WHEN MACHINES MAKE HIRING DECISIONS: EXAMINING THE RISKS AND LIMITATIONS OF AI-BASED RECRUITMENT TOOLS

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INTRODUCTION

It seems as if Artificial Intelligence ("AI") has burst into all aspects of society. From providing answers to our most conceptual questions, enabling facial recognition to unlock our phones, to managing our homes, AI has permanently carved out a spot in our lives. Despite being seemingly sophisticated, AI is completely misunderstood in our world today. Whether it is understanding how AI systems work or the potential threats that using AI imposes, the general knowledge of AI is scarce. While limited general knowledge is cause for concern, alarm bells should be ringing at the fact that our legal system also doesn't understand AI and is largely unprepared to regulate AI, resolve disputes involving AI, and establish appropriate standards for using AI. Despite its creation around 1950, few laws have been enacted to protect individuals from AI harm.

It is clear that AI produces numerous benefits in our lives, but it is not without its risks. A risk area is AI used in the job hiring process. Currently, this is an issue that those involved in the hiring process are often unaware of—employers and employees alike. The lack of understanding of AI, when paired with a lack of necessary laws and standards to support and reign in AI creates an alarming situation when it is used as a hiring tool.

This Note will delve further into this area by showing the complex issues that using AI as a hiring tool creates, including the lack of clear law to resolve the complexities, and an idea of what the law should look like when established. To begin, the Note will address relevant information on AI, including a brief history, how to define AI, and subsets of AI relevant to the job hiring

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process. After setting out the basic knowledge of AI, the Note will move to explaining how using AI as a hiring tool may be problematic in the way it assesses job candidates. To expand on these issues, the Note will specifically analyze resume screening AI tools and one-way interview AI tools. Then, the Note will address the current state of the law, especially Title VII and its two spheres of discrimination: disparate treatment and disparate impact. The Note will then move into the focal point of this Note by addressing the complications and gaps with the current state of the law, including archaic employment laws, employment laws that do not account for complex AI algorithms, and the employers' inability to modify the AI hiring tool. Finally, the Note will conclude by discussing potential ways to regulate AI used as a hiring tool. Ideas that have been previously stated in other academic pieces, such as redefining the disparate impact analysis and identifying a clear target will be discussed. However, the suggestion this Note strongly advocates for is creating a disclosure and waiver policy within the disparate impact analysis that can account for the difficulties both employees and employers face when dealing with AI employment discrimination issues.

I. Relevant Information on Artificial Intelligence

A. History of Artificial Intelligence

From the dramatic increase in conversations regarding Artificial Intelligence in recent years, one might be under the impression that AI is a new phenomenon—with its inception tied to the modern technological era.[1] However, AI has been discussed in scholarly work since 1950.[2] The birth of the AI discussion is credited to Alan Turing's Article, Computing Machinery and Intelligence. In this seminal piece, Turing considers the question, "Can machines think?"[3] To answer this question, Turing proposes what has become known as the "Turing Test," where a human prober attempts to distinguish between a computer and a human text response.[4] Much of Turing's work has faced intense scrutiny as AI has advanced since its publication, but Turing remains largely credited as the "father of computer science," for his work in attempting to define AI.[5]

B. Defining "Artificial Intelligence"

Since 1950, various ways of defining AI have been proposed and attempting to settle on a single definition of AI can fill an entire article on its own. To avoid the theoretical complications that arise when attempting to define AI, for the purposes of this Note, AI will be defined according to the definition established by John McCarthy in his 2007 piece, What is Artificial Intelligence?[6] According to McCarthy, AI is "the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to biologically observable

1. *See What is Artificial Intelligence?,* IBM, https://www.ibm.com/topics/artificial-intelligence (last visited Apr. 12, 2023).

2. Jet New, *A Summary of Alan Turing's Computing Machinery and Intelligence*, MEDIUM (Aug. 12, 2020), https://medium.com/@jetnew/a-summary-of-alan-m-turings-computing-machinery-and-intelligence-fd714d187c0b (highlighting Turing's argument from the 1950's "that there is no convincing argument that machines cannot think intelligently like humans").

3. A.M. Turing, *Computing Machinery and Intelligence*, 49 MIND 433, 433 (1950).

4. *Id.* at 446.

5. IBM, *supra* note 1.

6. John McCarthy, *What is Artificial Intelligence*, STAN. COMPUT. SCI. DEPT., Nov. 12, 2007, at 2.

methods."[7] From this definition we can understand that AI has been technologically advanced in nearly all aspects of human life to enable problem-solving. However, we may not always be able to understand or observe the ways in which AI solves the task it has been created to assist with.

C. Subsets of Artificial Intelligence

Two subsets of AI that are commonly discussed, and are especially relevant to this Note, are deep learning and machine learning.[8] Deep learning is inspired by how the human brain processes information and uses what can be compared to a "neural network" to combine, abstract, and transform input attributes as they pass through multiple layers of the neural network.[9] While the process works much like a human brain,[10] it is repeated thousands or millions of times more and makes minuscule adjustments to its data parameters each pass through until the AI finds its ideal set of parameters.[11] The parameters will be deemed "ideal" when the deep learning model reaches the point where any further adjustments will no longer improve the accuracy of the model and settles on this point to make its predictions.[12] The "ideal" parameters are incredibly complex and cannot be expressed or interpreted easily.[13] In addition, the path which the deep learning AI took to reach its ideal parameters may not even be traceable or able to be reconstructed.[14] Because of this, deep learning algorithms are commonly referred to as "black box algorithms."[15] Even if the human developer of the original algorithm knows and can understand all the input variables and target variables (which is a big if in the advanced technological era), the final algorithm may be "effectively opaque" to the developer.[16] This causes intense scrutiny in the context of making hiring decisions, where transparency is imperative in order to coincide with modern employment law.[17]

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7. *Id.*

8. *See* IBM, *supra* note 1 (illustrating the prevalence of discussions on deep learning and machine learning within the artificial intelligence space).

9. Chris V. Nicholson, *A Beginner's Guide to Neural Networks and Deep Learning*, A.I. WIKI (2023), https://wiki.pathmind.com/neural-network ("Neural networks are a set of algorithms, modeled loosely after the human brain").

10. *What Is Deep Learning?*, AMAZON, https://aws.amazon.com/what-is/deep-learning/#:~:text=Deep%20learning%20is%20a%20method,produce%20accurate%20insights%20and%20predicti on%20s (last visited Mar. 31, 2024).

11. *See* Alexander S. Gillis, *Deep Learning*, TECHTARGET, https://www.techtarget.com/searchenterpriseai/definition/deep-learning-deep-neural-network (last visited Mar. 31, 2024).

> "Deep learning programs have multiple layers of interconnected nodes, with each layer building upon the last to refine and optimize predictions and classifications. Deep learning performs nonlinear transformations to its input and uses what it learns to create a statistical model as output. Iterations continue until the output has reached an acceptable level of accuracy. The number of processing layers through which data must pass is what inspired the label *deep*." *Id.*

12. Nicholson, *supra* note 9.

13. *See generally* IBM, *supra* note 1.

14. Matthew U. Scherer, Allan G. King & Marko N. Mrkonich, *Applying Old Rules to New Tools: Employment Discrimination Law in the Age of Algorithms*, 71 S.C. L. REV. 449, 456 (2019).

15. Yavar Bathaee, *The Artificial Intelligence Black Box and the Failure of Intent and Causation*, 31 HARV. J. L. & TECH. 889, 901 (2018).

16. Scherer *supra* note 14, at 456.

17. *See generally* Title VII of the Civil Rights Act of 1964, 42 U.S.C. § 2000 (1964).

Machine learning is the branch of AI that creates algorithms learned from data. AI "learns" by using "statistical methods and data-driven insights" to improve its algorithms without human intervention.[18] The "data-driven insights" used by AI consist of instances and attributes.[19] One can think of instances as a row on an Excel spreadsheet. In terms of machine learning being used to make hiring decisions, an instance usually represents an individual. Attributes are different characteristics or measurable properties that an instance is being observed on.[20] To make hiring decisions, an attribute may be "years of experience" or "highest degree obtained." Machine learning approaches can be separated into two categories: supervised learning and unsupervised learning.[21] Supervised learning uses data labeled through human intervention and unsupervised learning uses its algorithm to search for patterns not readily interfered with or touched by human intervention.[22] Overall, machine learning uses its algorithm to compare various instances in different attribute categories to best predict an outcome based on the constantly improved, with little to no human intervention, data.[23] This is distinguishable from human-coded algorithms because the AI or another computer program is constantly modifying the algorithm to emphasize patterns it deems important, rather than a human modifying the data based on the patterns it finds.[24] Not only can machine learning algorithms alter themselves based on patterns at incredible speed, and with incredible precision, but they can also modify themselves to a level too complex for human comprehension.

II. ARTIFICIAL INTELLIGENCE USED AS A HIRING TOOL

In recent years, especially in light of the post COVID-19 world, developers have increasingly marketed AI technologies for use in making employee hiring decisions. These developers tout that using AI technologies, such as in the form of resume screening or one-way interviews for pre-employment testing can "enhance efficiency and enable data-driven judgments."[25] For example, AI hiring technologies have the ability to screen a stack of resumes in a matter of seconds, compared to the hours an employer would spend reviewing the same stack. Some predict that reviewing resumes can take up to twenty-three hours to fill one position.[26] In a professional world where every second seems to matter, this saves valuable time and decreases costs associated with resume review. These technologies are also endorsed as a way to avoid racial and gender discrimination since implicit human bias is said to be cut out.[27] An employer implementing AI

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18. Tobias Baer & Vishnu Kamalnath, *Controlling Machine-Learning Algorithms and Their Biases*, MCKINSEY & CO. (Nov. 10, 2017), https://www.mckinsey.com/capabilities/risk-and-resilience/our-insights/controlling-machine-learning-algorithms-and-their-biases#/.

19. Jason Brownlee, *Data, Learning and Modeling*, MachineLearningMastery (Jan. 6, 2017), https://machinelearningmastery.com/data-learning-and-modeling/.

20. *Id.*

21. Nicholson, *supra* note 9.

22. *Id.*

23. David M. Skanderson, *Managing Discrimination Risk of Machine Learning and AI Models*, 35 A.B.A. J. LAB. & EMP. L. 339, 342 (2021).

24. *Id.*

25. Vinay Johar, *Artificial Intelligence In Hiring: A Tool for Recruiters*, FORBES (June 10, 2022, 8:15 AM), https://www.forbes.com/sites/forbesbusinesscouncil/2022/06/10/artificial-intelligence-in-hiring-a-tool-for-recruiters/?sh=51234fd13200.

26. Emily Heaslip, *AI In Resume Screening: Expectations vs. Reality*, VERVOE (Jan. 4, 2023), https://vervoe.com/ai-in-resume-screening/.

27. Aaron Rieke & Miranda Bogen, *Help Wanted: An Examination of Hiring Algorithms, Equity, and Bias*, UPTURN (Dec. 2018), https://www.upturn.org/static/reports/2018/hiring-algorithms/files/Upturn%20--

hiring technology may feel confident that their business is protected from lawsuits over employment discrimination based on these assurances. However, using AI to assist in making hiring decisions opens up a whole new set of complicated legal issues that may still leave the business "on the hook" for employment discrimination, despite seemingly cutting out human decision-making.

Various AI hiring assistance systems are available for businesses to use in making hiring decisions. These systems vary in the data used to create a hiring algorithm. Some businesses may choose traits and experiences possessed by their current employees as their starting data to train the hiring algorithm whereas others may rely on training data that includes a wider pool of employees from several similar competing companies.[28] Regardless of which option a business settles on, the model will begin its training by assessing employee candidates to coincide with past employment decisions.[29] To best replicate past employment decisions, AI algorithms will use various characteristics to attempt to discern whether a potential candidate will be a good hire. Commonly, job-relevant attributes such as education, prior employment, or certifications will be drawn from a candidate's resume or application and imputed into the AI algorithm.[30] Additionally, the algorithm may acquire other types of data from various sources, some of which are unlikely to be job-related.[31] These attributes include social media profiles, criminal history, and even web browsing history.[32] Using such a wide range of attributes to compare job candidates may cause the algorithms to have "a very high dimensionality," where some of the algorithm inputs have no clear connection to job performance.[33] Using all of this data, and trying to connect it all, may lead to hindsight bias because the algorithm may conclude one of two things—(1) certain characteristics equate to successful job performance, rather than being a mere correlation; or (2) characteristics that have previously led to successful hires will lead to future successful hires.[34] This makes using algorithms in job hiring decision issues significantly more complex than traditional employee selection tools because what were previously implicit choices when hiring are now made explicit, and in a way that can be incredibly difficult to decipher and resolve.

Simply put, we do not have a metric of what makes for a good employee.[35] Is the most successful hire necessarily the smartest, most productive, most creative, or the best leader from the stack of resumes?[36] Moreover, what data points used by an AI system are considered the most

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%20Help%20Wanted%20-
%20An%20Exploration%20of%20Hiring%20Algorithms,%20Equity%20and%20Bias.pdf.

28. Drew Harwell, *A Face-Scanning Algorithm Increasingly Decides Whether You Deserve the Job*, WASH. POST (Nov. 6, 2019, 12:21 PM), https://www.washingtonpost.com/technology/2019/10/22/ai-hiring-face-scanning-algorithm-increasingly-decides-whether-you-deserve-job/ ("The best candidates, in other words, end up looking and sounding like the employees who had done well before the prospective hires had even applied.").

29. Manish Raghavan & Solon Barocas, *Challenges for Mitigating Bias in Algorithmic Hiring*, BROOKINGS (Dec. 6, 2019), https://www.brookings.edu/research/challenges-for-mitigating-bias-in-algorithmic-hiring/.

30. Scherer *supra* note 14, at 493.

31. *Id.*

32. *Id.*

33. *Id.*

34. Jack Hensler, *Algorithms as Allies: Regulating New Technologies in the Fight for Workplace Equality*, 34 TEMP. INT'L & COMPAR. L.J. 31, 43-44 (2019) (using the example of a data set containing gender but not college majors in an employee evaluation).

35. *See* Lori Andrews & Hannah Bucher, *Automating Discrimination: AI Hiring Practices and Gender Inequality*, 44 CARDOZO L. REV. 145-53 (2022).

36. *Id.*

important traits to ensure a successful hire?[37] It is incredibly difficult, even for an overly complex AI algorithm, to predict the traits that ensure job success and may lead to the classic "correlation does not equal causation" issue. For example, the "best" employees in a company may all have the experience of previously being a Boy Scout listed on their resume. An AI system that is constantly trying to figure out the most ideal algorithm to hire employees with may assume that being a Boy Scout is a trait that lends itself to success since all the best employees share it.[38] However, while the experience of being a Boy Scout may show desirable employment traits such as hard work, perseverance, and versatility—being a Boy Scout on its own is likely unrelated to performing a job well. In addition, an AI system that focuses on experiences such as Boy Scouts causes a potential gender discrimination issue. There very well may be scenarios in which the "best" employees share an experience or trait that is exclusive to one gender or race because the existing workforce lacks diversity.[39] An AI system will use traits that are shared by those top employees to assist in hiring decisions and may unknowingly create results that also lack diversity by attempting to find successful top candidates that match the already undiversified workforce.[40] This example highlights a concern rarely considered when utilizing AI technologies to assist in the hiring process.

III. ARTIFICIAL INTELLIGENCE HIRING TOOLS

AI is commonly used in three stages of the hiring process: (1) sourcing, (2) screening, and (3) interviewing.[41] This Note will next discuss hiring tools in which AI systems are commonly implemented and the potential issues that may arise when using each AI tool. The tools discussed are resume screening and one-way interviews.

A. Resume Screening Tools

In March 2023, the United States Bureau of Labor Statistics reported that there were approximately 10.8 million job openings in the United States.[42] This number significantly exceeds the unemployment rate, which was 3.6% as of February 2023, equating to approximately 5.9 million unemployed people.[43] This imbalance can lead to frustration in job recruitment as there are more job openings than unemployed persons, many of which may not fit a job description. On average, a job recruiter receives 250 resumes for a single position with only around twelve percent meeting the desired requirements for the position.[44] This means that a lot of time and effort is used to sort through resumes, resulting in wasted money since most of the resumes being reviewed do not fit the job description. To increase efficiency, more companies are turning to AI resume screening tools to quickly screen out unqualified or undesired candidates. Resume screening tools typically fall into one of three categories.[45] First, a resume screener can be

37. *Id.*

38. *Id.*

39. Ketki V. Deshpande, Shimei Pan & James R. Foulds, *Mitigating Demographic Bias in AI-Based Resume Filtering*, 28 UMAP ADJUNCT: ADJUNCT PUBL'N OF THE 28TH ACM CONF ON USER MODELING, ADAPTATION AND PERSONALIZATION 268, 269 (2020).

40. Rahgavan, *supra* note 29.

41. Heaslip, *supra* note 26.

42. U.S. Dep't of Lab. *The Employent Situation—March 2023*, BUREAU OF LAB. STAT. (Apr. 7, 2023, 8:30 AM), https://www.bls.gov/news.release/pdf/empsit.pdf.

43. *Id.*

44. Heaslip, *supra* note 26.

45. *Id.*

keyword-based, where the AI algorithm searches for "keywords, phrases, and patterns" in a candidate's resume or job application.[46] Second, a resume screener can be grammar-based, where the AI algorithm uses inputted grammatical data to break down words and phrases to understand what the candidate is attempting to say in their resume or job description.[47] Finally, a resume screener can be statistical-based, where the algorithm screens resumes by searching for desired numerical values such as addresses and timeline dates.[48] A human developer will decide in advance which words, phrases, grammar patterns, or numbers should be included in the job applications. From here, the AI algorithm will determine whether an applicant should be rejected or moved to the next stage in the hiring process. The benefits of using AI to screen resumes include improving the candidate shortlist, reducing implicit human bias, and allowing small businesses to hire at scale.[49]

However, the negatives associated with resume screening tools are numerous. Overall, resumes are well known to be a poor representation of an applicant's true ability.[50] This issue is only exasperated by the infusion of gender, racial, ethnic, geographic, socioeconomic, and age biases that are apparent in all three categories of resume screening.[51] Using resume screening tools has become a double-edged sword in terms of bias. On the one hand, it reduces the unconscious bias that may intrude into hiring decisions when made without the assistance of AI.[52] On the other hand, a level of human touch is needed when reviewing resumes to understand differences that may arise from being a minority. Differences such as educational attainment, time gaps in job history, or the terminology used in a resume are often unaccounted for in the screening algorithms causing qualified candidates to be "vetted out" of the hiring process because their resume does not match the exact criteria used by the AI algorithm.[53] Harvard Business School and professionals from Accenture conducted a joint study in 2021 and found that approximately twenty-seven million people have been stopped by AI resume screening from gaining full-time employment.[54] The study additionally reported that eighty-eight percent of the employers surveyed reported that "qualified high-skills candidates were vetted out of the process because they did not match the exact criteria established by the job description."[55] The percentage rose to ninety-four percent for intermediate-skilled candidates.[56] Improper "vetting out" of the hiring process is so prevalent because AI systems do not possess the human capability to

46. *Id.*

47. *Id.*

48. *Id.*

49. Heaslip, *supra* note 26 ("AI tools help level the playing field for small businesses to compete with larger enterprises.").

50. *Id.*

51. *Id.*

52. *Id.*

53. Joseph B. Fuller, Manjari Raman, Eva Sage-Gavin & Kristen Hines, *Hidden Workers: Untapped Talent*, HARV. BUS. SCHOOL 25 (Oct. 4, 2021), https://www.hbs.edu/managing-the-future-of-work/research/Pages/hidden-workers-untapped-talent.aspx.

54. Yellow Stephen Jones, *AI Tools That Companies Use to Scan Resumes Are Stopping 27 Million People Finding New Jobs, a Harvard Report Says*, BUS. INSIDER (Sept. 8, 2021), https://www.businessinsider.com/ai-recruitment-tools-cv-scanners-automated-hiring-overlook-hidden-workers-2021-9.

55. Fuller, *supra* note 53.

56. *Id.*

understand context clues.[57] For example, time gaps on an applicant's resume are commonly red flags for the algorithm, oftentimes resulting in an automatic rejection. However, if a human were reading the same resume, a suburban address, a distant graduation year, or volunteer experience at an elementary school may create the assumption that the applicant is a woman who took a job break to raise children.[58] But to an AI resume screening algorithm, all that is factored in is the work experience time gap, causing what was otherwise a qualified applicant's resume to go to the bottom of the pile, potentially never being seen by a human recruiter.

Additionally, resume screening can also enhance discrimination based on differences in language. Different cultures can result in differences in language that we inherently use.[59] For example, an applicant of Asian descent is more likely to use "we" rather than "I" on their resume when describing a previous job because Asian cultures are socialized to think of the collective whole, rather than the individual self. However, a white applicant is more likely to use "I" when talking about similar experiences. Therefore, an algorithm trained using resumes from one culture group may be biased towards candidates who use similar language, especially when the algorithm is keyword- or grammar-based.[60] While there are benefits to using resume screening tools, such as efficiency and a decrease in implicit human biases, if not properly used, an AI resume screening algorithm can create more substantial problems than the ones the tool sought to alleviate. Even the most minuscule detail, like a difference in personal pronouns, can result in a highly qualified applicant being denied by an AI resume screening tool.

B. One-Way Interview Tools

In addition to resume screening tools, AI is commonly used in connection with one-way interview systems. Also referred to as asynchronous interviews, one-way interviews allow job candidates to answer predetermined questions through recorded answers without a human on the other line of the conversation—ultimately increasing the efficiency of recruiters and human resources professionals in reviewing applicants.[61] One-way interview tools incorporate AI to analyze whether an applicant may possess certain desirable traits, such as creativity, strategy, discipline, drive, outgoingness, assertiveness, persuasiveness, stress tolerance, or optimism.[62] Once the one-way interview is recorded, the AI algorithm can search for these traits through the video components, the audio components, or the written transcript of the interview.[63] The benefits of using one-way interviews in the hiring process are that they offer flexibility to the recruiter and candidate, accommodate remote candidates, create a baseline to compare candidates, allow more of the hiring team to be involved in the hiring process, and give candidates the opportunity to have some control over the image they present to the employer.[64]

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57. Andrews, *supra* note 35, at 170 ("Discrimination can also result from the lack of context in resume scanning.").

58. *Id.* at 171.

59. *Id.*

60. Heaslip, *supra* note 26.

61. Sam Blum, *One-Way Video Interviews are Impersonal, Candidates Say and Raise Privacy Concerns*, HR BREW (Apr. 25, 2022), https://www.hr-brew.com/stories/one-way-video-interviews-bias.

62. Andrews, *supra* note 35, at 175.

63. Harwell, *supra* note 28.

64. Tamara E. Holmes, *The Pros and Cons of One-Way Video Interviews*, LINKEDIN (July 19, 2022), https://www.linkedin.com/business/talent/blog/talent-acquisition/pros-and-cons-of-one-way-video-interviews (It seems odd that utilizing AI to conduct one-way interviews can lead to more of the hiring team to be involved in the process but one-way interviews allow recruiters and hiring managers to all review the same video, compared to relying on the notes of those who sat in on an interview.).

The benefits of using a one-way interview tool need to be weighed against the disadvantages of using the tool. Once an employer decides to use a one-way interview tool, the algorithm developer can customize an algorithm by recording existing employees and favoring applicants whose traits match those considered successful.[65] There is a risk in creating an algorithm based off of existing employees because the AI algorithm may then "discount" applicants who "look, speak, express, dress, or present themselves differently from the existing employees."[66] An employer could run into the issue of trying to configure how appearance, voice, or expressions correlate to job success. A neuroscientist who studies emotion described AI one-way interview tools as "worryingly imprecise in understanding what those movements actually mean and woefully unprepared for the vast cultural and social distinctions in how people show emotion or personality."[67] These components are still potential issues when the AI algorithm makes decisions through transcribed text. The AI algorithm makes determinations based off of minor details in an applicant's linguistic style. An applicant's linguistic style includes their "directness or indirectness, pacing and pausing, word choice, and use of such elements as jokes, figures of speech, stories, questions, and apologies."[68] Differences in linguistic styles arise from different cultural and gender norms and can impact a job applicant negatively if their linguistic style doesn't match that of the existing employee sample.

The risk of discrimination, especially gender discrimination, is heightened when using one-way interview tools, where the algorithm is created in a male-skewed workforce.[69] The tech industry is an example of an area where one-way interview tools may give way to gender discrimination. According to data provided by the following companies, in 2018, men made up 81% of Microsoft's technical workforce, 79% of Google's, 78% of Facebook's, and 77% of Apple's.[70] If a one-way interview tool was trained using the existing workforce as its data sample, the algorithm may presume that male traits like "being tall, wearing a tie, or having a deep voice" are traits correlated with job success.[71]

IV. STATE OF THE LAW

Title VII of the Civil Rights Act is the leading federal law behind employment discrimination. Enacted in 1964, Title VII prohibits a wide range of discriminatory conduct—including employment discrimination based on race, color, religion, sex, and national origin.[72] Discriminatory actions in the workforce include refusing to hire an applicant, discharging an employee, refusing to promote an employee, or demoting an employee based on any of the categories listed above.[73] The two theories that make up Title VII are disparate treatment and disparate impact.

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65. Harwell, *supra* note 28. ("To train the system on what to look for and tailor the test to a specific job, the employer's current workers filling the same job—"the entire spectrum, from high to low achievers"—sit through the AI assessment, Larsen said.").

66. Andrews, *supra* note 35, at 177.

67. Harwell *supra* note 28.

68. Deborah Tannen, *The Power of Talk: Who Gets Heard and Why*, HARV. BUSINESS REV. (Sept. – Oct. 1995), https://hbr.org/1995/09/the-power-of-talk-who-gets-heard-and-why.

69. *Id.*

70. Andrews, *supra* note 35, at 151.

71. Andrews, *supra* note 35, at 177.

72. Civil Rights Act of 1964, 42 U.S.C. § 703(a)(1).

73. Civil Rights Act of 1964, 42 U.S.C. § 703(b).

A. Disparate Treatment

The theory of disparate treatment arises from Title VII section 703(a), which prohibits employers from taking adverse action against an employee or applicant "because of" a protected category.[74] The language of section 703(a) lacks a requirement of an employer's intent to discriminate, rather, it prohibits all discrimination "because of such individual's race, color, religion, sex, or national origin."[75] The lack of a required element of explicit intention has created, and continues to create, ambiguity over Title VII's scope.[76] Even though there is no requirement of explicit intent, the overwhelming majority of disparate treatment case law focuses on intentional discrimination in the workplace.[77] These disparate treatment cases commonly follow the framework established in *McDonnell Douglas Corp. v. Green*, which allows plaintiffs to make an inference of intent without direct evidence of discriminatory animosity.[78] The use of circumstantial evidence to establish an inference of discrimination is almost necessary in the modern workplace because, in most employment discrimination cases, there is no direct evidence of discriminatory intent. Very rarely is there an employment discrimination case with a "smoking gun" demonstrating that the employer used a protected class as the justification for "an adverse employment action."[79]

B. Disparate Impact

While disparate treatment focuses on direct employment discrimination, often intentionally proven through circumstantial evidence, disparate impact occurs when "policies, practices, rules or other systems" appear to be neutral on their face but result in a discriminatory impact on a protected class under Title VII.[80] *Griggs v. Duke Power Co.* created the theory of disparate impact. The Supreme Court held that Title VII not only intended to prohibit openly discriminatory workplace practices but also intended to prohibit workplace policies that seemed neutral yet in practice discriminated on the basis of race, color, religion, sex, or national origin.[81] The majority stated:

> The objective of Congress in the enactment of Title VII is plain from the language of the statute. It was to achieve equality of employment opportunities and remove barriers that have operated in the past to favor an identifiable group of white employees over other employees. Under the Act, practices, procedures, or tests neutral on their face, and even neutral in terms of intent, cannot be maintained if they operate to 'freeze' the status quo of prior discriminatory employment practices.[82]

In *Griggs,* while the Court expanded the coverage of Title VII to cover what is often seen as unintentional discrimination, they also offered employers more protection through the

74. Civil Rights Act of 1964, *supra* note 72.

75. *Id.*

76. Joseph A. Seiner, *Disentangling Disparate Impact and Disparate Treatment: Adopting the Canadian Approach*, 25 YALE L. & POL'Y REV. 95, 96 (2006).

77. Scherer, *supra* note 14, at 459.

78. McDonnell Douglas Corp. v. Green, 411 U.S. 792, 802 (1973).

79. Scherer, *supra* note 14, at 459.

80. *What are Disparate Impact and Disparate Treatment?*, SHRM, https://www.shrm.org/resourcesandtools/tools-and-samples/hr-qa/pages/disparateimpactdisparatetreatment.aspx (last visited Apr. 12, 2023).

81. Griggs v. Duke Power Co., 401 U.S. 424, 435-36 (1971).

82. *Id.* at 429-30.

establishment of the business necessity defense.[83] Seemingly neutral policies that have discriminatory results are considered Title VII violations unless the policies are "shown to be related to job performance" or to "business necessity."[84] The employers in *Griggs* were unable to demonstrate that possession of a high-school diploma and satisfactory scores on two aptitude tests was a business necessity, so despite seemingly neutral requirements, Title VII prohibited those requirements in order to remove the discriminatory results that arose through these requirements.[85]

Griggs introduced the framework to support the disparate impact theory*,* which was later established in *Albemarle Paper Co. v. Moody.* The first step in a successful disparate impact claim is for the complaining party to "[make] out a prima facie case of discrimination, i.e. has shown that the tests in question select applicants for hire or promotion in a racial pattern significantly different from that of the pool of applicants."[86] The Court in *Albemarle* did not establish whether "significantly different" was meant to refer to a statistical equation or more of a colloquy.[87] The Uniform Guidelines on Employee Selection Procedures adopted a colloquial definition for "significantly different" when they adopted a "four-fifths" rule.[88] Under this rule, "a selection rate for any race, sex, or ethnic group which is less than four-fifths (or eighty percent) of the rate for the group with the highest rate will generally be regarded by the Federal enforcement agencies as evidence of adverse impact, while a greater than four-fifths rate will generally not be regarded by Federal enforcement agencies as evidence of adverse impact."[89] Case law generally rejects the Uniform Guidelines "four-fifths" rule and instead tests "significantly different" using a statistical test.[90] *Hazelwood School District v. United States* stated that a statistical difference "of more than two or three standard deviations" between the expected and actual number of protected class employees would make the policies claiming to be neutral, suspect.[91] Since *Hazelwood* was decided, courts have ordinarily used a statistical significance around the five percent level rather than relying on the standard established in Hazelwood, which lacks precision.[92] Other courts still attempt to determine significant differences in a colloquial sense. In *Ricci v. DeStefano*, the Court mentions that a prima facie case of disparate impact requires proof of a statistically significant disparity and "nothing more."[93] While statistical analysis seems to be favored in determining whether there is a significant difference, these cases show that case law is not even close to establishing a uniform statistical analysis to determine whether there is a "significant difference" in the disparate impact analysis. When looking at the first step of the disparate impact analysis in terms of AI algorithms, the employee is favored.[94] Even the smallest difference in the selection algorithm can produce a "significantly different" result, especially when a court uses some sort of statistic to determine if there is a "significant difference" between "the expected and actual

83. *Id.* at 431.

84. *Id.* ("The touchstone is business necessity. If an employment practice which operates to exclude Negros cannot be shown to be related to job performance, the practice is prohibited.").

85. *Id.* at 436.

86. Albemarle Paper Co. v. Moody, 422 U.S. 405, 425 (1974).

87. *Id.*

88. 29 C.F.R. § 1607.4(D) (2019).

89. *Id.*

90. Scherer, *supra* note 14, at 463.

91. Hazelwood School District v. United States, 433 U.S. 299, 308 (1977).

92. Scherer, *supra* note 14, at 463.

93. Ricci v. DeStefano*,* 557 U.S. 557, 587 (2009).

94. Scherer, *supra* note 14, at 464.

number of protected class employees."[95] This potential issue for employers only increases as their data sets increase, even if the differences connect very loosely to the applicant pool.[96]

If a plaintiff is able to establish a prima facie case of disparate impact employment discrimination, the burden then shifts to the employer. The employer can rebut the prima facie case by showing that the practice in question is "job related for the position in question and consistent with business necessity."[97] The Civil Rights Act of 1991, the statutory text that enshrined job relatedness and business necessity, did not clarify if job relatedness differs, if at all, from the business necessity doctrine—nor did the case law that preceded the statutory text.[98] However, similar text appears in the Americans with Disabilities Act, which was enacted one year prior to the Civil Rights Act of 1991 and has been used to decipher the meaning of job relatedness and business necessity.[99] While the judicial interpretations of job relatedness and business necessity are sparse, the common theme that arises in the materials is that both concepts "require linking the selection criteria to specific, articulable, and important job functions."[100] This tells employers that courts are likely to look to the validity of the selection procedures to rebut a prima facie case of disparate impact employment discrimination. *Albemarle Paper* gave employers some idea of what the court should look to in terms of validity when it appeared skeptical of the usefulness of generic or subjective measures of performance to validate selection criteria.[101] The Court stated:

> There is no way of knowing precisely what criteria of job performance the supervisors were considering whether each of the supervisors was considering the same criteria or whether, indeed, any of the supervisors actually applied a focused and stable body of criteria of any kind. There is, in short, simply no way to determine whether the criteria actually considered were sufficiently related to the Company's legitimate interest in job-specific ability to justify a testing system with a racially discriminatory impact.[102]

The Equal Employment Opportunity Commission ("EEOC"), a group that drafts uniform guidelines meant to help employers comply with federal employment law, published three types of validity that it deems should be acceptable when analyzing the selection procedures.[103] The first is criterion-related validity, which looks at the correlation between performance in the selection procedure and performance on the job.[104] The second validity type is content validity,

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95. *Id.* at 463.

96. Ricci v. DeStefano, 557 U.S. 557, 587 (2009).

97. Title VII of the Civil Rights Act of 1964, 42 U.S.C. § 2000e-2(k)(1)(A)(i) (2012).

98. *Id.*

99. Americans with Disabilities Act of 1990, 42 U.S.C. § 12112(b)(6) ("Using qualification standards, employment tests or other selection criteria that screen out or tend to screen out an individual with a disability or a class of individuals with disabilities unless the standard, test or other selection criteria, as used by the covered entity, is shown to be job-related for the position in question and is consistent with business necessity"; According to case law, ADA regulations, and Equal Employment Opportunity Commission Guidelines the Title VII provision is closely connected to the ADA's inquiry into whether an individual is able to perform the "essential functions" to the position.).

100. Scherer, *supra* note 14, at 467.

101. Albemarle Paper Co. v. Moody, 422 U.S. 405, 433 (1975).

102. *Id.*

103. 29 C.F.R. § 1607.14(B) (2019).

104. 29 C.F.R. § 1607.14(B)(3) (2019).

which requires employers to design a test that sufficiently stimulates job performance.[105] The third validity type is construct validity, which measures more abstract characteristics that are deemed important to job performance.[106] All three of these acceptable validity tests seem to stress the importance of proper criteria in the selection procedure. However, conducting an appropriate criterion-related validity study is a major feat, even for the most sophisticated employers.[107] Despite all the emphasis on proper criteria, even the most sophisticated criterion-related validity tests have imperfections that can lead to discriminatory results.[108] Many legally acceptable validity tests still lack a relation to true indicators of success, such as productivity. Instead, the validity tests tend to relate more minuscule predictors of job success, such as work attitudes to the overall goal of hiring the best candidate.[109] An AI algorithm that is focused on less important job success indicators is likely to produce undesirable results. If an AI algorithm is latching onto unimportant factors in relation to job success because of how the initial data is fed to the algorithm, it will have difficulty being able to weigh the important considerations fully and correctly in the hiring process. In addition, the algorithm may instead put weight into things that are irrelevant for finding the ideal candidate—including elements that may be considered discriminatory. The difficulty in having an AI algorithm put proper weight into different factors is why relying on human judgment in the hiring process is still not fully a thing of the past.

Even if the defendant-employer is able to establish job relatedness and business necessity, the employee is not out of luck. An employee may prevail in their claim if they can show "that other tests or selection devices, without a similarly undesirable racial effect, would also serve the employer's legitimate interest in efficient and trustworthy workmanship."[110] The third stage of the disparate impact discrimination analysis has been relatively confusing, and courts have typically strayed away from deciding disparate impact discrimination cases because of the uncertainty of the relevant legal standards.[111] This confusion is only heightened when AI algorithms come into the picture. AI algorithm models trained on biased samples or undiversified features are likely to have a less discriminatory alternative.[112] While proving a less discriminatory alternative, creating an algorithm that ignores discriminatory data, or gives less weight to it will almost always be possible. However, issues regarding how much less discriminatory the alternative must be and how employees and employers would be able to sort through the complex AI data to show or rebut the alternative have still not been resolved.[113] Because a plaintiff can almost always create a less discriminatory algorithm but may not be able to prove its improved results, it seems like the third step of the disparate impact analysis becomes futile when analyzing AI hiring tools.

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105. 29 C.F.R. § 1607.14(C) (2019) ("Users choosing to validate a selection procedure by a content validity strategy should determine whether it is appropriate to conduct such a study in the particular employment context.").

106. *Id.*

107. Scherer, *supra* note 14, at 481.

108. Winfred Aruthur Jr., Suzanne T. Bell, Dennis Doverspike, & Anton J. Villado, *The Use of Person-Organization Fit in Employment Decision Making: An Assessment of Its Criterion-Related Validity*, 91 J. OF APPLIED PSYCH. 786, 787 (2006).

109. *Id.*

110. Albemarle Paper Co. v. Moody, 422 U.S. 405, 425 (1975).

111. Scherer, *supra* note 14, at 509.

112. Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 710.

113. *Id.*

V. COMPLICATIONS AND GAPS WITH THE CURRENT STATE OF THE LAW

A. Archaic Employment Discrimination Laws

It has proven difficult to fit the complexities of AI hiring tools into federal employment law. The rules and tests governing employee selection procedures, established between the 1960s and 1990s, have remained largely unchanged.[114] Despite the development of AI since its inception in 1950, the laws have not evolved to harness AI's power in the hiring process. Even with outdated laws that don't seem to cover AI hiring tools, it is not just theoretical to think that an AI hiring tool could violate the existing employment laws. Until rules and tests that are catered more towards AI algorithms are established, employers and employees are forced to try and fit a complex AI issue into the current law's established parameters—which although complicated and imperfect, is possible. For example, you can take judicial statements found in the benchmark cases described above and apply them to an AI algorithm situation. The majority in *Griggs* explained that an employer must demonstrate that the hiring metrics have a "manifest relationship to the employment in question" and a "demonstrable relationship to successful performance of the jobs for which it is used."[115] This was enough for a court to hold that an employer's hiring mechanism, which favored previous military service or participation in shop classes, was not "a reasonable measure of job performance" and had a disparate impact on women.[116] However, under the current laws, an employer might still have the advantage when attempting to clear the job-relatedness and business necessity test. For example, seemingly discriminatory aspects, such as favoring an individual who was on a football team, can show leadership abilities and team skills.[117] Or a time gap on a resume may show an individual is not career-devoted.[118] When a court is trying to decipher whether scenarios like these pass muster as being job-related, it becomes complicated for the court to answer in the negative—especially when there are unresolved questions of how the AI algorithm is taking these aspects into account and how much emphasis the algorithm puts on these aspects compared to others.

B. Employment Discrimination Laws that do not Account for Complex Algorithms

An added complication of the current state of employment laws is that they don't account for how complex AI algorithms are. The complex and constantly changing nature of AI algorithms makes it difficult for employees and employers alike to discern an AI's decision and why it came to that decision.[119] It is incredibly difficult to see how an employee would be able to establish a prima facie case of employment discrimination when they can't see how or why an algorithm came up with its scores, rankings, or recommendations.[120] Plaintiffs will have difficulty determining how the discriminatory output has been generated, making a showing of a prima facie case

114. *See generally* Title VII of the Civil Rights Act of 1964, 42 U.S.C. § 2000 (1964).

115. Griggs v. Duke Power Co., 401 U.S. 424, 430-31 (1971).

116. Bailey v. Se. Area Joint Apprenticeship Comm., 561 F. Supp. 895, 913 (N.D.W. Va. 1983).

117. *Id.*

118. *Id.*

119. Gregory Barber, *Shark or Baseball? Inside the 'Black Box' of a Neural Network*, WIRED (Mar. 6, 2019), https://www.wired.com/story/inside-black-box-of-neural-network/#:~:text=By%20inserting%20a%20postage%2Dstamp,a%20whale%20was%20a%20shark.&text=It's%20true%2C%20Olah%20says%2C%20that,ways%20of%20causing%20such%20mayhem ("Just as humans can't explain how their brains make decisions, computers run into the same problem.").

120. *Id.*

difficult when AI algorithm attributes are "not capable of separation for analysis."[121] This may suggest that employers cannot be held liable for employment discrimination. Ironically, it is just as difficult to see how an employer would be able to defend a lawsuit when they cannot decipher the final results of the algorithm if an employee were to make out a prima facie case. Due to the complexity of AI algorithms, it is difficult to predict if an employee or an employer suffers the greater disadvantage from the current imbalance in employment law. Someone who believes AI algorithms carry less of a risk than human judgment in making neutral hiring decisions may point to the overall objective difficulty in deciphering the algorithm and how it is favorable to a human's implicit and subjective bias.[122] However, an AI tool cannot take the stand in an employment discrimination case to explain their decisions. While human judgment is imperfect, a human risks having to explain their decisions under oath. In addition, humans leave behind a paper trail, often in the form of emails or text messages, that can be used to add support to an explanation of a decision. An AI hiring tool may also leave a paper trail, but it will be in the form of incredibly complex computer code. A subjective human, and their decisions, may be preferred to an AI algorithm when the algorithm's discriminatory decisions are nearly impossible to decipher or explain.

C. Employer's Inability to Modify the Artificial Intelligence Hiring Tool

Even if an employer is successful in designing an AI hiring tool that has no discriminatory disparate impacts during its initial training and algorithm basis, it is inevitable that disparate impacts may "creep in" as the characteristics of applicants and successful employees are inputted into the algorithm, forcing the algorithm to adapt.[123] Employers are then put in the position where they must determine how to manage these adverse impacts, with the adjustments reduced to computer code that would have to be explained in litigation, likely by an expert witness. Making changes to account for adverse impact after an AI hiring tool has been deployed can also be problematic. In *Ricci v. DeStefano*, the court held that while there was a well-intentioned effort to correct bias in an employee test, the fact that the employer made an employment decision based on a protected class amounts to disparate treatment and a violation of Title VII.[124] The employer in this case decided not to certify the results of a pre-employment test because the test disadvantaged minority applicants.[125] Subsequently, White and Hispanic applicants, who likely would have been promoted based on the test results sued the city alleging that the employer's refusal to certify the results constituted disparate treatment discrimination in violation of Title VII.[126] *Ricci's* holding creates a catch-22 for employers, where inaction to mitigate disparate treatment liability leaves them vulnerable to a Title VII claim, attempting to mitigate the

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121. 42 U.S.C. § 2000e-2(k)(1)(B)(i) (2012).

122. Kimberly A. Houser, *Can AI Solve the Diversity Problem in the Tech Industry: Mitigating Noise and Bias in Employment Decision-Making*, 22 STAN. TECH. L. REV. 290,332, 352 (2019).

123. *Id.* at 332, 496 ("Given the manner in which disparate-treatment case law has developed, concerns have been raised regarding whether companies might be effectively immune from disparate treatment liability if they use algorithmic selection devices that learn, without any express human programming, to classify workers in a discriminatory manner on the basis of protected characteristics.).

124. Ricci v. DeStefano, 557 U.S. 557, 579 (2009) ("Whatever the City's ultimate aim—however well-intentioned or benevolent it might have seemed—the City made its employment decision because of race. The City rejected the test results solely because the higher scoring candidates were white. The question is not whether that conduct was discriminatory but whether the City had a lawful justification for its race-based action.").

125. *Id.* at 578.

126. *Id.* at 579.

disparate impact could also subject them to a Title VII claim.[127] The only avenue the Court left open to mitigate discriminatory impact is to make modifications to account for adverse impact towards a protected class prospectively.[128] The Court stated that "once the process has been established and employers have made clear their selection criteria, they may not then invalidate the test results, thus upsetting an employee's legitimate expectation not to be judged on the basis of race."[129] The holding in *Ricci* can be extended to protected classes other than race. This holding proves substantially more complicated when applied to AI hiring tools because it seems like the direction an algorithm takes is out of the employers' hands. Even when adverse impact "creeps in" to the algorithm, an employer is stuck in the "catch-22" and unable to attempt to put effort into modifying the algorithm when it takes an undesired turn towards discriminatory results.[130] That is, if the employer can even recognize what aspect of the algorithm is creating a disparate impact and determine how to modify a complex algorithm.[131]

VI. REGULATION OF ARTIFICIAL INTELLIGENCE USED AS A HIRING TOOL

This Section will lay out three potential ideas to resolve the complications using AI poses in the employment law sphere: redefining the disparate impact analysis, identifying a clear target, and a disclosure and waiver policy.

A consideration discussed in other scholarly pieces on this topic that is worth mentioning is redefining the first step in the disparate impact framework, the establishment of a prima facie case. Instead of placing the heart of the analysis of a prima facie case in determining whether the hiring tool makes selections that are "significantly different" than the pool of applicants, the first step should become a rule of reason test.[132] It is clear from the stark differences in case law attempting to define "significantly different," nobody really knows how to analyze the first test. In addition, since the first test doesn't fully fit in today's hiring landscape and tools used in the hiring process, courts should allow a plaintiff to establish a prima facie case of disparate impact by "producing evidence demonstrating that the gap between protected groups is large enough to give a reasonable employer concern that the algorithmically generated model may be disproportionately disadvantaging members of a protected group."[133] I believe this consideration could be helpful in reducing the unknown of how to interpret the first step of the disparate impact framework, but I don't believe it goes far enough in protecting both parties in fighting the complexities that the use of AI hiring tools has introduced. Instead, this idea is worthy of being a temporary solution for answering how courts should interpret the established disparate impact framework while the true solution is established in legislation or in EEOC Guidelines specifically designed for the use of AI hiring tools. I propose that legislation and EEOC guidelines focus on identifying a clear target and creating a disclosure-waiver rule to ease two of the largest complications created by AI algorithms.

A complication that must be resolved through legislation or EEOC guidelines is who can and should be held liable when an AI-algorithm goes astray and has discriminatory results, despite an employer's best effort to create an objectively neutral algorithm. The entire point of using an AI hiring tool is to take desired characteristics and reduce them to a data set, which is inputted

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127. *Id.* at 629.

128. *Id.* at 585

129. *Id.*

130. Scherer, *supra* note 14, at 475.

131. *Id.* at 456.

132. *Id.* at 503.

133. *Id.* at 501.

into an algorithm, shielded from subjective human bias. However, this objective algorithmic process does not work unless the algorithm assesses the applicants in a uniform manner.[134] This means the undesired, yet consistent, effects of using an AI algorithm are entrenched into the algorithm. In turn, these undesired effects may cause an employer who ensures that their hiring algorithm does not use a protected characteristic as an input when assessing a job applicant but are rendered helpless when the algorithm effectively reconstructs the protected class characteristics through encodings and assesses all applicants with this algorithm, despite the algorithm modifying itself in a discriminatory way. The question then arises of how we can legally hold an employer liable when they did everything in their power to create an unbiased, anti-discriminatory algorithm and it resulted in disparate impact discrimination that cannot be comprehended or recreated by a human decision maker. The challenge here differs from strict liability situations found in other areas of the law, where defendants are held at fault despite their intention not to cause an injury, because here, the human has no impact on the result whatsoever. In these situations, even though a human developed the algorithm and knew the starting points of the algorithm, a human would have no input past this point and wouldn't be capable of deciphering or comprehending how the data is being interpreted in the algorithm. Despite the acknowledged undesirable results that will occur in some situations, the only option is to hold the employer liable for the results of their algorithm. The only rationale for this decision is that the employer chose to use an algorithm, despite the risks, over the alternative of subjective human judgment and in turn must be liable for their decision. However, I propose employer protection be established in connection with a uniform employer-liability law regarding AI algorithms.

While both types of discrimination under Title VII can arise in AI hiring algorithms, disparate impact discrimination is likely more common. The current disparate impact framework is unsustainable for AI hiring tools. As previously stated, this is because there is legal ambiguity in how courts should analyze the third step of the disparate impact framework (alternative selection procedures). In terms of AI algorithms, it is not impossible to imagine a scenario where a plaintiff is able to generate an algorithm with equal or better accuracy that has less of a disparate impact just through its imputed basis data and lack of time for the algorithm to really evolve on its own. This creates an unfair situation for employers who did everything in their power to create a neutral application, which turned discriminatory in ways too complex for humans to comprehend. A plaintiff's identification of an algorithm with equal or better accuracy and less disparate impact should not be able to defeat an employer's business necessity defense when the employer discloses its use of AI hiring tools. Disclosure of the use of AI hiring tools should serve as a "waiver" of a plaintiff's ability to prevail if the employer is able to prove job-relatedness or business necessity. Under a policy of disclosure, an employer would be permitted to use AI hiring tools so long as they disclose to the applicants what technology they are using and at what steps of the hiring process AI is being used.[135] An example of disclosure-based legislation is the Illinois Artificial Intelligence Video Interview Act. Passed in 2019, the law requires an employer to secure an applicant's consent before using AI tools to analyze a one-way video interview.[136] The law states that an employer who uses AI in this situation must "provide each applicant with information before the interview explaining how the artificial intelligence works and what general types of characteristics it uses to evaluate applicants."[137] An ideal disclosure law would be structured similarly to the Illinois Video Interview Act, but be more general to include any AI used at any

134. *Id.* at 495.

135. Andrews, *supra* note 35, at 195.

136. Artificial Intelligence Video Interview Act, 820 ILL. COMP. STAT. 42/1-4/20 (2020).

137. *Id.*

stage of the hiring process. If an employer obtains the consent of the applicant, the applicant should waive their rights to show an alternative in an attempt to defeat a defendant's business necessity claim. We should not subject an employer to disparate impact discrimination liability for a valid test constructed using established methods simply because a plaintiff "chances onto a more accurate and less discriminatory model later."[138] This would not hinder an injured party from bringing a disparate impact discrimination claim as they could still establish a prima facie case, but it would protect employers who are burdened with the complex results of their AI algorithm.

Conclusion

As of the writing of this paper, there is no movement in legislation towards resolving the complications AI has caused in the employment sphere, despite AI's popularity growing each day. Creating laws and tests which identify a clear target and implement a disclosure and waiver rule is imperative in ensuring AI hiring tools fit squarely into the established employment discrimination framework.

138. Scherer, *supra* note 14, at 511.