

The Innate Biases Involved in Interviews Conducted By Artificial Intelligence

Tegan A. McBride

Washington College: Senior Capstone Experience

Dr. Kyle Wilson and Dr. Aaron Lampman

Abstract

Our world's most influential companies conduct interviews led by artificial intelligence. Because their power is so significant, multidisciplinary testing and well-rounded perspectives should be considered when designing and implementing this software. The purpose of my study is to assess the factors that may cause bias to be programmed into artificial intelligence interviewing software. To do this, I conducted interviews with companies that make this software and other people impacted by this technology, reviewed contemporary literature, reviewed diverse media sources, reviewed algorithmic audits from multiple disciplines, and examined previous uses of similar technology. This research is significant because not only is this a new and upcoming reality for most applicants, but also because we want our society to accept and promote diversity and inclusion in the workplace.

Keywords: artificial intelligence(A.I), machine learning, bias, interviews, hiring, algorithm, intersectionality, systematic racism

Acknowledgement

I would like to express my greatest gratitude to those who contributed to my Senior Capstone Experience . My SCE advisors, Dr. Kyle Wilson and Dr. Aaron Lampman guided me through the process and edited my drafts throughout multiple stages. Georgina Bliss was an integral part of my interview process. She connected me to every interviewee discussed in the paper. Next, I would like to extend my gratitude to my interviewees who not only agreed to interviews, but also provided several references and related articles. Lastly, I would like to thank my supportive family and friends for their support throughout the process. Without these people, my research would not have been possible.

Table of Contents

ACKNOWLEDGEMENT	2
INTRODUCTION	4
DEFINITIONS	5
CHAPTER 1: HOW MACHINES LEARN	8
CHAPTER 2: RESEARCH QUESTION	10
CHAPTER 3: METHODS	11
3.1 LITERATURE REVIEWS	12
3.2 MEDIA ANALYSIS	12
3.3 INTERVIEWS	13
3.4 FREE WRITES	14
CHAPTER 4: THE IMPLEMENTATION OF AUTOMATED HIRING	15
4.1 COMPANIES THAT CREATE A.I. HIRING SOFTWARE	15
4.2 COMPANIES THAT USE A.I. HIRING SOFTWARE	15
4.3 USER EXPERIENCE	16
CHAPTER 5: VARIABLES MEASURED AS DATA	18
5.1 SPEECH	19
5.2 VISUAL COMPONENTS	20
5.3 DISCLOSURES IN APPLICATIONS	22
CHAPTER 6: HOW THE AUTOMATED HIRING PROCESS IS VIEWED	23
CHAPTER 7: PREVIOUS USES OF ARTIFICIAL INTELLIGENCE	26
7.1 TEACHER EVALUATIONS	27
7.2 FACIAL RECOGNITION IN THE UNITED KINGDOM	27
7.3 AMAZON'S RESUME SCANNER	28
7.4 TENGAI UNBIASED	29
7.5 COMPAS	30
CONCLUSION	32
I. SOURCES TO COMBAT ALGORITHMIC INJUSTICE	32
II. CHALLENGES FROM A LEGAL STANDPOINT	34
III. ALTERNATIVES	36
IV. WARNING TO THE FUTURE	37
REFERENCES CITED	39

Introduction

The progress that was made in the Civil Rights Era could be rolled back under the guise of machine neutrality. ~Joy Boulamwini

Artificial intelligence systems, highly complex predictive models, has been given the authority to determine life-altering decisions. Beginning in 1951 with a harmless reactive checkers game, artificial intelligence now possesses the ability to analyze micro-expressions to determine personality traits, decipher between speech patterns, and rank people based on their personality and capabilities. Our world's most influential corporations have begun to utilize A.I. in the hiring process with the intent of maximizing efficiency and minimizing financial expenditure. They do so by purchasing a personalized program from software developing companies such as HireVue. HireVue develops this software with the intention of “prevent[ing] the introduction or propagation of bias against any group or individual.”¹ While their intentions may be noble, the final product may prove to be even more biased than a person-to-person interview.

In this paper, I will explore the application of artificial intelligence in the hiring process and the potential resultant biases. My methods include reviewing audits from a multitude of disciplines, interviewing people who have completed one-way interviews, interviewing Career Center Directors, interviewing HireVue staff, completing literature and media reviews, and examining previous uses of artificial intelligence. Throughout my methods, HireVue will serve as my principal software developing business of investigation because they appear to be the leading company in this industry. The thesis will begin by explaining how artificial intelligence operates and clarifying the necessary foundational definitions. In Chapters 1 through 3, I will

¹ “Bias, A.I. Ethics and The HireVue Approach.” hirevue.com. Accessed April 1, 2022.
<https://www.hirevue.com/why-hirevue/ai-ethics>.

more thoroughly explain background information essential to understanding this thesis. Chapter 4 will describe the interview process, so those who are unfamiliar with the process will be able to fully comprehend the experience. Chapter 5 will discuss how audits have discovered that nuances in clothing, lighting, and background can alter final scoring. This same chapter will delve into the impossibility of accounting for all cultural differences and neurodivergent tendencies. In Chapter 6, I will share the perceptions of the students, career center staff, and HireVue staff on the process based on the interviews I led. In Chapter 7, I will describe the previous uses of artificial intelligence and the significant consequences of failed programs. The concluding section will address legal concerns and pose suggestions for the future of automating hiring. While many may try, algorithmic injustice is not easy to recognize or combat. Serious consequences can result from the misuse of this technology.

Before I begin, I would like to acknowledge and claim my own negligence in the advanced studies that are essential to thoroughly evaluating such a process. Ideally, a scholar criticizing this interdisciplinary process would be fully versed in all applicable fields such as, but not limited to, linguistic anthropology, cultural anthropology, advanced computer science, statistics, sociology, psychology, econometrics, communications, and law. Because of my gap in knowledge, I encourage you, upon completion of reading this paper, to further educate yourself and form your own opinion. Likely, you will be required to interact with interviews conducted by artificial intelligence in your future. Educating yourself will not only prepare you for a potential interview but will also equip you with knowledge to combat algorithmic injustice.

Definitions

Within software developing companies' websites and throughout my literature reviews, the word "bias" appears frequently but lacks a clear definition. Most hiring software development companies claim to "mitigate bias" on several pages on their website but avoid

providing specific definitions or methods of doing so. Therefore, scholars from different disciplines will likely read the term through their discipline-specific lenses. According to *Statistics How To*, “bias” in Statistics refers to “the tendency of a statistic to overestimate or underestimate a parameter.”² According to Psychology Today, bias is “is a tendency, inclination, or prejudice toward or against something or someone.”³ However, Simply Psychology states that bias is “unconscious errors in thinking that arise from problems related to memory, attention, and other mental mistakes.”⁴ A group of psychologists auditing an automated hiring software for algorithmic bias plainly stated in their findings that “psychological researchers often find themselves excluded due to mismatches in terminology, values, and goals across disciplines.”⁵ As can be seen, between disciplines and even among disciplines “bias” can lack definitive clarity.

Prefacing my research, I will provide definitions to preemptively clarify any misunderstandings. While the definitions may shift in certain disciplines, they will remain constant throughout this paper. I will provide a definition and then considerations for each of the following key terms: bias, discrimination, intersectionality, algorithm, and artificial intelligence. Context can fluctuate the meanings of these terms, but hopefully this provides guidance for further reading.

² Stephanie. “Bias in Statistics: Definition, Selection Bias & Survivorship Bias.” *Statistics How To*, July 29, 2013. <https://www.statisticshowto.com/what-is-bias/#DefBias>.

³ “Bias.” Psychology Today. Sussex Publishers. Accessed April 1, 2022. <https://www.psychologytoday.com/us/basics/bias>.

⁴ Ruhl, Charlotte. “What Is Cognitive Bias?” What Is Cognitive Bias? | Simply Psychology, May 4, 2021. <https://www.simplypsychology.org/cognitive-bias.html>.

⁵ Landers, R. N., & Behrend, T. S. (2022). Auditing the AI auditors: A framework for evaluating fairness and bias in high stakes AI predictive models. *American Psychologist*. Advance online publication. <http://dx.doi.org/10.1037/amp0000972>

Bias (noun) is “a particular tendency, trend, inclination, feeling, or opinion, especially one that is preconceived or unreasoned.”⁶ Unconscious biases are “social stereotypes about certain groups of people that individuals form outside their own conscious awareness.”⁷ Another form of bias that is not easily recognized or combatted is systemic bias. This happens when the foundational processes to operate an institution are biased. Everyone possesses bias, even if they simply prefer the color red over the color orange. The word “biased” relays the same meaning as an adjective. Bias usually leads to discrimination, the “treatment or consideration of, or making a distinction in favor of or against, a person or thing based on the group, class, or category to which that person or thing belongs rather than on individual merit.”⁸ Discrimination can occur against a singular class or group but can also occur at the intersection of several groups. Kimberlé Crenshaw coined the term “intersectionality” to define the intersection at which one or more social categorizations intersect and how one can be discriminated against for these colliding identities.⁹ For example, many Black women face bias and discrimination because of being Black *and* being a woman. These two identities are linked and should not be consistently viewed separately.

⁶ “Bias Definition & Meaning.” Dictionary.com. Dictionary.com. Accessed April 1, 2022.
<https://www.dictionary.com/browse/bias>.

⁷ “Unconscious Bias Training.” Unconscious Bias Training | Office of Diversity and Outreach UCSF. Accessed April 10, 2022. <https://diversity.ucsf.edu/programs-resources/training/unconscious-bias-training>.

⁸ “Discrimination Definition & Meaning.” Dictionary.com. Dictionary.com. Accessed April 1, 2022.
<https://www.dictionary.com/browse/discrimination>.

⁹ Crenshaw, Kimberlé W., “On Intersectionality: Essential Writings” (2017). *Faculty Books*. 255. <https://scholarship.law.columbia.edu/books/255>

Next, the word “algorithm”, in computer science, refers to “a process or set of rules to be followed in calculations or other problem-solving operations.”¹⁰ In other words, an algorithm is the formula or process required to complete a task. Lastly, artificial intelligence (A.I.), for the purpose of this paper, are computations that attempt to mimic complex human behaviors such as judgement. Interviews conducted by artificial intelligence are synonymously called “one-way interviews” and “automated interviews”. Many renowned computer scientists such as Alan Turing, also known as the father of computer science, have questioned whether artificial intelligence could genuinely think like humans. Alan Turing devised a test called the Turing Test to judge whether artificial intelligence could think indistinguishably from a human.

In my analysis of artificial intelligence used in hiring, the factors compiled to create this possibly indistinguishable thought process will be thoroughly evaluated. The process will be broken down so that the components of A.I. hiring can be analyzed individually. Additionally, examples will be provided. Hopefully, by the conclusion, the evidence will support my claim that artificial intelligence is not advanced enough to evaluate humans in the hiring process.

Chapter 1: How Machines Learn

Artificial intelligence theories were first presented by John McCarthy and Marvin Minsky in 1955 at a Dartmouth conference.¹¹ With the innovation of computers being able to store commands, scholars suggested that they could code the computer to learn and think like humans. The Chinese Room analogy¹² imitates, at its simplest form, how a computer learns. The

¹⁰ “Introduction to Algorithms.” GeeksforGeeks, January 13, 2022. <https://www.geeksforgeeks.org/introduction-to-algorithms/>.

¹¹ McCarthy, J., et al. *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. 31 Aug. 1955.

¹² Cole, David, "The Chinese Room Argument", *The Stanford Encyclopedia of Philosophy* (Winter

analogy portrays an English-speaking man in a room. Notes written in Chinese are slipped underneath the door. Because he possesses a formula for converting the questions into adequate replies, he is able to write down response in Chinese and slip it back under the door. The people outside the door think that the man inside knows how to speak Chinese; however, he was just using the formula. The purpose of this analogy is to generalize the claim that while we can teach a computer *how* to think like humans, they cannot *actually* think like humans. Contrary to the metaphor, the machine learning process is quite detailed and complex.

Several types of machine learning exist; however, we shall focus on the type used in automated hiring software. First, the machine is supplied with various inputs and the desired outcome. This given data is referred to as the “training set”. The machine “learns” by finding patterns and manipulating the weight, or the level of importance, of aspects of the input data in order to achieve the desired outcome. The weights are tuned using statistical inference. The machine cannot always articulate or interpret the characteristics it chooses, which can lead to a lack of transparency to the developers and users. In general, these systems are more accurate when they are trained on large and diverse datasets. Applying diverse inputs strengthens the machine because machines struggle when making predictions on data that is unlike the training set. Once the machine learns how to produce the desired output by creating a model, a testing set can be applied to validate the accuracy.

To clarify the process, let us consider an example where I am creating an artificial intelligence program that would judge whether a cat is, in my opinion, considered adorable. In this example, the input data would be cats. I would provide the machine with the desired output of pictures of cats that I find adorable: mostly large tabby brown or orange cats that have longer

2020 Edition), Edward N. Zalta (ed.), URL =
 <<https://plato.stanford.edu/archives/win2020/entries/chinese-room/>>.

fur. The machine would then identify the characteristics that my desired data has and tune the weights of these characteristics to create a model. Ideally, then the program could be supplied with testing data of cats and the machine would be able to rank the cats as I would.

The automated hiring process follows these steps to judge applicants; however, video input can add extra challenges. Additionally, the model must be trained on quality data that incorporates people of an array of genders, races, ethnicities, religions, financial statuses, and more because artificial intelligence struggles when encountering data that it has not been trained on. Crafting a program to judge potential employees better than humans can is a task that requires constant updates and adjustments. According to a HireVue staff member that I interviewed, their company reviews their program six months to a year after releasing them. Once they complete an adverse impact analysis, they can “systematically remove that[features or elements that lead to bias] from the algorithm... so that way we [HireVue] get fairer outcomes.” If this truly does eliminate bias better than humans, we shall see.

Chapter 2: Research Question

During a mandatory Career Center event, I listened to an advisor lecture us on interview skills. As a sophomore in college, I had not considered interviewing skills to be a significant priority in my life. Truthfully, I was planning to attend the event, but not to commit much information to memory. About halfway through the event, the advisor played a clip produced by the Wall Street Journal titled “Artificial Intelligence: The Robots Are Now Hiring | Moving Upstream.”¹³ The video sparked an interest that led to years of educating myself about the topic, and then crafting a culminating senior capstone on it.

¹³ “Artificial Intelligence: The Robots Are Now Hiring | Moving Upstream.” Youtube. Wall Street Journal, September 20, 2018. <https://www.youtube.com/watch?v=8QEK7B9GUhM>.

I dove into this topic because I realized the life-altering effect this innovation could have. Without functioning properly, programs such as these could potentially form a barrier to job opportunities, and in turn, to financial stability. Furthermore, the consequences occur without an explanation from the machine. Automating hiring should be thoroughly inspected and then made transparent, so the applicant can understand the process. Any human who may apply for a job in the future should educate themselves on automated hiring because they too will be asking, “Are machines a better judge of character than a human?”

Through this paper, I plan to dispute the question “Would artificial intelligence be the optimal choice for conducting interviews?” The criteria I am using to evaluate this question includes personal experiences of the employee during automated interviews, how the automated interview process is conducted, how clothing and background affect scoring, previous uses of artificial intelligence, and legal implications. By comparing these artificial intelligence interviews to the in-person interviews, I can effectively argue the point that artificial intelligence has not advanced enough to be the least biased method in assessing potential employees.

Chapter 3: Methods

In order to holistically analyze the automated hiring process, I employed multiple ethnographic methods including interviews, media analysis, literary reviews, and free writes. Interview methodology is approved by the Washington College Institutional Review Board. The interviewees ranged from students going through the interview process to HireVue staff. The literature review included audits, past uses of A.I., peer reviewed articles, preprint articles, and news articles. Additionally, I thoroughly examined HireVue’s website as well as other hiring software developing companies’ websites. To incorporate multiple viewpoints, I reviewed diverse sources of media such as the documentary *Coded Bias*, an MIT podcast called *In Machines We Trust*, and the *All Things Considered* station on National Public Radio(NPR) .

Lastly, so that I could form my own opinions on the process, I was able to observe someone taking a one-way interview. My well-rounded research methods took several months to complete.

3.1 Literature reviews

My research began with a search for previous studies, published and unpublished. Because computer science evolves at such a rapid pace, peer-reviewed or published articles, which can take years to review, may not be the most accurate. Therefore, I collected many of my sources from academically accepted websites such as arXiv¹⁴, a Cornell University database. Upon selecting a reading, I would evaluate the source. First, I would research the author for credibility and affiliations. This approach prepared me to read while being cognizant of the author's background. Next, I would research the intent of the paper. Was the article written to persuade the reader or simply provide information? Was the paper funded by a group with a particular agenda? Lastly, I would review the publishing date. As stated earlier, recent papers lower the risk that the methods and conclusions are outdated. In total, I was able to review over thirty articles and papers.

3.2 Media Analysis

I included media reviews because with proper research, they can prove just as valuable as academic papers. I used NPR, National Public Radio, to hear from Ifeoma Ajunwa, a decorated academic scholar. While she does have several published scholarly articles, the radio segment labeled "Cornell Professor Ifeoma Ajunwa Discusses Artificial Intelligence Used In Hiring"¹⁵

¹⁴ "Global Survey." arXiv.org e-Print archive. Accessed April 10, 2022. <https://arxiv.org/>.

¹⁵ Chang, Ailsa. "Cornell Professor Ifeoma Ajunwa Discusses Artificial Intelligence Used In Hiring." Broadcast. *All Things Considered*, April 8, 2019.

conveys her raw unedited thoughts. Podcasts allowed me to listen to minimally edited dialogue. In the podcast *In Machines We Trust* from MIT media lab, students expose specific examples of the misuse of A.I., including first-person accounts. Lastly, I watched the documentary, *Coded Bias*. *Coded Bias* highlights the work of Joy Buolamwini, whose name is often preceded the epithet “the Poet of Code”. More will be introduced about her and her mission towards algorithmic justice in Chapter 5. Media reviews served as means of hearing individual accounts of people’s experiences with automated hiring.

3.3 Interviews

Similarly, conducting my own interviews allowed me to analyze several unique perceptions from a range of people. After receiving my approved IRB, Georgina Bliss, the Assistant Director of the Career Center at Washington College, generously offered to connect me to possible interviewees. My first interview was with an undergraduate student who has completed several one-way interviews. His perspective was unique in that he was a student new to the process, but nevertheless was determined to succeed. Next, I interviewed a graduate student who has completed numerous automated interviews in his goal to work for a major banking firm. Afterwards, I interviewed the Career Center Director at Notre Dame University of Maryland, Alan Jones, and the Career Center Director at Thomas Jefferson University, Chris Miciek. Both Mr. Jones and Mr. Miciek are tasked with preparing undergraduate students to succeed at one-way interviews. They provided valuable insights about how they view the novel process. Lastly, I was fortunately able to speak with a HireVue staff member. I was nervous that his responses would be over-generalized to avoid divulging HireVue secrets. However, this employee was relatively transparent, which helped me better understand HireVue’s methods and mission. Upon completion of the interviews, I would transcribe all blurbs or sentences relative to my research. The interviews allowed me to see a diverse range of opinions on this technology.

Some people fully supported the process while others believed it to be even more biased than humans.

After hearing about other's experiences with one-way interviews, I was eager to also be immersed in this technology myself. First, I was able to find YouTube video of people completing their interviews. I took detailed notes of the user interface layout, the types of people portrayed in their videos, the mechanics (such as time limits and video and audio options), accessibility options, questions asked, and the terms and conditions. After this vicarious interview experience, an informant, who shall remain anonymous, invited me to watch their one-way interview. Similar to the previous experience, I took detailed notes. After these, I reviewed my notes and recorded my personal feelings.

3.4 Free Writes

Throughout all of my research, starting before I even began the literature review process, I have written my personal accounts. At random times, I have completed "free-writes", where I have written my stream of consciousness without regard to appearing academic or kind. I documented how I was feeling physically and emotionally, how I felt about my research, and any other thoughts that arose. Doing this allowed me to see how my own biases might have affected my research and writing at the time. Additionally, I can see how my opinions of one-way interviews have evolved as I completed more research. My opinions will be apparent throughout my thesis.

However, I have employed multiple methods, so that mine is not the sole opinion. As stated earlier, I urge you to consider my opinion, my interviewee's opinions, and all the other data collected through my methods when formulating your own opinion. Please continue to educate yourself on the topic and do as you feel right.

Chapter 4: The Implementation of Automated Hiring

4.1 Companies that create A.I. hiring software

Several companies have faced the challenge of developing A.I. hiring software. A primary motive for automating the hiring process is allocating funds and time elsewhere while still meeting the high standards necessary during the hiring process to be a successful company. Therefore, this software creates an enticing offer to large companies that may have hundreds of job applications to assess per week. Companies that have been founded with the purpose of creating A.I. hiring software include, but are not limited to, HireVue, MyInterview, Curious Things, Mya Systems, Wade and Wendy, and Hiretual. Several companies use the visual and audio components to assess the candidate. On the contrary, HireVue, founded in 2004, switched to only recording audio in March of 2020¹⁶. All companies not only claim to complete the interviews for you, but also claim to complete the interviews without bias.

4.2 Companies that use A.I. hiring software

HireVue sells hiring software to companies such as Thurgood Marshall, Boston Red Sox, Unilever, and Atlanta Public Schools.¹⁷ According to their website, when they create a new software for a specific company, one of their primary focuses is “finding and eliminating factors that cause bias”.¹⁸ They accomplish this by auditing the training data to analyze any outlying output data.

¹⁶ Maurer, Roy. “Hirevue Discontinues Facial Analysis Screening.” SHRM. SHRM, February 3, 2021. <https://www.shrm.org/resourcesandtools/hr-topics/talent-acquisition/pages/hirevue-discontinues-facial-analysis-screening.aspx>.

¹⁷ “Case Studies: Customer Successes: Hirevue.” hirevue.com. Accessed April 1, 2022. <https://www.hirevue.com/case-studies?msegment=na-education>.

^{18,16} “HireVue Assessments and Preventing Algorithmic Bias.” hirevue.com, July 15, 2021. <https://www.hirevue.com/blog/hiring/hirevue-assessments-and-preventing-algorithmic-bias>.

“Here’s an example: The model might notice that most of a company’s top technical support representatives tend to speak more slowly than the rest. It may also happen to be the case that speaking slowly is more common in men than women, and this might skew the results so that the model rates men more highly than women. If we find this during testing, we can “shut off” the feature that measures for the speed of spoken communications in order to prevent men being given higher scores than women based on this feature. We then retest the model to ensure we’ve addressed the adverse impact.”¹⁶

However, they make this alteration on the assumption that the disproportionate outcome is due to speech speed. Because the machine cannot outrightly disclose the variables that are assessed, the software developing team must rely on statistics to make the most well-informed decision. How can the A.I. distinguish between a cultural norm and neurodiverse expression? Statistical data does not exist in every situation. The software development team must be consistently updating the software because culture changes. In the interview process, the applicant is not made aware of all the variables being evaluated either.

4.3 User Experience

While all A.I. hiring software differs slightly, the general user interface remains the same. Before the interview begins, the user receives one practice question, so they can feel more comfortable and prepared for the judged questions. During the practice question, the audio and visual quality are examined for sufficiency. Once they receive the prompt, they have thirty seconds to craft their response. When the program is ready to receive their response, they will often have one attempt and two to three minutes to respond. The interviewee’s live reflection is shown on the screen with a dotted outline of where their face should be positioned; however, a button on the bottom of the screen allows the interviewee to hide their face. Even though

HireVue only records audio, they continue to keep the camera aspect on to add a personal feel, according to the HireVue staff member I interviewed. A fluctuating bar lying horizontally under the interviewee reflection displays the current audio input level. There is a timer in the top-left corner of the screen inaudibly ticking down the response time. Once the timer has ended, the recording is stopped regardless of if the interviewee completed their response.

Several components of the automated interview may be viewed as more helpful than those of an in-person interview. For example, during the thirty seconds of preparation time, the interviewee can write down main ideas and a powerful opening sentence. With their thoughts organized, they optimize their response time. Another potentially useful addition includes the visual timer. The clock allows for the interviewee to pace their response accordingly while also keeping their response from being unnecessarily wordy. Lastly, having the ability to view your appearance allows the user to adjust any flaws. Because most hiring programs judge appearance, just as an in-person interviewer would, the interviewee should be dressed professionally. While all these supplemental aspects have the potential of assisting the interviewee, they also have the potential to hinder their abilities.

Because most people lack experience with automated interviews, anything that differs from the in-person interview may add shock, distraction, or pressure. To argue previous points, the additional preparation time lends the possibility of over-analyzing responses to the point where the interviewee is flustered after the thirty seconds. Similarly, the timer can place pressure on the interviewee to rush their reply. Because the recording will cease directly at three minutes, the interviewee might be stressed that they did not adequately express their point. Lastly, the interviewee may become overly concerned with appearance once the screen displays their

reflection, causing them to lose focus on the interview. Depending on the person, the automated interview process can be overwhelming.

Some of these software developing companies, including HireVue, have included assessments from pymetrics¹⁹, a software developing company that creates behavioral assessments in the form of digital games. Pymetric's tools can evaluate behaviors based on the response given to a simulated situation that might relate to a decision in the work environment. Unlike the interview, pymetric's games have open-source code readily available on platforms such as GitHub. Admirably, they provide base code that may help other start-up companies or programmers. Unfortunately, without their testing data, drawing wholistic conclusions about any bias is difficult.

Developing and selling A.I. hiring technology continues to increase in popularity. As more companies convert to using an automated process, more people will be subject to these types of interviews. Most applicants are required to complete an automated interview or resume scan of some kind before they are even introduced to a real team member. Artificial intelligence has the power to deny applicants before a human even assesses the applicant.

Chapter 5: Variables Measured As Data

Automated hiring software analyzes several variables, each being weighted appropriately, in order to holistically judge an applicant. The majority of companies collect data on clothing, micro-expressions, word-choice, and resume background. Because the interviewer would also subconsciously collect this data, the methods seem logical. However, once you attempt to

¹⁹ "Ai Recruiting & Job Matching Platform." pymetrics. Accessed April 10, 2022. <https://www.pymetrics.ai/>.

consider how many intersectional characteristics must be accounted for without bias, these methods become questionable. For example, the machine must be able to fairly assess someone who is an ex-convict, someone who is neurodivergent, someone who wears a religious garment, or someone who does not speak Standard American English (SAE). While taking into account the endless diversity one can possess, the machine must also search for the specific qualities of the ideal candidate. Collecting a comprehensive view of the employee may lead to a better choice, or it may lead to an increased susceptibility to bias.

5.1 Speech

According to a HireVue staff member, HireVue has collected only speech data since 2020 and “nothing is being transcribed visually from an algorithmic standpoint”. HireVue does not indicate whether this switch to audio-only includes speech patterns such as speed, intonation, and clarity. All newly released programs solely analyze speech because “their internal evaluations figured out that findings from visual analysis were only weakly related to job performance.”²⁰ Because interviews are transcribed using the most innovative transcription technology, the machine can more accurately interpret accents and dialects than the average human could, according to the HireVue member that I interviewed. Therefore, bias is less likely to occur in the presence of an accent or dialect.

Contrary to early beliefs by linguistic anthropologists such as Robin Lakoff, speech style cannot be attributed to only one identifying trait. Our birth location, gender, race, ethnicity, current location, upbringing, and academic levels are all example of traits that our influence speech. Because individual speech is influenced by multiple intersection traits, each human’s

²⁰ “Objective or Biased.” BR24. Accessed April 1, 2022. <https://interaktiv.br.de/ki-bewerbung/en/>.

speech is fairly unique; therefore, a machine is unlikely to find a pattern to discriminate against. Hence, the audio-only approach may help mitigate bias in an automated interview.

5.2 Visual Components

For software that still analyzes visual components such as background, lighting, and clothing, unfair discrepancies are being found by independent auditors. The organization Bavarian Broadcasting conducted a joint investigation with the organization München in February of 2021 on a Munich-based automated hiring software developing company.²¹ The company forms a character profile by assessing the candidate according to the OCEAN model of personality. This model ranks the potential employee by five traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism.

By altering one aspect of the interview such as clothing, they were able to assess whether that change made a significant difference in overall scoring. As expected, clothing differences affected the final scoring. After covering her head with a scarf, the auditor was ranked higher in every category except neuroticism, in which she scored lower. This data prompts the question of whether religious garments or jewelry such as a hijab or a bhindi would change the final scores. Unexpectedly, the background and lighting changes also changed the final profile. Therefore, if the candidate cannot afford sufficient lighting, their application may be ranked lower compared to those more affluent. With these visual components alone, bias may disadvantage certain religions or economic statuses.

Recording visuals can disadvantage neurodivergent people or people with cultural norms that deviate from the standard. One common trait for people on the autism spectrum is limited

²¹ “Objective or Biased.” BR24. Accessed April 1, 2022. <https://interaktiv.br.de/ki-bewerbung/en/>.

emotional expression. Would someone be scored adversely based on this? At the beginning of most automated interviews, a link is provided for those who may need accommodations, so the company can adhere to the law against discrimination of people with a mental health condition. One of my interviewees, Mr. Miciek, brought up an alarming question that if someone does disclose their condition, will they be ranked adversely if they portray characteristics that oppose this condition? For example, if some disclosed that they are autistic, would they be ranked lower for being emotionally expressive? HireVue attempts to address this aspect by saying “Many neurodiverse professionals excel in job roles that don’t require you to be chatty or socially charismatic in some particular way” and that “only competencies and skills directly related to success in the job role are being measured.”²² Essentially, their advice to neurodiverse people is to not apply to jobs that require you “to be chatty or socially charismatic”. However, they also have the option to disclose their disability and request accommodations such as having an in-person interview instead.

Video recording may also hinder the application of people with social norms that deviate from standard norms of the country that the software was designed in. According to a study done by Linda Chiang in 1993, some Cherokee, Navajo, and Hopi tribes refrain from maintaining eye contact, especially with elders, because it is “not appropriate”.²³ Would a member of these tribes be penalized for this cultural difference? Because cultural norms evolve and expand daily, accounting for such norms is an impossible task, even for a machine. The vastly diverse range of

²² “FAQ: Frequently Asked Questions for Candidates: Hirevue.” hirevue.com. Accessed April 10, 2022. <https://www.hirevue.com/candidates/faq>.

²³ Chiang, Linda H. 1993. “Beyond the Language: Native Americans’ Nonverbal Communication,” October. <https://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED368540&site=eds-live>

neurodivergent tendencies and cultural norms is unlikely to be fully accounted for and fairly evaluated by artificial intelligence.

Even well-known human differences and primary categories for bias and discrimination such as race have been unaccounted for. Joy Boulamwini, the founder of The Algorithmic Justice League, discovered that the majority of facial recognition technologies were mainly trained on white people²⁴. Therefore, as a Black woman, her face was not recognized as a face by the software. After she placed a white mask over her face, the technology was able to identify a face. Thankfully, she has taken action to bring awareness to this discrimination, and many companies have since altered their datasets. While software companies have been able to recognize some of the major areas for potential bias, they must consider *all* of the potential areas for bias for automated hiring to be successful.

5.3 Disclosures in applications

Ifeoma Ajunwa, a leading expert on the ethics of technology, was first made aware of the unfairness machine judgement can exhibit when talking to a person who was previously incarcerated.²⁵ Because this person was required to disclose their incarceration in all job applications, they were never offered an interview. Finding jobs for people with a history of incarceration has already been a struggle even when they could explain themselves to a human

²⁴ TEDtalksDirector. “How I’m Fighting Bias in Algorithms | Joy Buolamwini.” YouTube. YouTube, March 29, 2017. https://www.youtube.com/watch?v=UG_X_7g63rY.

²⁵ TEDxTalks. “Controversies of Ethics & Technology in Modern Workplace | Ifeoma Ajunwa | Tedxcornelluniversity.” YouTube. YouTube, December 3, 2018. https://www.youtube.com/watch?v=X5WXSXSK_wm6s.

interviewer. With the extra layer barrier of a machine, being given a chance in the job sphere becomes nearly impossible.

These are only some of the examples which have been identified and for which solutions have been sought. In all instances, the programmers did not deliberately program the software to discriminate against a certain group. Our algorithmic techniques for identifying and removing bias are relatively new. Mistakes are being cultivated by the inability for humans to account for every type of human or group of humans. The obvious discrepancies such as gender and race have likely all been accounted for by the major software developing companies. My worries arise for the less directly noticeable nuances such as cultural norms or religious garments. Machines are not yet advanced enough to account for every minute discrepancy that each intersectional applicant might possess.

Chapter 6: How The Automated Hiring Process is Viewed

Conducting my own interviews allowed for a valuable introspective view on how people from different backgrounds experience interviews conducted by A.I.. As stated earlier, I talked with five people from different disciplines with unique experiences. My first interview was with an undergraduate student currently in the job application process with several sports management companies. Next, I interviewed a graduate student searching for jobs at banks. Then, I interviewed the Career Center Director at Notre Dame of Maryland University, Alan Jones. Following, I interviewed the Career Center Director at Thomas Jefferson University, Chris Miciek. Both Mr. Jones and Mr. Miciek train students on successfully navigating through the automated hiring process. Lastly, I gained insight on the software development, implementation, auditing, and editing process through an interview with a HireVue staff member. Because most of the questions I asked remained relatively the same among interviewees, I have been able to

compare their responses and identify themes. The major themes included preference of in-person interviews at the final stage of the interview process, disfavor for the lack of transparency, and contradicting opinions on if artificial intelligence is less biased than humans. Because of the small sample size, we should be weary to assume their opinions accurately reflect those of the population.

Every interviewee was asked the question, “Would you prefer your interview to be conducted by artificial intelligence or by a human and why?” Because the modern hiring process usually involves multiple interviews, they typically responded by addressing both the initial interviews and the final interview. With the exception of the HireVue staff member, every interviewee preferred their final interview to be conducted by A.I.. The undergraduate student replied without hesitation saying “Oh, a person, 100%.” The graduate student acknowledged the benefits of using A.I., but then said because of his extroverted personality, he would prefer a human final interview. However, three out of the five preferred to have their initial interview to be with A.I.. Their reasoning was mainly so the machine could sort through the abundance of applications and reject obviously non-ideal candidates. Additionally, some believed that the machine could perform interviews with less bias than a human. The HireVue staff member said that he preferred artificial intelligence software because he could take it wherever he wanted, he could practice before answering the question, and he understood the automated interview process from a bias standpoint. As of right now, since most companies utilize in-person final interviews, they felt fairly confident they would be able to express their capabilities and characteristics sufficiently if they received a final interview.

While many of these interviewees had their reservations about automated interviewing for a multitude of reasons, they were not actively combatting the process. The graduate student, having completed over eight automated interviews, said “it’s the new standard now, and I have to adapt to it.” Similarly, Mr. Jones said “They are a reality for me.” Understandably, they, alone, would not be able to reverse a hiring technique that has been disseminated among the world’s most influential companies. Their occupations and opportunities rely on assimilating to this new norm. Additionally, some believed automating hiring to be more beneficial than in-person interviews anyways.

Most of the interviewees seemed to be actively educating themselves on the process, so they had informed opinions. When asked if he knew about Joy Boulamwini, Mr. Miciek replied with “Algorithmic Justice League?! Yes please!” Mr. Jones and Mr. Miciek proceeded to refer me to informative articles, audits, and influencers after their interviews. Mr. Jones even shared with me his personally designed crash course for his students. Both are passionate about educating themselves, so they can best help their students succeed. However, as Mr. Miciek pointed out, we should be careful to breed a complacency around automated interviews.

The last major theme through my interviews was an uneasy feeling about the uncertainty and lack of transparency. With the exception of the HireVue staff member, every interviewee mentioned some aspect denoting a desire for more information. The graduate student said that he was uncomfortable with automated interviews because “You’re not given any rubric. You’re are not given any criteria, you’re just kinda’ thrown out there to see what they[employers] are looking for.” Similarly, Mr. Jones said that increasing transparency would benefit not only their training models, but also to the candidates. From his recollection, the HireVue website has been

“retracting information” throughout the years; however, he has added that HireVue publishes statements explaining their technology separately. Mr. Jones brought up an excellent point that an in-person interview allows the interviewee to learn how the organization represents themselves, so the interviewee can gauge *their* impression of the organization. Without a human interviewer, the interview process literally does become a “one-way” interview. HireVue has already implemented automated follow-up texts to give the process a more human feeling.²⁶ The HireVue staff member is confident that automated hiring will evolve to address these problems, and make users become more comfortable with the process.

Each interview brought valuable and insightful opinions to this research. Much of what I had previously known about automated interviews was expanded and challenged. Hearing from people who were strongly opposed to the software while also hearing from people who fully trust this technology allowed me to have a more well-rounded understanding of the opinions of one-way interviews. I urge you to also find additional sources that challenge your opinion of this software.

Chapter 7: Previous Uses of Artificial Intelligence

Using artificial intelligence to accelerate human processes has been happening for decades. Several of these projects have failed due to their prejudiced models. Because these projects were used in advising the legal system, identifying criminals, and evaluating teachers, the implications of malfunctioning can severely alter someone’s life. However, humans still

²⁶ “Better Engage Candidates with Text Recruiting: Hirevue.” hirevue.com. Accessed April 11, 2022.
<https://www.hirevue.com/platform/text-recruiting>.

pursue automation as a faster, more cost-efficient means to model fundamentally human processes.

7.1 Teacher evaluations

An example of a failed automation attempt took place in Houston, Texas when a school district employed the Educational Value Added Assessment System (EVAAS) from 2011 to 2015.²⁷ A private company developed this A.I. software to determine whether teachers should be given a bonus or fired. This algorithm essentially scored the value of a teacher. Without access to the algorithm, teachers were not made aware of the categories in which they were being rated. After the program decided that one beloved teacher, Daniel Santos from Yolanda Black Navarro Middle School of Excellence, was not fit to be teaching, seven teachers created a judicial case stating that this software was not equitable based on the 14th amendment. They were being fired without due process. Because the algorithm was protected by the claim that it was property of the company, the specific algorithms did not have to be shown to the court. The court deemed the software a violation of rights; therefore, the Houston Independent School District was required to discontinue running the software and to pay legal fines for the distress caused.

7.2 Facial recognition in the United Kingdom

Another example appears with a facial recognition software which incorrectly assessed people in the United Kingdom. As of 2018, police have been using facial recognition software in public locations with the intent of finding criminals²⁸. The Big Brother Watch, an activist group

²⁷ Amrein-Beardsley, Audrey, and Clarin Collins. "The SAS Education Value-Added Assessment System (SAS® EVAAS®) in the Houston Independent School District (HISD): Intended and Unintended Consequences." *education policy analysis archives* 20 (2012): 12. <https://doi.org/10.14507/epaa.v20n12.2012>.

²⁸ "Stop Facial Recognition." Big Brother Watch. Accessed April 2, 2022. <https://bigbrotherwatch.org.uk/campaigns/stop-facial-recognition/>.

in the UK, immediately began to warn people when they saw this taking place. Members would distribute flyers to people on the street. Civilians could receive fines for covering their faces. Members intervened in incidents where the police officers would mandate that a civilian's face be uncovered. Big Brother Watch reports one incident of a man being fined £90 for refusing to cooperate. Laws do not exist in the UK to protect a facial scan as private property. The Big Brother Watch published that 93% of people were wrongly identified from 2016-2019. Since the COVID-19 pandemic, surveillance has stopped due to the need for people to wear masks. Facial recognition was prematurely used and caused several people distress.

7.3 Amazon's resume scanner

Even one of the most relied upon and influential companies of the United States, Amazon, attempted to implement an automated resume scanner in 2014 to hire software developers²⁹. With the excessive number of resumes evaluated per day, Amazon deployed a machine that would be inputted with several hundred resumes, rank them each, and hire the top five percent. The program had been trained using ten years of previous data from when the field was male dominated; hence, their data significantly lacked gender diversity. Because the machine made statistical inferences based on the training set, the program started “learning to penalize resumes including the word ‘women’s’ until the company discovered the problem.”²³ This significant oversight not only devalued any female organizations, clubs or awards, but also devalued any applicants who reported being from an all-women's college. After the company realized this, they immediately altered the program to make it gender-neutral. The developing

²⁹ Dastin, Jeffrey. “Amazon Scraps Secret AI Recruiting Tool That Showed Bias against Women.” Reuters. Thomson Reuters, October 10, 2018. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G>.

team disbanded in early 2017 because they “lost hope for the project.”²³ Amazon has made claims that the program “was never used by Amazon recruiters to evaluate candidates”²³; however, they did not address whether recruiters considered the suggestions of the program. Other companies learned from Amazon’s mistake, but many still use software to detect key words in resumes and cover letters.

7.4 Tengai Unbiased

Another company in Sweden has recently attempted to create an A.I. hiring process but has preemptively combatted the tainted image of A.I. by inserting the description “Unbiased” directly into the title of their program. Created in 2019, Tengai Unbiased was created by TNG to “perform bias-free job interviews free from age, looks, or gender.”³⁰ Tengai Unbiased’s website preached un-biased processing from the home page on the website and throughout almost every branching link. While they clearly value equality, they fail to give specific details on how they ensure equality. Their website even acknowledges that the hiring process “has been a mysterious ‘black box’”, but then does not contrast that statement with proof that their automated hiring process is any less mysterious.²⁴

In June of 2019, a validation study was conducted by Associate Professor Anders Sjöberg, CEO at Psychometrics Sweden AB. According to Mr. Anders, the objective of the study involved “assessing the robot’s unbiased methodology and ensuring quality assurance by measuring the correlation between the candidate’s answers and other objective

³⁰ “Social AI-Robot Mitigates Bias in the Job Interview.” Tengai Unbiased, October 6, 2021. <https://www.tengai-unbiased.com/mitigate-job-interview-bias/>.

information.”³¹ In March of 2020, the study was concluded, and the results were released. The entire study is available but is unfortunately only available in Swedish. Using an online translator, I was able to distinguish the methods of the experiment. Thirty-four participants took a written exam to determine their personality traits according to the Five-Factor Model, a personality categorization chart. Their results were then compared to Tengai’s evaluation of each participant. According to Professor Anders Sjöberg, the experiment was a success in that it “confirms that Tengai can ask questions that are relevant for work performance and can interpret the answers independently, without human involvement.” While the program may have mastered the methods required to complete an interview, Sjöberg does not compare the potential of bias in a Tengai Unbiased interview to a person-to-person interview. Additionally, thirty-four participants is a small sample size to make a definitive answer on bias. Furthermore, the Five-Factor Model is a theory that all personality traits can be summarized by five traits: extraversion, neuroticism, openness to experience, agreeableness, and conscientiousness. Because the study fails to address outcomes involved discrimination and only samples thirty-four people, Tengai Unbiased should not definitively say their program works flawlessly. Because this program is still relatively new, more studies will likely critically analyze Tengai’s algorithms.

7.5 COMPAS

Another example that has been implemented, analyzed, and reconsidered is COMPAS, Correctional Offender Management Profiling for Alternative Sanctions. Northpointe Incorporated developed an artificial intelligence system to ease, automate, and accurately predict the judgment process for convicts. COMPAS judges a convict’s chances at recidivism by

³¹ “Tengai’s Interview Methodology in Validation Study.” Tengai Unbiased, August 28, 2019. <https://www.tengai-unbiased.com/psychometric-study/>.

collecting a standard set of data from each person. Each defendant is rated on a 1-10 scale for “Risk of Recidivism,” “Risk of Violence” and “Risk of Failure to Appear” with 1 being low and 10 being high.³² Judges are allowed to use the defendant’s COMPAS scores as an influence in their verdict. Kevin Whiteacre in 2006, Sarah Desmarais and Jay Singh in 2013, and Jennifer Skeem in 2016 produced critical analyses to test the accuracy and reliability of the program. Most recently, ProPublica in May 2016 completed another full analysis.

ProPublica analyzed how the predictions compared to actual outcomes and why the data was skewed. While the data prompts are identical between people, the program still seems to differentiate between groups of people. Black people disproportionately received a prediction of high risk in all categories.²⁶ In contrast, white people seemed to be judged less harshly.²⁶ The reason for this difference in proportions is due to the questions having severely asymmetrical answers between groups of people. Simple inquiries about economic status can unlock strong statistical trends that differ between Blacks and Whites. Because of slavery, segregation, and institutional prejudice in the United States, Black people can lack connections with people of power, “old” money, and properties passed down through generations; therefore, white people are more financially privileged. ProPublica’s final report concluded that “Black defendants were twice as likely as white defendants to be misclassified as a higher risk of violent recidivism, and white recidivists were misclassified as low risk 63.2 percent more often than black defendants.”²⁶ Through a hypothesis test for the difference of proportions, we can reject the idea that this difference was due to chance because there is enough evidence of the alternative.

³² Jeff Larson, Julia Angwin. “How We Analyzed the Compas Recidivism Algorithm.” ProPublica, May 23, 2016. <https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm>.

Ultimately, the research completed by ProPublica and others exposed systematic racism. Even after the audit, according to a journal article published in August of 2021, the dataset is still “sold and used in American courts”.³³

As seen by all of these examples, artificial intelligence is not sufficiently equipped to evaluate humans. These attempts to make processes more efficient disrupted and negatively impacted so many human lives, including devoted teachers wrongfully losing their jobs, street-walkers fined for covering their face, and even convicts wrongfully sent back to prison. Using artificial intelligence has severe consequences; however, we continue to pursue the option.

Conclusion

i. Sources to combat algorithmic injustice

Because computer science as a discipline is relatively new compared to other fields, software companies were allowed to conduct unsupervised and unreviewed experiments. After some controversial experiments took place with some of the tech-giants like Facebook³⁴, review boards became more popular. In 2013, Microsoft designed an ethics advisory board. Other well-known companies followed, such as Google and IBM similarly crafted review boards. However, Google dismantled their board shortly after its creation. Their advisory board began to crumble when one member resigned, and others were being ousted. According to an article in *The Washington Post*, Timnit Gebru, one of Google’s lead ethical researchers, got fired for writing a

³³ Govindu, Venu Madhav. “Artificial Intelligence and Its Discontents-II.” The India Forum. TheIndiaForum, August 22, 2021. https://www.theindiaforum.in/article/artificial-intelligence-and-its-discontents-ii?utm_source=website&utm_medium=organic&utm_campaign=homepage&utm_content=Top-article.

³⁴ “Facebook Emotion Study Breached Ethical Guidelines, Researchers Say.” The Guardian. Guardian News and Media, June 30, 2014. <https://www.theguardian.com/technology/2014/jun/30/facebook-emotion-study-breached-ethical-guidelines-researchers-say>.

paper criticizing Google's large language models.³⁵ While establishing an ethics board can ease the minds of the public, an ethics board is useless unless given governing power to stop or alter any experiment or study without fear of being fired or silenced. While I do believe these companies' review boards hold some power, I wish they were more transparent with the specifics of the checks and balances of the power dynamic. For example, does the ethics board have the authority to shut down an experiment requested by Senior Project Manager? How about the CEO? Timnit Gebru said she gained more meaningful responses when publishing to external sources than confronting Google internally with concerns. After being fired, she created DAIR, Distributed Artificial Intelligence Research Institute, in order to “create an environment that is independent from the structures and systems that incentivize profit over ethics and individual well-being.”³⁶ Properly structured ethic boards and independent research companies are potential solutions to uncovering unconscious biases in algorithms.

One activist, Joy Boulamwini, has created her own independent review board that searches for sources of algorithmic injustice and combats them with legal action. Boulamwini became aware of the threat of biased algorithms while completing her undergraduate studies. She was creating an interactive mirror; however, her mirror would not recognize her Black face until she wore a white mask. The reason for this is that the software's data was trained mostly on white people; therefore, the A.I. did not recognize Black faces as faces. This discovery captured her curiosity in the biases embedded in algorithms. Joy starred in a documentary called *Coded Bias* that discussed other biased algorithms that are still active. She brought these concerns to

³⁵ Tiku, Nitasha. “Google Fired Its Star AI Researcher One Year Ago. Now She's Launching Her Own Institute.” The Washington Post. WP Company, December 2, 2021. <https://www.washingtonpost.com/technology/2021/12/02/timnit-gebru-dair/>.

³⁶ “The Dair Institute.” The DAIR Institute. Accessed April 22, 2022. <https://www.dair-institute.org/press-release>.

Capitol Hill. Eventually some states banned the use of facial recognition software by police. Her activism continues currently through the Algorithmic Justice League, a group of activists working to expose biased algorithms, especially in larger corporations such as Facebook. The movie concluded with the words “intelligence without ethics is not intelligence at all”.³⁷ Joy Boulamwini and the Algorithmic Justice League continue to apply ethics to artificial intelligence daily.

ii. Challenges from a legal standpoint

Taking legal action against bias in algorithms tends to be a tedious task. Ifeoma Ajunwa J.D. Ph.D works as a law professor at the North Carolina School of Law, where she founded the A.I. Decision Making Research Program. In her NPR interview, she discussed the challenges of accusing an algorithm on the claim of discrimination:

*“The algorithms that are part of the hiring system, they are considered proprietary, meaning that they're a trade secret. So, you may not actually be able to be privy to exactly how the algorithms were programmed and also to exactly what attributes were considered.”*³⁸

The algorithms are the company’s intellectual property. Releasing the algorithm exposes their innovative processes that they may have spent significant amounts of time developing. The government has laws that protect intellectual property. With the algorithm not being released in court, the plaintiff has little evidence to support their claims.

³⁷ *Coded Bias*. Netflix. Accessed April 2, 2022.
<https://www.netflix.com/watch/81328723?trackId=14277281&tctx=-97%2C-97%2C%2C%2C%2C%2C%2C>.

³⁸ Chang, Ailsa. “Cornell Professor Ifeoma Ajunwa Discusses Artificial Intelligence Used In Hiring.” Broadcast. *All Things Considered*, April 8, 2019.

Fortunately, state and national laws exist to regulate the uses of A.I.. At the state level, the National Conference of State Legislators reports that “artificial intelligence bills or resolutions were introduced in at least seventeen states in 2021, and enacted in Alabama, Colorado, Illinois and Mississippi.”³⁹ On a national level, the United States has signed onto the Organization for Economic and Cooperation and Development’s (OECD) 2019 Principles on Artificial Intelligence in 1961. The OECD upholds their policies “by measuring and analyzing the economic and social impacts of A.I. technologies and applications, and engaging with all stakeholders to identify good practices for public policy.”⁴⁰ According to their website, there are 391 global initiatives dedicated to A.I. research and education and 484 government entity initiatives.³¹

Additionally, the OECD created the Uniform Guidelines on Employee Section Procedures in 1978, which declares the 4/5th rule. This rule quantifies bias by saying that an algorithm has adverse impact if “the selection rate for a certain group is less than 80 percent of that of the group with the highest selection rate, there is adverse impact on that group.”⁴¹ In other words, if equal numbers of people from Group A and Group B apply and less than 80% of Group A gets hired and 100% of Group B gets hired, there is likely an adverse impact on Group A. Locating and disrupting that adverse characteristic can be challenging because as stated before, machines struggle to interpret the traits they chose to recognize to humans. However, creating the

³⁹ “Legislation Related to Artificial Intelligence.” National Conference of State Legislators. Accessed April 2, 2022. <https://www.ncsl.org/research/telecommunications-and-information-technology/2020-legislation-related-to-artificial-intelligence.aspx>.

⁴⁰ “Artificial Intelligence.” OECD. Accessed April 2, 2022. <https://www.oecd.org/digital/artificial-intelligence/>.

⁴¹ “What Is Adverse Impact? and Why Measuring It Matters.” hirevue.com, July 19, 2021. <https://www.hirevue.com/blog/hiring/what-is-adverse-impact-and-why-measuring-it-matters>.

policy is an effective initial step. With increasing law and research, artificial intelligence regulation may ensure the mitigation of bias.

iii. Alternatives

While I do notice significant improvements in automated hiring technology, I do not think humans have advanced their understandings of A.I. enough to be regularly using it to replace fundamentally human tasks. However, I, alone, cannot dismantle a process that is now an integral aspect of the country's wealthiest and most powerful companies. Because for the indefinite future, this process will remain active, I can only provide suggestions for the creation of further applications.

As I stated at the beginning of this paper, the creation of software that analyzes human beings for life-altering outcomes should be reviewed by multidisciplinary teams. Judging a holistic human profile with accuracy involves an array of disciplines including, but not limited to, advanced mathematics, psychology, sociology, anthropology, data analytics, political science, philosophy, and more. Not only should the multidisciplinary teams conduct individual analyses, but also cooperative analyses. After they have reviewed the program individually and cooperatively, there should be a third-party team to audit the auditors. A third-party would not feel the pressure or incentive to force a fast, positive result. Additionally, diverse knowledge can create a diverse program.

Secondly, I would advise the software developing company to choose data other than from previous years at that specific job. Creating synthetic data could potentially replicate the diverse representation of people who may apply. However, humans also struggle accounting for every interviewer identity, so partially synthetic data would be more feasible to consider. Modified data could be added to the training set. For example, if the field had previously been

dominated by men, data analysts can keep the same data while changing the gender of some of the profiles. I realize that training sets for these programs require substantial amounts of data.

The likelihood of software development companies heeding these suggestions is low because the suggestions require significantly more money and time. However, if this process must continue, additional steps should be taken to avoid creating a machine that would reinforce the bias already present in our country. After the software has been created, audited, and deployed, it should be regularly reconsidered upon addition of new data. With all these suggestions, I believe interviews conducted by artificial intelligence could be closer to surpassing humans in their ability to be unbiased.

iv. Warning to the future

Making decisions based on the suggestions of a machine without questioning its reliability can lead to serious consequences. The decisions machines can make now can catastrophically alter someone's life. In one example from the MIT podcast *In Machines We Trust* in the episode *When an Algorithm Gets it Wrong*, a man had been falsely accused of a crime because a facial recognition software matched his license photo to the surveillance photo of a person stealing watches.⁴² He was arrested on his lawn in front of his wife and daughter and then put in jail for the night. He said "if [the police office] had just brought the picture with him, he could've looked it up and down and he could've left and said 'oh, my bad'." The whole situation could have been avoided by questioning the reliability of the machine. Blindly trusting these machines can have significant consequences.

⁴² Review, MIT Technology. "In Machines We Trust: When an Algorithm Gets It Wrong on Apple Podcasts." Apple Podcasts, August 12, 2020.
<https://podcasts.apple.com/us/podcast/when-an-algorithm-gets-it-wrong/id1523584878?i=1000487884962>.

Artificial intelligence can blind us to civil injustice and unconscious biases by marketing corporate efficiency; however, we must not remain content. In terms of machine learning, singularity is the theory that artificial intelligence will exponentially advance to the point where it is “outstripping the capabilities of human minds.”⁴³ While I do not believe the dystopian theory that robots will cause the extinction of humans in the imminent future, I do believe they can cause increasingly more severe social consequences. If we fail to educate ourselves or pursue what we believe to be moral, artificial intelligence will reverse our social justice progress.

⁴³ Govindu, Venu Madhav. “Artificial Intelligence and Its Discontents-I.” The India Forum. TheIndiaForum, August 27, 2021. <https://www.theindiaforum.in/article/artificial-intelligence-and-its-discontents-i>.

References Cited

- “Ai Recruiting & Job Matching Platform.” pymetrics. Accessed April 10, 2022.
<https://www.pymetrics.ai/>.
- Amrein-Beardsley, Audrey, and Clarin Collins. “The SAS Education Value-Added Assessment System (SAS® EVAAS®) in the Houston Independent School District (HISD): Intended and Unintended Consequences.” *education policy analysis archives* 20 (2012): 12.
<https://doi.org/10.14507/epaa.v20n12.2012>.
- “Artificial Intelligence.” OECD. Accessed April 2, 2022. <https://www.oecd.org/digital/artificial-intelligence/>.
- “Artificial Intelligence: The Robots Are Now Hiring | Moving Upstream.” Youtube. Wall Street Journal, September 20, 2018. <https://www.youtube.com/watch?v=8QEK7B9GUhM>.
- “Better Engage Candidates with Text Recruiting: Hirevue.” hirevue.com. Accessed April 11, 2022. <https://www.hirevue.com/platform/text-recruiting>.
- “Bias Definition & Meaning.” Dictionary.com. Dictionary.com. Accessed April 1, 2022.
<https://www.dictionary.com/browse/bias>.
- “Bias, A.I. Ethics and The HireVue Approach.” hirevue.com. Accessed April 1, 2022.
<https://www.hirevue.com/why-hirevue/ai-ethics>.
- “Bias.” Psychology Today. Sussex Publishers. Accessed April 1, 2022.
<https://www.psychologytoday.com/us/basics/bias>.
- “Case Studies: Customer Successes: Hirevue.” hirevue.com. Accessed April 1, 2022.
<https://www.hirevue.com/case-studies?msegment=na-education>.
- Chang, Ailsa. “Cornell Professor Ifeoma Ajunwa Discusses Artificial Intelligence Used In Hiring.” Broadcast. *All Things Considered*, April 8, 2019.
- Chiang, Linda H. 1993. “Beyond the Language: Native Americans’ Nonverbal Communication,” October.
<https://search.ebscohost.com/login.aspx?direct=true&db=eric&AN=ED368540&site=eds-live>
- Coded Bias*. Netflix. Accessed April 2, 2022.
[https://www.netflix.com/watch/81328723?trackId=14277281&tctx=-97%2C-97%2C%2C%2C%2C%2C](https://www.netflix.com/watch/81328723?trackId=14277281&tctx=-97%2C-97%2C%2C%2C%2C%2C%2C).
- Cole, David, "The Chinese Room Argument", *The Stanford Encyclopedia of Philosophy* (Winter

2020 Edition), Edward N. Zalta (ed.),
 URL=<<https://plato.stanford.edu/archives/win2020/entries/chinese-room/>>.

Crenshaw, Kimberlé W., "On Intersectionality: Essential Writings" (2017). *Faculty Books*.
 255. <https://scholarship.law.columbia.edu/books/255>

Dastin, Jeffrey. "Amazon Scraps Secret AI Recruiting Tool That Showed Bias against Women." Reuters. Thomson Reuters, October 10, 2018. <https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G>.

"Discrimination Definition & Meaning." Dictionary.com. Dictionary.com. Accessed April 1, 2022. <https://www.dictionary.com/browse/discrimination>.

Eckert, Penelope, and Sally McConnell-Ginet. "Positioning Ideas and Subjects1." Essay. In *Language and Gender*, 157–91. Cambridge: Cambridge University Press, 2018.

"Facebook Emotion Study Breached Ethical Guidelines, Researchers Say." The Guardian. Guardian News and Media, June 30, 2014. <https://www.theguardian.com/technology/2014/jun/30/facebook-emotion-study-breached-ethical-guidelines-researchers-say>.

"FAQ: Frequently Asked Questions for Candidates: HireVue." hirevue.com. Accessed April 10, 2022. <https://www.hirevue.com/candidates/faq>.

"Global Survey." arXiv.org e-Print archive. Accessed April 10, 2022. <https://arxiv.org/>.

Govindu, Venu Madhav. "Artificial Intelligence and Its Discontents-I." The India Forum. TheIndiaForum, August 27, 2021. <https://www.theindiaforum.in/article/artificial-intelligence-and-its-discontents-i>.

Govindu, Venu Madhav. "Artificial Intelligence and Its Discontents-II." The India Forum. TheIndiaForum, August 22, 2021. https://www.theindiaforum.in/article/artificial-intelligence-and-its-discontents-ii?utm_source=website&utm_medium=organic&utm_campaign=homepage&utm_content=Top-article.

"HireVue Assessments and Preventing Algorithmic Bias." hirevue.com, July 15, 2021. <https://www.hirevue.com/blog/hiring/hirevue-assessments-and-preventing-algorithmic-bias>.

"Introduction to Algorithms." GeeksforGeeks, January 13, 2022. <https://www.geeksforgeeks.org/introduction-to-algorithms/>.

Jeff Larson, Julia Angwin. "How We Analyzed the Compas Recidivism Algorithm." ProPublica, May 23, 2016. <https://www.propublica.org/article/how-we-analyzed-the-compas-recidivism-algorithm>.

Landers, R. N., & Behrend, T. S. (2022). Auditing the AI auditors: A framework for evaluating fairness and bias in high stakes AI predictive models. *American Psychologist*. Advance online publication. <http://dx.doi.org/10.1037/amp0000972>

"Legislation Related to Artificial Intelligence." National Conference of State Legislators. Accessed April 2, 2022. <https://www.ncsl.org/research/telecommunications-and-information-technology/2020-legislation-related-to-artificial-intelligence.aspx>.

Maurer, Roy. "Hirevue Discontinues Facial Analysis Screening." SHRM. SHRM, February 3, 2021. <https://www.shrm.org/resourcesandtools/hr-topics/talent-acquisition/pages/hirevue-discontinues-facial-analysis-screening.aspx>.

McCarthy, J., et al. *A Proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. 31 Aug. 1955.

"Objective or Biased." BR24. Accessed April 1, 2022. <https://interaktiv.br.de/ki-bewerbung/en/>.

Review, MIT Technology. "In Machines We Trust: When an Algorithm Gets It Wrong on Apple Podcasts." Apple Podcasts, August 12, 2020. <https://podcasts.apple.com/us/podcast/when-an-algorithm-gets-it-wrong/id1523584878?i=1000487884962>.

Ruhl, Charlotte. "What Is Cognitive Bias?" What Is Cognitive Bias? | Simply Psychology, May 4, 2021. <https://www.simplypsychology.org/cognitive-bias.html>.

"Social AI-Robot Mitigates Bias in the Job Interview." Tengai Unbiased, October 6, 2021. <https://www.tengai-unbiased.com/mitigate-job-interview-bias/>.

Stephanie. "Bias in Statistics: Definition, Selection Bias & Survivorship Bias." Statistics How To, July 29, 2013. <https://www.statisticshowto.com/what-is-bias/#DefBias>.

"Stop Facial Recognition." Big Brother Watch. Accessed April 2, 2022. <https://bigbrotherwatch.org.uk/campaigns/stop-facial-recognition/>.

Strong, Jennifer. "In Machines We Trust." MIT Technology Review. Accessed April 1, 2022. <https://www.technologyreview.com/supertopic/in-machines-we-trust/>.

TEDtalksDirector. "How I'm Fighting Bias in Algorithms | Joy Buolamwini." YouTube. YouTube, March 29, 2017. https://www.youtube.com/watch?v=UG_X_7g63rY.

TEDxTalks. "Controversies of Ethics & Technology in Modern Workplace | Ifeoma Ajunwa | Tedxcornelluniversity." YouTube. YouTube, December 3, 2018. https://www.youtube.com/watch?v=X5WXSX_wm6s.

“Tengai's Interview Methodology in Validation Study.” Tengai Unbiased, August 28, 2019.
<https://www.tengai-unbiased.com/psychometric-study/>.

“The Dair Institute.” The DAIR Institute. Accessed April 22, 2022. <https://www.dair-institute.org/press-release>.

Tiku, Nitasha. “Google Fired Its Star AI Researcher One Year Ago. Now She's Launching Her Own Institute.” The Washington Post. WP Company, December 2, 2021.
<https://www.washingtonpost.com/technology/2021/12/02/timnit-gebru-dair/>.

“Unconscious Bias Training.” Unconscious Bias Training | Office of Diversity and Outreach UCSF. Accessed April 10, 2022. <https://diversity.ucsf.edu/programs-resources/training/unconscious-bias-training>.

“What Is Adverse Impact? and Why Measuring It Matters.” hirevue.com, July 19, 2021.
<https://www.hirevue.com/blog/hiring/what-is-adverse-impact-and-why-measuring-it-matters>.