers often challenging to work with? (Yes/No/Sometimes)
8. After a candidate is hired, do you ever receive feedback on their performance? (Yes/No/Sometimes)
    a. After receiving the feedback, what do you do with this information? (Open text)

9. How often do you know whom you will hire before posting the position externally? (Multiple choice)
10. Please provide any additional comments about ATS tools and working with hiring managers throughout the recruiting process. (Open text)

APPENDIX 2

MANAGER SURVEY

1. What is the name of the company you work for? (Open text)
2. How long have you worked for this company? (Multiple choice)
3. Which industry is this company in? (Multiple choice)
4. How many direct reports do you have on your team? (Multiple choice)
5. How much do you agree or disagree with the following statements about your experience working with your designated HR Recruiter to recruit and hire your most recent new hire? (Likert scale)
    a. My HR Recruiter responded promptly throughout the hiring process.
    b. My HR Recruiter offered valuable strategic suggestions throughout the hiring process.
    c. My HR Recruiter set clear expectations when the hiring process was initiated.
    d. My HR recruiter communicated effectively with me throughout the hiring process.
    e. My Talent Acquisition Partner identified high-quality candidates for review during the hiring process.
    f. I was satisfied with the quality of talent in the candidate pool presented to me by the HR Recruiter.
    g. The candidate selections provided by the HR Recruiter were diverse
6. Please describe what went well in the recruiting process. (Open text)
7. Please describe what could be improved in the recruiting process. (Open text)

8. How much do you agree or disagree with the following statements about your recent new hire? (Likert scale)
    a. This new hire is a good fit for my Team and Company
    b. This new hire's performance to date matches my expectations for their role(s).
    c. This new hire has the skills outlined as a requirement in the posted job description.
    d. This new hire has been in production since they have been hired (e.g., able to contribute to projects in the program area, participation in critical decision-making, etc.).
    e. This new hire compares favorably to others on my team who occupy similar positions (s)
    f. This new hire will likely stay at this company and grow in their role(s).
    g. Overall, I am satisfied with this new hire.
9. Are you familiar with Applicant Tracking Systems in the hiring process? (Yes/No/Not sure)
    a. If NO, SKIP TO
        i. Which hiring tool does your company use for candidates to submit their resumes? (Multiple choice)
    b. If NO, SKIP TO
        i. Of the candidates you interviewed, did you ultimately hire your top choice? (Yes/No)
    c. If NO, SKIP TO

i. Please explain. (Open text)

10. Approximately how long did the hiring process take before your new hire accepted their offer? (Multiple choice)
11. In hindsight, would you change your hiring decision? (Yes/No/Depends with an open text)
12. Please provide any additional comments relating to the overall quality of this recruiting experience and your recent new hire. (Open text)

APPENDIX 3

SUBJECT MATTER EXPERTS IN RECRUITING SURVEY

Section l – Efficiency

Dimension: Repetition

1. How often are repetitive tasks encountered in the recruiting process?
2. How often are you performing resume screening in the recruiting process?
3. How often are you updating candidate profiles in the Applicant Tracking System (ATS)?
4. How often are you scheduling interviews?

Dimension: Efficiency

5. How does the repetition of hiring tasks impact the overall efficiency of the hiring process?
6. In your experience, what specific tasks in the hiring process become more efficient with repetition?
7. Are there any challenges or bottlenecks that arise due to the repetition of certain hiring tasks? (Select all that apply)
8. In your experience, which of the following strategies or technologies have you observed to improve the efficiency of repetitive hiring tasks?

Dimension: Cost-Effectiveness

9. How does the repetition of hiring tasks affect the overall cost of the hiring process?
10. Are there specific areas within the hiring process where cost savings can be achieved through task automation?

11. What are some potential cost drivers that arise from the repetition of hiring tasks?
12. Have you encountered any cost-saving measures or best practices related to repetitive hiring tasks?

Demographics

13. What industry do you work for?
14. What is your highest level of education?
15. What is your age?
16. What is your gender?