**Automated Employment Decision Tools and Ableism:**

**A Critical Analysis with Recommendations**

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This study examines the potential for harm to job seekers with disabilities due to inadequate accommodations and accessibility features in automated employment decision tools (AEDTs) based on artificial intelligence or machine learning (AI/ML). Data was collected and analyzed from 30 organizations offering such AEDTs, focusing on publicly available information regarding accommodations and accessibility features, organizational size, specific products offered, bias testing practices, and accessibility staff. Most organizations in the study do not offer accommodations in their AI/ML-enabled AEDT products and are not actively addressing the needs of candidates with disabilities. Worse, some AEDT providers misrepresent their tools with claims of “bias-free” decision-making or offer employment assessments based on questionable video analysis approaches. These findings align with broader concerns about the potential for screen-out discrimination and other harms as a result of flaws in the design and implementation of AEDTs.

CCS Concepts: • Social and professional topics → People with disabilities; • Human-centered computing;

Additional Key Words and Phrases: Automated Employment Decision Tools, Bias, Screen-out

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1. INTRODUCTION

In 2021, individuals in the United States (US) aged 16 to 64 with disabilities had an unemployment rate of 10.8%, more than double that of individuals without disabilities.[1] In 2020, the percentage of persons with a disability earning $75,000 or more a year was 40.01% less than those without disabilities.[2] Diminished workforce representation has been a persistent concern for disability activists, and some fear this trend may be exacerbated with the rapid advancement of automated employment decision tools (AEDTs) based on artificial intelligence or machine learning (AI/ML).[[1]](#footnote-1)[2, 3] Yet, nearly all Fortune 500 organizations have AI/ML tools and AEDTs in their talent acquisition technology plans.[4]

Examples of AEDTs include resume screening based on natural language processing (NLP), gamification of hiring interviews and processes, AI/ML-based video interview analysis, and interview chatbots. AEDTs affect candidates with disabilities in different ways, in the worst case, perpetuating a kind of digital ableism. For example, some gamified employment tests may not be designed to accommodate neurodivergent candidates or candidates with physical disabilities. AI video interview software can also negatively impact both neurodivergent candidates and those with physical disabilities. In addition to other bias and validity concerns,[5] AI/ML video analysis algorithm may not recognize a candidate with a speech impairment or reduce the score of neurodivergent candidates based on atypical facial expressions. Shockingly, some AI video analysis algorithms are known to diagnose candidates as disabled.[2]

AEDTs are often marketed as objective, and as a means to reduce or eliminate bias. At least five of the products surveyed are misrepresented as “bias-free,” or are described with similar verbiage. But official guidance from the US National Institute of Standards and Technology (NIST) points out “it is not possible to achieve zero risk of bias in an AI system.”[5] Even for the small number of examined vendors that acknowledge an attempt to measure systemic bias in their offerings with statistical testing, physical design, graphical user interfaces (GUI), or other features can present difficulties for users with disabilities and lead to subsequent screen-out discrimination, where certain populations are unfairly disqualified from employment opportunities.[[2]](#footnote-2) While screen-out discrimination is a significant concern for impacted communities, often leading to adverse social and financial outcomes, screen out is also a potentially serious legal liability for employers operating AEDTs. 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."[2]

Graphical user interface, text, application

Description automatically generated

Fig. 1. A clipping from an AEDT vendor website. Bias-free is a striking claim given that official guidance from NIST recently stated this is not possible for AI systems.[5] Five vendors in the study use similar language on their websites.

In an effort to highlight the prevalence of screen-out discrimination risks due to AEDTs and to contribute to the broader dialog around AI/ML, AEDTs, and bias against those with disabilities, this study presents straightforward summary information related to 30 AEDT offerings, covering accommodations and accessibility features, organizational size, specific products offered, bias testing practices, and accessibility staff. Section [2](#methodology) outlines data collection. Analysis in Section [3](#analysis) indicates that some vendors appear to be actively addressing screen-out discrimination risks, while most are not. Section [4](#conclusion) closes this paper with recommendations for AEDT developers based on presented results and authoritative guidance.[[3]](#footnote-3) Appendix [A](#appenix_a) presents visual summaries of collected data, and for improved reproducibility, the GitHub repository https://github.com/xxxxxx/aedt-analysis contains anonymized data, scripts for analysis, and other related artifacts.

1. DATA COLLECTION

A broad search resulted in a list of 30 software vendors, including well-known companies and smaller start-ups, offering AI/ML-enabled AEDTs with data regarding their characteristics available for examination via public channels like websites and LinkedIn. No formal sampling methodology was applied as identifying large numbers of AEDT vendors that affirmatively acknowledge the use of AI/ML proved challenging. The sample represents a good faith effort to create a snapshot of the AI/ML AEDT vendor market, and the tools in this study are likely applied to millions of people each year.[[4]](#footnote-4) However, the sample should not be considered exhaustive and may suffer from sampling bias, despite the authors’ best efforts to create a representative dataset for analysis. A description of the compiled data is presented in [Table 1](#tb1) and a summary of results is available in Figure [A.1](#figa1).

Table 1: Dictionary for complied data.

| AEDT Characteristic | Assigned Values | Description |
| --- | --- | --- |
| "Bias-Free"/No bias | 1 = yes, 0 = no, 2=maybe | If yes, organization’s website displays the phrase "Bias-Free" or similar language, such as “eliminates bias,” in relation to organization’s AEDT offering(s) or AI/ML technology in general. |
| Video Screening | 1 = yes, 0 = no, 2=maybe | If yes, organization’s website declares that organization integrates AI/ML video screening algorithms in their AEDT offering. |
| Resume/Profile Screening | 1 = yes, 0 = no, 2=maybe | If yes, organization’s website declares that organization integrates AI/ML text screening algorithms for candidates’ resumes or profiles into their AEDT offering(s). |
| Chatbots | 1 = yes, 0 = no, 2=maybe | If yes, organization’s website declares that organization integrates chatbots into their AEDT offering(s). |
| Addresses Physical Disabilities | 1 = yes, 0 = no, 2=maybe | If yes, organization’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, organization’s website addresses ways to assist and/or the benefits of hiring neurodivergent candidates. |
| Accessibility Staff | 1 = yes, 0 = no, 2=maybe | If yes, there is public evidence of accessibility staff on the organization’s website or LinkedIn profile. |
| Offers Accommodations | 1 = yes, 0 = no, 2=maybe | If yes, organization mentions accommodations specifically for AEDT offering(s). |
| Immediate/Timeframe for Accommodations | 1 = yes, 0 = no, 2=maybe | If yes, organization provides immediate accommodations or a timeframe for when accommodations are made available for candidates subject to the AEDT offering(s). |
| Reports Bias Testing | 1 = yes, 0 = no, 2=maybe | If yes, organization states that it has submitted to a third-party audit or performs its own audits for bias in their AEDT offering(s). Note that such audits may not fully address bias testing for those with disabilities. |
| Number of Total Staff | Small ≤ 100,  100 < Medium ≤ 1000, Large > 1000 | Estimated total employee count. |

LinkedIn was used to determine the approximate size of the organizations, and to understand whether any staff with experience in software accessibility was associated with each firm. The type of software features offered by each organization’s AEDT(s) was then assessed, typically from the vendors’ websites. Software features considered included video screenings, resume or profile screening, and chatbots. The text of the website was examined for key phrases such as “eliminate bias” or “bias free,” and for references to statistical bias testing, accommodations, the timeliness of accommodations, text specifically addressing physical disabilities, and text specifically addressing neurodivergent candidates. Organization size was categorized as small, medium, and large. All other AEDT characteristics were coded with a simple rubric: 2 for partial evidence of the characteristic (“maybe”), 1 for affirmative evidence of the characteristic (“yes”), and 0 for no evidence of the characteristic.

1. ANALYSIS

Section 3 investigates five pertinent aspects of AEDTS and their relationship to screen out risks. To understand possible relationships between vendors who engage in statistical bias testing and those that offer accommodations for their AEDTs, [Table 2](#tb2) presents the percentage of AEDT vendors that offer accommodations, out of those that report bias testing. Given the questionable validity of video employment assessments, and their potential relationship to screen out risks, [Table 3](#tb3) summarizes the intersection between vendors who offer video assessments and vendors who offer accommodations. As smaller organizations may have a more difficult time developing and supporting accessibility features, [Table 4](#tb4) compares smaller organizations to medium and larger size organizations across various AEDT attributes. [Table 5](#tb5) presents summary information about organizations that appeared to offer no accommodations for their AEDTs. Because neurodivergent candidates and candidates with physical disabilities may face different bias and stereotyping harms during the application process and may require different types of accommodations, [Table 6](#tb6) presents a summary comparison of organizations in terms of whether their AEDT offerings or public documentation address neurodivergent candidates or those with physical disabilities.

The majority of AEDT vendors (76.67%) do not address accommodations on their websites or in public documentation. Market dynamics and regulation may enable vendors to pass this responsibility onto employers, small vendors may lack resources to support the necessary staff or additional system functionality, and some vendors may be unaware of screen out risks. Since some vendors provide or address accommodation, some vendors are themselves large employers, and because accommodations are a direct mitigant for screen out risks, much of the following analysis focuses on the relationships between various vendor characteristics, AEDT features, and whether a vendor offers accommodations.

Bias testing on the part of a vendor should indicate some awareness of AI/ML bias issues. But [Table 2](#tb2) displays that most vendors in the study who report bias testing, do not offer accommodations. Out of the organizations that report bias testing, the majority (54.55%) do not offer accommodations, indicating that organizations that are aware of, or that conduct, statistical bias testing are often not addressing screen out discrimination.

Table 2: Vendors that report bias testing grouped by whether they also offer accommodations.

| Vendors that Report Bias Testing | |
| --- | --- |
| Accommodations: **Yes** | 27.27% |
| Accommodations: **No** | 54.55% |
| Accommodations: **Maybe** | 18.18% |

[Table 3](#tb3) highlights the potential for screen out discrimination arising from employment video screening for candidates with disabilities. AI/ML video screenings present myriad challenges for candidates with disabilities (in addition to their questionable scientific underpinnings and potential for other bias harms). Unfortunately, the vast majority of AEDT vendors who offer video screenings do not offer or address accommodations for those with disabilities who may be unfairly disqualified by these screenings.

Table 3: Vendors that offer video screening grouped by whether they also offer accommodations.

| Vendors that Offer Video Screenings | |
| --- | --- |
| Accommodations: **Yes** | 16.67% |
| Accommodations: **No** | 83.33% |
| Accommodations: **Maybe** | 0% |

The data presented in [Table 4](#tb4) highlights differences between small vendors with less than 100 employees and larger organizations. It is evident that smaller vendors tend to market their products as "Bias-Free" at a lower rate (11.67%) compared to larger organizations, despite the fact that larger organizations should have more resources and better access to compliance, legal, marketing and scientific expertise. When examining other categories such as *Offers Accommodations*, *Accessibility Staff*, and *Reports Bias Testing*, data indicate that smaller organizations perform less favorably, and resource advantages may enable larger vendors to better facilitate accommodations for candidates with disabilities.

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Table 4: Comparison of smaller organizations to medium and large organizations.

| Percent Differences Between Small and Larger Vendors | | | | | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Bias-Free'/No bias | Video Screening | Chatbots | Resume/  Profile  Screening | Addresses Physical Disabilities | Addresses Neurodiversity | Accessibility Staff | Offers Accommo-dations | Reports Bias Testing | Bias-Free'/No bias |
| **Yes** | 8.34 | -5.00 | 1.66 | 5.00 | 15.00 | 18.33 | 16.67 | 16.67 | 28.34 | 8.34 |
| **No** | -11.67 | 3.33 | -5.00 | -5.00 | -15.00 | -18.33 | -16.67 | -23.33 | -31.67 | -11.67 |
| **Maybe** | 3.33 | 1.67 | nan | nan | nan | nan | nan | nan | 3.33 | 3.33 |

[Table 5](#tb5) shows a surprising trend of the highest count performing better across other categories/features specifically not marketing their product as ‘Bias-Free'/No bias and conducting AI Video Screening.

Table 5: Organizations that don’t offer accommodations performance; To read this table start from the left most column and if a cell is blank then follow the first filled cell above

| Bias-Free'/No bias | Video Screening | Offers Accommodations | Count |
| --- | --- | --- | --- |
| Maybe | Maybe | Yes | 1 |
|  | No | No | 5 |
| No | Maybe | No | 2 |
|  | No | Maybe | 2 |
|  |  | No | 9 |
|  |  | Yes | 3 |
|  | Yes | No | 2 |
|  |  | Yes | 1 |
| Yes | No | No | 2 |
|  | Yes | No | 3 |

As shown in [Table 6](#tb6), we can observe that half of our organizations 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 organizations that do offer accommodations, most only address neurodiversity. There is only one organization out of the sample that addresses both physical disabilities and neurodiversity. Another interesting observation is that the four organizations that do not offer accommodations address both physical disabilities and neurodiversity.

Table 6: Neurodiversity vs. Physical Disabilities; To read this table start from the left most column and if a cell is blank then follow the first filled cell above

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

Note that Figure [A.2](#figa2) presents a simple decision tree, trained on the relatively small group of analyzed organizations, to predict whether an organization offers accommodations along with its AEDTs. While the decision tree should not be used as a generalizable predictive tool, it achieves high accuracy for the examined vendors. The tree presents some of the trends in the collected data as a flow chart, and maybe a helpful visual summary of overall findings.

1. RECOMMENDATIONS AND CONCLUSION

Cite/augment check against NIST AI RMF playbook and peatworks

Accessibility staff – main data driven contributor

After our analysis, there is clear evidence that AI organizations 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 important that organizations offer accessibility features and accommodations. However, issues go beyond accommodations. Only offering accommodations does not necessarily mean the risk of screen-out is significantly less. Specifically we recommend:

* Consideration of the timeframe of applicants receiving approval for accommodations. (Candidates need accommodations quickly.)
* Enabling information sharing could assist with accommodations. (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. Such information sharing may provide candidates with disabilities better opportunities to receive accommodations and do so in a timely manner, without having to request accommodations separately for each role.)
* Audits of AI/ML systems used in hiring for disparate treatment, disparate impact, screen out and other types of discrimination, particularly for resume/profile screening and other systems that rely more on AI/ML processes, since accommodations are not as applicable in these circumstances.
* Avoiding false and misleading language such as "bias-free" when describing AI/ML systems used in hiring.
* Organizations should collect demographically representative training data, sample and reweigh training data if necessary, and consider fairness metrics when selecting hyperparameters and cutoff threshold for employment decision making.
* Organizations should also have opt-out options for selection methods based on AI/ML. (E.g., providing a live interview in place of algorithmic evaluation.)
* Inclusion of those who have disabilities in product design, implementation, or testing. (This is especially important for organizations that do not have the resources for specific accessibility staff).
* Increased diversity in design teams. (This is important in producing more producing a more inclusive and accurate products. Teams with employees who have disabilities have 72% more productivity and produce 30% higher profit margins.[[9](#bib9)])
* Organizations should apply external, independent standards to the design of AI/ML systems to mitigate bias, e.g., [NIST's Standard for Identifying and Managing Bias in Artificial Intelligence](https://nvlpubs.nist.gov/nistpubs/SpecialPublications/NIST.SP.1270.pdf).[[10](#bib10)]

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APPENDIX A



Figure A.1: Frequency of all collected characteristics displayed as bar charts.

[Figure A.1](#fig1) summarizes collected data. Note that 23 of 30 (76.67%) vendors do not offer accommodations for job seekers with disabilities, 25 of 30 (83.33%) appeared not to employ accessibility staff, and 17 of 30 (56.67%) vendors do not provide accommodations for their AEDTS.

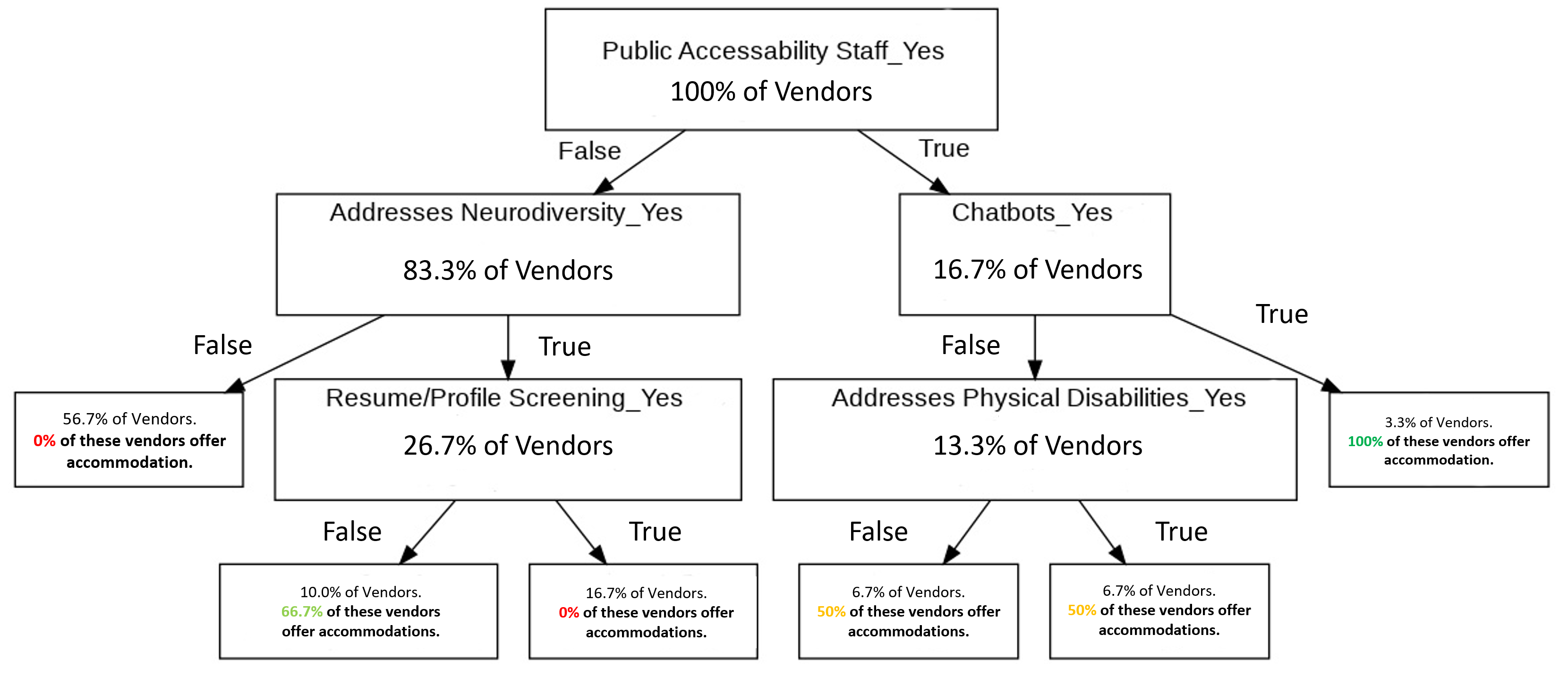


Figure A.2: Decision tree trained to predict whether a vendor offers accommodations (i.e., *Accommodation\_Yes = True*) as the prediction target. This figure is a data-driven flow chart that describes the conditions in the collected data that correlate with vendor offering accommodations.

The decision tree presented in [Figure A.2](file:///C:\Users\patrickh\Downloads\AEDT_ACM_submission.docx#fig2) provides several interesting observations. For example, the most likely combination of characteristics that contribute to a vendor offering accommodations is no public evidence of accessibility staff (*Public Accessibility Staff\_Yes = False*), addressing neurodiversity (*Addresses Neurodiversity\_Yes = True*), but not engaging in resume or profile screening (*Resume/Profile Screening\_Yes = False*). Two sets of characteristics appear most correlated to vendors not offering accommodations:

* A lack of evidence of public accessibility staff (*Public Accessibility Staff\_Yes = False*) and failing to address neurodiversity (*Addresses Neurodiversity\_Yes = False*).
* A lack of evidence of public accessibility staff (*Public Accessibility Staff\_Yes = False*), addressing neurodiversity (*Addresses Neurodiversity\_Yes = True*), and offering resume or profile screening features (*Resume/Profile Screening\_Yes = True*).

These observations should not be considered generalizable trends, rather concise summaries of characteristics of the examined vendors in the context of whether the vendor offers accommodations along with AEDTs.

1. An AEDT can be defined as ”any computational process, derived from machine learning, statistical modeling, data analytics, or artificial intelligence, that issues simplified output, including a score, classification, or recommendation, that is used to substantially assist or replace discretionary decision making for making employment decisions that impact natural persons.”[6] [↑](#footnote-ref-1)
2. Screen out discrimination occurs when “a disability prevents a job applicant or employee from meeting—or lowers their performance on—a selection criterion, and the applicant or employee loses a job opportunity as a result..”[3] Crucially, screen out can arise from physical mechanisms, interface designs, or other features that present unfair difficulties for those with disabilities. Even if vendors somehow attain demographic parity in assessment scores, screen out risks may not be adequately mitigated. [↑](#footnote-ref-2)
3. Results and guidance are validated, in part, by the author’s experience as a job seeker with a disability. [↑](#footnote-ref-3)
4. A single vendor in the study employees over 250,000 people, while another’s public customer list includes an employer of over 700,000, and several additional top worldwide employers. [↑](#footnote-ref-4)