Automatic Employment Decision Technology Analysis with Focus on Bias Against Those with Disabilities

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Abstract

In this paper, we analyze if a lack of accommodations and accessibility features in AI/ML in HCM/TA is causing screen-out harm to candidates with disabilities. We collected and explored data for 30 AI companies that offer HCM/TA products. Specifically, we looked at the information they made public regarding their accommodations and accessibility features related to their AI products. We also collected and categorized further information on the size of each company, the specific products being offered, if they conduct bias testing, and if the company has accessibility staff. We found a majority of companies in our study do not offer accommodations in their AI products and are not actively addressing candidates with disabilities in the public eye which can lead to screen-outs and can harm candidates with disabilities even before the involvement of human bias.

Introduction

In 2021, persons aged 16 to 64 with a disability had more than double the rate of employment for typically abled people at 10.8%[1]. Persons with disabilities are the largest minority group in the United States, but often have the least representation.This has been an ongoing issue that disability activists feel has been exacerbated with the rapid growth of some technologies. In general AI systems are marketed as being objective and helping to reduce or eliminate bias, however traditional bias testing often ignores those with disabilities and related issues around screen-out, when companies even attempt to tackle these issues. Many companies do not even opt to perform bias testing, as will be explored herein.

There are two main types of Algorithmic Decision-Making Tools used in the HCM/TA industry; “Resume/Profile Screening” and “AI Video Screening.” Resume Screening uses Natural Language Process(NLP) algorithms to search for keywords and grammar which are used to pick to rank candidates. Previous studies like STUDY_NAME, have already found gender based biases in AI systems, which indicated that these systems do not perform as advertised and fail to be objective along some vectors of discrimination. For example, if a resume contains keywords like "Women’s Honors Society" the algorithm could rank a candidate lower. This tends to be the fault of poor training data for these algorithms, the lack of a diverse dataset can lead to screen outs and poor representation. Some algorithms use current employees’ resumes as training data, which may only create an algorithm that reflects that built-in hiring biases the algorithm was built to subvert. Though companies have attempted to address and solve this issue by removing these stop words[2] before running the text through the algorithm, there is little data or discussions on whether NLP algorithms are negatively impacting candidates with disabilities. Profile screening often uses recommendation systems with simpler and more transparent parameters, based on https://www.pnas.org/doi/10.1073/pnas.1915006117 ?. AI Video screening uses Convolutional Neural Networks (CNN) which are network architectures for deep learning to find patterns in images to recognize objects, faces, and scenes. Because CNNs can automatically identify the key features without the need for manual feature extraction, there is a lack of explainability with these models. Emotion recognition systems are particularly worrisome when it comes to CNNs, which attempt to determine a person's emotions from their body language and facial expressions. "Developments in the biometrics and emotion AI market are immature. They may not work yet, or indeed ever." - NIST. This is concerning and should be alarming for typically able individuals but can be more overtly detrimental for individuals with disabilities.

WARNING	99% of Fortune 500 companies had AI tools somewhere within their hiring plans

The Americans with Disabilities Act (ADA) states that "Screen out because of a disability is unlawful if the individual who is screened out is able to perform the essential functions of the job, with a reasonable accommodation if one is legally required". Some examples are Gamification, AI video interview software, and Chatbots without providing accommodations. These AI technologies affect candidates with different disabilities in various ways. Some "gamified" tests maybe present an advantage for some neurodivergent candidates but not for others candidates with physical disabilities. AI video interview software can negatively impact both neurodivergent and physical disabilities candidates. For example, an algorithm may not recognize a candidate with a speech impairment, or for neurodivergent candidates face reading software may score them low for not showing socially acceptable facial expressions. The lack of employees with disabilities in the technology industry contribute to the proliferation of these technologies and an increase in screen-outs. In 2020, the percentage of persons with a disability making $75k or more a year was 40.01% less than those without a disability[3]. There is a significant gap of representation among higher paying careers and screen-outs caused by AI hiring technology creates a larger gap.

Methodology of Study

Code implementation

First we created a 30 companies list of the top AI companies offering HCM/TA products including both well-know Fortune 500 companies and small start ups. Then we assessed what type of HCM/TA product(s) does the company offer such as video screening, resume/profile screening, and/or Chatbots. Further we invested if the company's website marketed their product as "Bias-Free" or or used similar language which is very concerning. Also we looked if there is public evidence of accessibility staff on the company's website or LinkedIn and has accommodations directly for the AI/ML software displays on their website.

Data Dictionary

Features	Values	Description
"Bias-Free"/No bias	1 = yes, 0 = no, 2=maybe	If yes, company's website displays the term "Bias-Free" or similar language, such as eliminates bias, in relation to company's AI/ML technology or AI/ML technology in general.

Features	Values	Description
Video Screening	1 = yes, 0 = no, 2=maybe	If yes, company's website displays that company integrates AI/ML screening algorithms in their TA/HR video software.
Resume/Profile Screening	1 = yes, 0 = no, 2=maybe	If yes, company's website displays that company integrates AI/ML screening algorithms on candidates resumes or profiles in their TA/HR software.
Chatbots	1 = yes, 0 = no, 2=maybe	If yes, company's website displays that company integrates Chatbots in their TA/HR software.
Addresses Physical Disabilities	1 = yes, 0 = no, 2=maybe	If yes, company's website addresses ways to assist and/or the benefits of hiring candidates with physical disabilities.
Addresses Neurodiversity	1 = yes, 0 = no, 2=maybe	If yes, company's website addresses ways to assist and/or the benefits of hiring neurodivergent candidates.
Public Accessibility Staff	1 = yes, 0 = no, 2=maybe	If yes, there is public evidence of accessibility staff on the company's website or LinkedIn.
Offers Accommodations	1 = yes, 0 = no, 2=maybe	If yes, company has accommodations directly for the AI/ML software
Immediate/Timeframe for Accommodations	1 = yes, 0 = no, 2=maybe	If yes, company gives immediate or a timeframe for when accommodations would be to candidates for AI/ML software.
Reports Bias Testing	1 = yes, 0 = no, 2=maybe	If yes, company states on the its website the company preforms a third Party audits or its own audits for bias in their AI/ML models. Note: this might not include bias testing for disability
Number of Total Staff	Small < 100, Medium < 1000, Large > 1001	Estimate total employee count on LinkedIn or other website

After data collection, we performed data exploration with categorical descriptive statistics, such as counts and frequencies, and decision tree. This gave us the ability to find trends and draw conclusions about our dataset and evaluate our hypothesis.

- Columns used as targets in the final model: 'Offers Accommodations_Yes'
- Type of models: Decision Tree Model
- Software used to implement the model: Python on colab, 'sklearn', 'numpy', 'pandas', 'time', 'matplotlib.pyplot', and 'matplotlib.lines'.
- Version of the modeling software:'python 3.7.15','numpy 1.18.5', and 'pandas 1.0.5
- Code implementation

Results and Discussion

- Layout major questions as bullets
    - Q1: How do smaller companies compare to the whole sample?

	‘Bias-Free'/No bias	Video Screening	Chatbots	Resume/Profile Screening	Addresses Physical Disabilities	Addresses Neurodiversity	Public Accessability Staff	Offers Accommodations	Reports Bias Testing
Yes	-8.34	5.00	-1.66	-5.0	-15.0	-18.33	-16.67	-16.67	-28.34
No	11.67	-3.33	5	5	15	18.33	16.67	23.33	31.67
Maybe	-3.33	-1.67	nan	nan	nan	nan	nan	nan	-3.33

        - In the pivot table above we can see in our dataset small companies which have lees than 100 employees vary on performance. For example, smaller companies tended to market their products as “Bias-Free” less than larger companies, at a rate of 11.67% less. However, smaller companies performed worse on the majority of categories, including “offering accommodations,” “having accessibility staff,” “reporting bias testing.” This makes sense on its face, smaller companies with access to less resources would not prioritize these accommodations, however this does not excuse such behavior.
    - Q2: Do companies that don’t offer accommodations perform poorly across other categories/features? -WIP
    - Q3: Does a disparity exist between companies mentioning neurodiversity on their website versus physical disabilities? / Does a company addressing neurodiversity make them more likely to offer disability accommodations versus when a company addresses physical disability?

Addresses Physical Disabilities	Addresses Neurodiversity	Offers Accommodations	Company ID
No	No	Maybe	0
		No	15
		Yes	0
	Yes	Maybe	2
		No	2
		Yes	4
Yes	No	Maybe	0
		No	2
		Yes	0
	Yes	Maybe	0
		No	4
		Yes	1

Addresses Physical Disabilities	Addresses Neurodiversity	Offers Accommodations	Count
No	No	Maybe	0
		No	15
		Yes	0
	Yes	Maybe	2
		No	2
		Yes	4
Yes	No	Maybe	0
		No	2
		Yes	0
	Yes	Maybe	0
		No	4
		Yes	1

- As shown in table 3, we can clearly observe that half of our companies in the sample do not address physical disabilities or neurodiversity and do not offer accommodations of any kind. However, we can also see that for the companies that do offer accommodations, they only address neurodiversity. There is only one company out of the sample that addresses both physical disabilities and neurodiversity. Another interesting observation is that four companies that do not offer accommodations address both physical disabilities and neurodiversity.
    - Q4: If a company reports bias testing is it more likely that they offer accommodations?

	Offers Accommodations
Yes	27.27%

	Offers Accommodations
No	54.55%
Maybe	18.18%

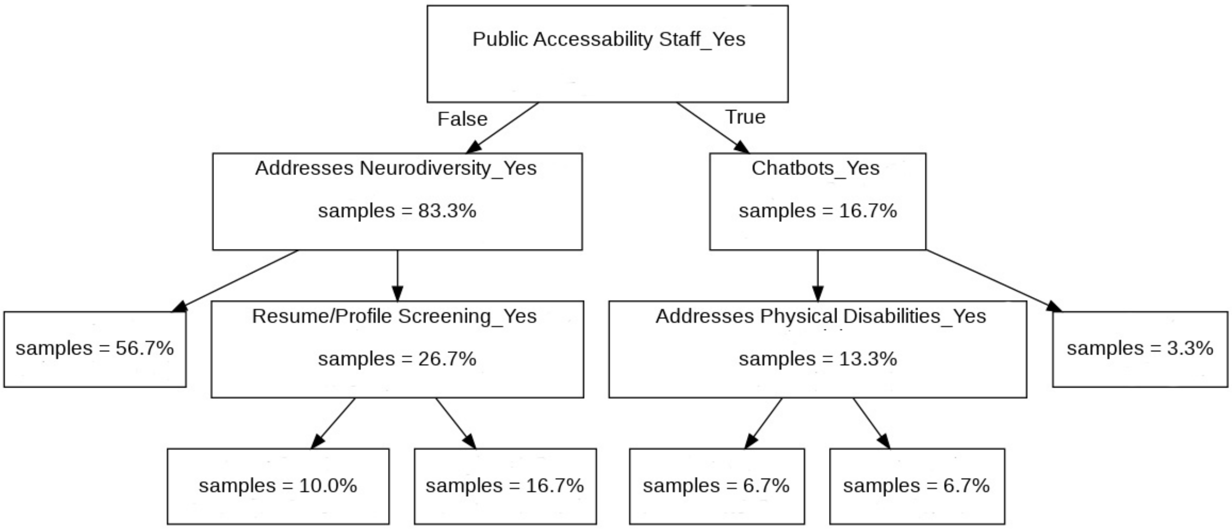
- In table 4 we see an interesting trend in companies reporting bias testing and offering accommodations. Out of the companies that do bias testing, the majority of those (54.55%) do not offer accommodations.
    - Q5: What percentage of companies offer AI/ML video screening, without any accommodations?

	Offers Accommodations
Yes	16.67%
No	83.33%
Maybe	0%

- In table 5, companies which offer AI/ML video screening 83.33% do not offer accommodations. This is particularly concerning because video screening is an AI technology that can severely impact candidates with disabilities. Relying so heavily on this one method can lead to screen outs.
    - Q6: What percentage of companies that offer accommodations also offer them immediately or provide a timeframe? (leading to screen out)

	Immediate/Timeframe for Accommodations
Yes	40.00%
No	40.00%
Maybe	20.00%

- In table 6 we see that only 40% of companies that offer accommodations offer these accommodations immediately or provide a timetable. Immediately providing accommodations or offering a timeframe can significantly reduce the chance of screen outs because the candidate is less likely to get passed by candidates that do not required accommodations.
    - Decision Tree



Conclusions and Recommendations

Over the course of this study we investigated if the lack of accommodation and accessibility features in AI/ML and HCM/TA is causing screen-out harm to candidates with disabilities. After our analysis, there is clear evidence that AI companies who produce HCM/TA products have the capability to improve their accessibility features and shrink the gap of screen-outs for candidates with disabilities. It's inherent that companies need to offer accessibility features and accommodations however it's deeper than that. Only offering accommodations does not necessarily mean the risk of screen-out is significantly less. The timeframe of applicants receiving approval for those accommodations can play a prominent role in job opportunities, information sharing could assist with this concern. By information sharing we mean the sharing of voluntarily given personal data between public entities or other organizations for a specific goal through the exchange, collection, use, or disclosure. This would provide candidates with disabilities the opportunity to input information about their disabilities and needed accommodations to a government database. When a candidate requests accommodations the AI company can connect to that database and automatically grant accommodations to the candidate immediately. This would have to come with some regulation like audits conducted by the government to ensure companies are not using this information to do disparate treatment.

Companies have the responsibility to market their products correctly and avoid misleading language such as "Bias-free" if it does not actually apply. Moreover, we recommend that companies conduct bias-testing and include candidates with disabilities to avoid disparate impact. Especially bias testing for resume/profile screening and other systems that rely more on AI/ML processes, since accommodations are not as applicable in these circumstances. To mitigate the risk of producing biased outcomes, companies should collect demographically representative training data, sample and reweigh training data, reconsider dictionaries for stopwords, and consider fairness metrics when selecting hyperparameters and cutoff thresholds. Companies should also have an opt-out option for selection methods like having a live interview and/or not permitting companies to use an algorithm in their decision-making process. Product or comparative testing with those who have disabilities is also recommended to iterate a company's prototype. This is especially important for companies that do not have the resources for specific accessibility staff. Furthermore, employing a diverse design team is important in producing a more inclusive and accurate product. Teams with employees who have disabilities have 72% more productivity and produce 30% higher profit margins.[4] Companies should always refer to the NIST's Standard for

Identifying and Managing Bias in Artificial Intelligence when designing any AI products.

References

Issuing Authority This technical assistance document was issued upon approval of the Chair of the U.S. Equal Employment Opportunity Commission., and This technical assistance document was issued upon approval of the Chair of the U.S. Equal Employment Opportunity Commission. “The Americans with Disabilities Act and the Use of Software, Algorithms, and Artificial Intelligence to Assess Job Applicants and Employees.” US EEOC. Accessed November 28, 2022. https://www.eeoc.gov/laws/guidance/americans-disabilities-act-and-use-software-algorithms-and-artificial-intelligence.

Appendix

[1] https://www.bls.gov/news.release/disabl.a.htm

[2] Stop words are words that are filtered out of a stop list before or after natural language data processing because they are irrelevant.

[3] https://data.census.gov/table?q=Disability&tid=ACSST5Y2020.S1811

[4] https://www.accenture.com/_acnmedia/pdf-89/accenture-disability-inclusion-research-report.pdf