Algorithmic Audits of HR-AI Tools in the United States

What Are HR Professionals' and Job Seekers' Perspectives?

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Abstract: *Algorithmic audits are gradually becoming more common, especially in the human resources (HR) sector. The use of Artificial Intelligence (AI) in HR and particularly regarding employment decisions is considered a high risk and can have long-term consequences for the affected stakeholders. In response to the risks involved, recent regulation in New York City and in the European Union requires audits of AI-based tools used in employment decisions. The market is responding by developing and offering a wide range of types of audits. While there is a growing amount of research centered on algorithmic audits in general and how they could be conducted and regulated, less research has focused on the perspectives on algorithmic audits of HR professionals and job seekers. This study aims to fill the gap in the literature by presenting research based on a survey conducted with 436 users of human resource AI tools (HR-AI tools), including 329 job seekers and 107 human resource managers and recruiters in the United States (U.S.) to learn about their perspectives. The survey shows substantial differences between the two stakeholder groups regarding knowledge of AI usage, trust in AI and HR-AI tools, and their knowledge and opinions with respect to algorithmic auditing. It also demonstrates the current general lack of information about algorithmic auditing and calls for more inclusion of all stakeholder groups in the future development of algorithmic auditing in the HR sector.*

Keywords: *AI; Human Resources; artificial intelligence; HR-AI tools*

Introduction/Background

Use of Artificial Intelligence in the Human Resource Sector

For our study, we understand human resource AI tools (HR-AI tools) as AI tools that are used to manage any part of an employee's life cycle (including recruiting, hiring, onboarding, training, evaluation, or promotional decisions).

Most of the current research in the field has focused on hiring decisions. The use of Artificial Intelligence (AI) tools for filtering and identifying suitable applicants has become increasingly common. Hilke Schellmann reports in her recent book "The Algorithm" that already 99% of Fortune 500 companies use algorithms and artificial intelligence for hiring (Schellmann 2024). AI tools influence who sees job offers, can be used to evaluate resumes, sometimes conduct job interviews, and may interact with job seekers in various other ways (Jarrahri et al. 2021; Li et al. 2021). Resume screeners, such as the one offered by Eightfold.AI[1], find candidates and provide ranked lists. They are often integrated into Applicant Tracking Systems (ATS) (Chavan et al. 2024). Some companies, like Hirevue[2], offer one-way interviews analyzed by AI. As a recent review on the use of AI in HR-management demonstrates, there is a wide range of different AI applications in the field (Bujold et al. 2024). While the use of AI in HR-management might lead to efficiencies and cost savings (Li et al. 2021), it can also lead to harmful results. Examples of potential harms are plenty and can be found in repositories of AI gone wrong.[3] Job seekers can be systematically excluded by algorithms because of age, sex, or other demographics (Chen 2023). Resume screeners might filter out candidates through variables that directly discriminate or by proxy variables (Raghavan 2020), and job interviews recorded and analyzed by AI have shown discrimination regarding race, religion, or other attributes, e.g., demonstrated in an experiment by a German TV station that tested AI used in automated interviews (Harlan & Schnuck 2021). In a famous case from 2023, a hiring algorithm from iTutor automatically excluded female applicants over 55 and male applicants over 60 and iTutor paid $ 365.000 to settle a hiring discrimination suit initiated by the Equal

1 https://eightfold.ai/use-case/candidate-screening/.

2 https://www.hirevue.com/.

3 https://incidentdatabase.ai/; https://www.aiaaic.org/home; https://airisk.mit.edu/ai-incident-tracker.

Employment Opportunity Commission (EEOC)[4]. The question of fairness regarding the use of AI in HR-decisions is raised by multiple researchers (Harlan & Schnuck 2021; Hunkenschroer et al. 2024; Rigotti & Fosch-Villaronga 2024). Though less researched, the use of AI-tools in other areas of the employment cycle can have similarly negative impacts. As a result of these potential negative outcomes, the use of AI for employment has been on the forefront of AI regulation and AI guidance.

Algorithmic Audits of HR-AI Tools

One way to ensure HR-AI tools provide what they promise to achieve and are trustworthy could be to have them audited. AI audits have been suggested increasingly in the literature as a useful way to create informed trust in AI (Mökander 2023, Mökander & Floridi 2021, Selinger 2023). Algorithmic audits are relatively new, even though Sandvig (2014) proposed the idea over a decade ago. Currently, many consider the situation in the algorithmic auditing ecosystem as the "Wild West" (Costanza Shock 2022; Lassiter & Fleischmann 2024). There is no one definition of an algorithmic audit, there are various ways to conduct algorithmic audits, and currently there is little regulation or standardization (Bandy 2021, Costanza-Shock et al. 2022, Goodman & Trehu 2023, Lam 2024, Raji et al. 2020, Selinger 2023). Recently, there were movements to change this, such as the formation of the International Association of Algorithmic auditors,[5] and there have been calls for common standards regarding algorithmic audits, for example from the National Telecommunications and Information Administration (NTIA 2024).

In our study, we aim to explore algorithmic audits in the widest sense. For this work, we follow the approach of the UK government, using it as an umbrella term describing any assessment of an algorithmic system which can be "*technical and non-technical measures that range from assessing organizational algorithmic governance policies to the specific data and models being used*" (DRCF 2022). This allows us to include a wide range of understandings regarding algorithmic audits. Auditing algorithms used in the human resource (HR) sector are particularly important as the decisions are highly consequential (Ajunwa 2020). Interest in algorithmic audits in HR is increasing (Dawson 2022, Lassiter & Fleis-

4 https://www.eeoc.gov/newsroom/itutorgroup-pay-365000-settle-eeoc-discriminatory-hiring-suit.

5 https://iaaa-algorithmicauditors.org/.

chmann 2024). Past experiences of voluntarily published audit reports regarding HR-tools have had mixed successes (Geiger et al. 2023), in particular the controversial audits from Pymetrics (Wilson 2021) and HireVue (Engler 2021). Recently, regulation has been introduced to require algorithmic audits in HR. The European AI Act (European Commission 2021) includes the recommendation to audit high-risk algorithms which include HR-AI tools. It also requires increased transparency requirements for high-risk AI systems such as employment decisions. If natural persons are directly interacting with an AI system, they need to be notified that they are interacting with an AI system (Art. 50 EU AI Act). The Digital Service Act (DSA) also requires assessments/audits (European Parliament 2022). In the US, the New York City (NYC) has taken further action specifically in the HR sector and has introduced the first law worldwide (Groves et al. 2024, Wright et al. 2024) to mandate AI bias audits for AI tools used for employment decisions (New York City Council 2022). The New York City Law 144 took effect in July 2023. It requires NYC-based employers who use automated employment decision-making tools (AEDTs) to hire a third-party auditor to conduct an annual bias audit and to make the audit report public (New York City Council 2022, Wright et al. 2024). In Section § 20–871 2 b of Law 144 it also requires a notice of the usage of an automated employment decision tool. The law went through several iterations before it was finalized. It is criticized because of its lack of defining key aspects leading to a failure to protect job applicants as intended (Groves et al. 2024, Fuchs 2023). Early research focusing on the implementation of Law 144 also found that only a small fraction of employers has conducted the required audits, most likely because of possible loopholes in the law, and additionally it was observed that records of the bias audits were of limited value for job seekers because of lack of accessibility and usability (Wright et al. 2024).

Research Focus

Our research is focused on algorithmic audits of HR-AI tools in the United States (U.S.) and how they could create calibrated trust of stakeholders who use the tools and/or are affected by them. Employment AI tools have been one of the first areas that have been explored by algorithmic audits, mainly due to the regulation by the NYC law. In anticipation of this regulation, algorithmic auditing companies prepared for the need for algorithmic audits in this sector and were most active in this area.

While there is a growing body of literature studying algorithmic audits in general and how they should be designed (e.g., Bandy 2021, Costanza-Shock et al. 2022, Goodman & Trehu 2022, Lassiter & Fleischmann 2024, Raji 2020), there is less research on the various stakeholders' perspectives on algorithmic audits. This lies in the nature of the matter. Algorithmic audits are not yet common, which explains the lack of experience with such audits. AI auditing professionals have also expressed that they have very limited knowledge about how their audits are received by end-users as they mostly focus on their relationship with the client who hires them to conduct an audit (Lassiter & Fleischmann 2024).

With this study, we aim to fill part of this gap by looking closer at the perspectives of users regarding algorithmic audits of HR-AI tools. We surveyed users of HR-AI tools and stakeholders affected by them to find out how much they know about algorithmic audits and how they feel about them. We chose to focus on the two stakeholder groups most impacted by HR decisions: human resource managers and recruiters (HR professionals) who use the tool to find employees and for other employment decisions, and job seekers, who are impacted by the tools by being the subject of them. It is important to look at these two stakeholder groups separately, as there is a notable power asymmetry between the two groups (Hunkenschroer 2023). While HR-professionals mostly have knowledge of the use of HR-AI tools, most job seekers will not know whether an HR-AI tool is used or not. Furthermore, several HR-professionals might have a choice to use AI for HR-decisions. Job seekers on the other hand, will most likely not be able to have a say in the use of HR-AI tools regarding their application. At the most, they might have an option to opt out, after being informed about the use of AI, for example in an automated job interview where the use of AI is obvious. In most circumstances, for example with resume screeners, they will not even know that there will be an AI decision. Furthermore, even if they knew that AI is used and would rather not have it used, they will not always opt out if they need to find a job.

Our research is guided by the following research questions (RQ):

1. How much do HR professionals and job seekers trust AI and HR-AI tools?
2. What do HR professionals and job seekers know about algorithmic audits?
3. What are HR professionals' and job seekers' perspectives on algorithmic audits of HR-AI tools?

Methods

Data Collection

The research results are part of a mixed method study in the U.S., exploring the opinions of users of human resource AI tools regarding algorithmic audits of such tools and how the latter can create trust in these tools. In previous research, we examined through an interview study with 19 AI auditing professionals how they aim to create calibrated trust in AI by users (Lassiter & Fleischmann 2024). This research was followed by a study surveying users of HR-AI tools on how algorithmic audits potentially influence their trust in AI in the HR sector.

Sampling Strategy

We conducted an online survey with 436 job seekers and human resource managers and recruiters (HR professionals) in the U.S. The survey was run in the fall of 2023 with purchased participant panels from Qualtrics[6] (requesting HR professionals with experience using HR-AI tools, and job seekers, defined as participants who are currently seeking a job or have recently been on the job market). Recruitment was undertaken by Qualtrics which sent out invitations to all potential participants. The survey resulted in 329 valid responses from job seekers and 107 valid responses from HR professionals.

Demographics

The participants on the job seekers side were overwhelmingly female (77% vs. 22% male and 2% non-binary/other). Thus, the sample includes a larger proportion of female participants than the population being sampled. According to 2023 data from the Bureau of Labor Statistics, around 55% of job seekers are male, and around 45% are female (BLS, 2023). An explanation for this discrepancy is that there is a general trend observed in online surveys where females are more responsive than males (Rourke & Lakner 1989, Smith 2008). As there were no significant differences between males and females in the responses seen when we separated the results according to gender, the gender distribution of participants does not present a challenge.

6 https://www.qualtrics.com/.

The detailed demographics of the participants are shown in table 2. About two thirds of the participants were between 25–54 years old, about 5% between 18 and 24, and about 29% were 55 and older. The participants were predominantly white/Caucasian (77%). Black/African American participants made up 11% of the sample, Hispanic 6%, Asian 3%, and Indian American/Native American or Alaska natives another 3% and others 1%. The educational background of the participating job seekers varied, with the majority having a 4-year or 2-year degree. All HR professionals have had experience with HR-AI tools, and we only included participants in this category who had at least a 4-year degree. Most job seekers were currently looking for a job (67%). The others have recently looked for a job (33%). We did not include anyone in the job seeker category who was not currently seeking a job or has not recently been on the job market.

Table 1: Demographics of participants

Demographics		**Job Seekers (329 total)**	**HR professionals (109 total)**	**Total**
Age	18–24	24	0	24
	25–34	55	27	82
	35–44	69	49	118
	45–54	65	19	84
	55–64	64	12	76
	Over 65	51	0	51
	Prefer not to say	1	0	1
Gender	Male	70	44	114
	Female	253	63	316
	Non-binary/third gender	5	0	5
	Prefer to self-identify	1	0	1
	Prefer not to say	0	0	0

Demographics		Job Seekers (329 total)	HR professionals (109 total)	Total
Race	African American or Black	37	19	56
	American Indian/ Native American, or Alasca Native	9	4	13
	Asian	12	4	16
	Hispanic/Latino	19	11	30
	Native Hawaiian, or Other Pacific Islander	1	2	3
	White or Caucasian	264	79	343
	Other	3	2	5
	Prefer not to say	1	0	1
Education	Some high school or less	6	0	6
	High school graduate or GED	54	0	54
	Some College	77	73	150
	2 year degree	52	34	86
	4 year degree	94	0	94
	Professional degree or graduate degree	42	0	42
	Other	3	0	3
	Prefer not to say	1	0	1

Survey Design

The survey contains 37 questions. The most relevant ones for this research are shown in table 1. The complete list can be found in the appendix. Most of the questions use a Likert scale of 1–5. Of these, 4 are attention check questions for validation. Following questions determining whether the participants are qualified for the study and demographic questions (Q1-Q8), we asked the participants about their experience and opinions regarding AI and HR-AI-tools. There are many different definitions of AI with no one settled standard. We provided a brief definition for the participants to have a common understanding of the concept for the purpose of this survey. In the survey, we explained to the participants that we understand Artificial Intelligence (AI) as: "*A machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations or decisions influencing real or virtual environments*", using the definition of the National Artificial Intelligence Initiative Act from 2020 (H.R. 6216). We explained HR-AI tools as "*AI tools managing any part of an employee's life cycle (including recruiting and hiring)*". We then asked the participants to rate their trust in AI in general (Q 9) and later their trust in HR-AI tools in particular (Q 15). Trust in HR-AI tools can be influenced by knowledge about use of AI and previous experience of AI. Therefore, the survey wanted to explore first the participants' knowledge of AI and then their previous experience with AI. All HR professionals had previous experience using HR-AI tools. This was a requirement for participation, as we wanted to focus on their experience as users knowingly using AI for their work. The same requirement was not made for job seekers, as we assume that many are not aware of the use of AI in HR. Therefore, Q11 specifically asks job seekers whether they were ever told about the use of AI regarding an HR-AI tool and how important it is for them to know AI is used (Q12). Building trust in HR-AI tools is likely based on the lived experience of the users with the tools. We therefore also wanted to explore the stakeholders' overall experience using the tools or being affected by them (Q 13, 14). To explore the perspectives of both stakeholder groups on algorithmic audits, we first wanted to know how much they know about these audits and what their experience with audits were (Q20, 21). We only asked HR professionals about their experience with algorithmic audits, as job seekers so far have very limited experience with algorithmic auditing.

The survey went through multiple iterations. In a pilot run, we tested a survey version without any explanations of AI auditing. In this first sample, most participants seemed to have not fully understood the concept of AI au-

dits. Their answers showed several inconsistencies and were not useful. In addition, participants also seemed to just have randomly answered questions to finish the survey quick. We adapted the survey accordingly and excluded data of low quality. Following a second successful pilot run, the survey questions were finalized. The most significant changes were adding an explanation of AI audits (Q19), and the addition of several validation questions (Q10, 16, 30 – see annex). After initially asking about the knowledge about algorithmic audits, we added a brief explanation of the basic concept and then continued with more detailed questions. We gave an operational definition of the term AI audit in Q19 by explaining: "*Since AI does not always work as expected or intended, in some cases, organizations audit AI, which checks to ensure that they comply with legal and ethical standards*." This description aims to not lead the answers of the participants too much but still gives them a very basic understanding of the concept. The question intends to elicit spontaneous reactions once the participants understand the basic concept. Validation questions have been shown to help improve the quality of surveys (Abbey & Meloy 2017, Kung 2018). The validation questions led to a significantly improved set of data.

Table 2: Survey Questions used in this study

Q9	In this survey we understand Artificial Intelligence (AI) as … How much do you trust Artificial Intelligence in general?	Slider question (scale of 1–5)
Q11	In our study we are examining AI tools used in Human Resources. We understand Human Resource AI Tools (HR-AI tools) as AI tools managing any part of an employee's life cycle (including recruiting and hiring). Were you told that AI was used in the application and hiring process when you applied for jobs?	Only for job seekers Slider question (scale of 1–5)
Q12	How important is it for you to know if AI is used in the application or hiring process?	Only job seekers Slider question (scale of 1–5
Q13	How was your overall experience using HR-AI tools as a Human Resource Manager or recruiter?	Only HR Slider question (scale of 1–5)

Q14	How was your overall experience with HR-AI tools as a jobseeker	Only job seekers Slider question (scale of 1–5)
Q15	How much do you trust Human resource AI tools?	
Q17	Have you ever heard of Algorithmic auditing?	Yes – No
Q18	Have you heard of the New York City Law 144?	Multiple Choice
Q19	Since AI does not always work as expected or intended, in some cases, organizations audit AI, which checks to ensure that they comply with legal and ethical standards. How important is it to audit AI, and when and how should this be done?	Open text
Q20	Have you ever worked with an HR-AI tool that has been audited?	Only HR Yes – Unsure – No
Q21	What kind of audit was performed?	Open text
Q22	How important are each of these aspects of audits of AI for you? (Safety and reliability of the AI tool, Legal compliance, Discovering of bias, Potential harm to the public)	Slider question for each (scale of 1–5)
Q23	Are there other important aspects of audits of AI for you that were not mentioned above? (Please explain)	Open text
Q24	What level of trust would you have in HR-AI tolls in these different situations (HR-AI tool is not audited, HR-AI tool is self-assessed by the company, HR-AI tool is audited by an external auditor)	Slider question for each (scale of 1–5
Q35	Please share any additional comments you have regarding audits of AI of Human Resource AI tools	Open text

Data Analysis

The data was analyzed by the first author, using Qualtrics, Excel, and ATLAS.ti[7].

Statistical calculations

An initial data analysis was performed with Qualtrics. Some values were transformed into percentages, and Excel was applied for the final charts and statistic

7 https://Atlasti.com.

calculations. For most statistical calculations, 2-tailed t-tests were performed to determine the difference between the means of the two analyzed groups (job seekers and HR-professionals). In section 3.2.1 (figures 9, 10), a Chi square test was chosen as most appropriate as the data is categorical (Yes, No). There has been a considerable debate among scholars whether Likert scales should only be analyzed with non-parametric statistics, or whether they could also be analyzed with parametric statistics, such as the t-test (DeWinter & Dodou 2010, Huh & Gim 2025). Non-parametric tests seem the appropriate choice for ordinal values, such as the Likert scale. Parametric statistics have, however, often been used in social science research when the intervals have been deemed equal and the sample size is large enough. Parametric statistics is seen as a powerful and comprehensive method (Norman, 2010). Research has also shown that both kinds of test mostly lead to similar results (DeWinter & Dodou 2010). Many scholars therefore consider the use of parametric tests for Likert scales as a valid choice (Norman 2010, Vieria, 2016). Following this approach, we apply parametric statistics like the t-test for our data, as our sample size is large enough and the intervals in the Likert scale can be considered equal.

Qualitative analysis

ATLAS.ti was used for the qualitative analysis of the open-ended text questions. The method was inductive, using a reflective thematic analysis according to Braun and Clarke (2021). The answers of both job seekers and HR professionals were coded by the first author. In a next step, codes were merged and sorted. The data analysis by atlas.ai was then transformed into charts through Excel. The second author supervised the data analysis and provided constructive feedback on it throughout the process.

Findings

RQ 1: Trust in AI and Trust in HR-AI Tools

Trust in AI

The overall trust in AI for all participants (figure 1) appears to be distributed like a bell curve, indicating an almost normal distribution with a slight tendency towards little or no trust. However, isolating the results for HR and for

job seekers (figure 2) shows a stark difference regarding trust in AI tools for the two groups.

Figure 1: Trust in AI of all participants

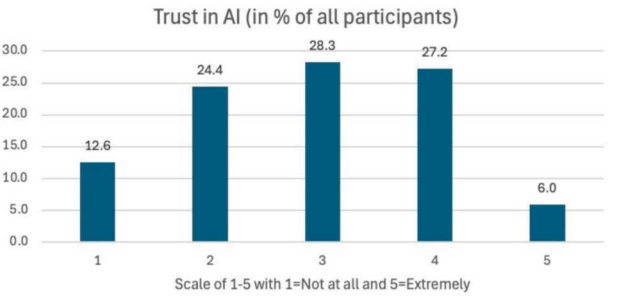
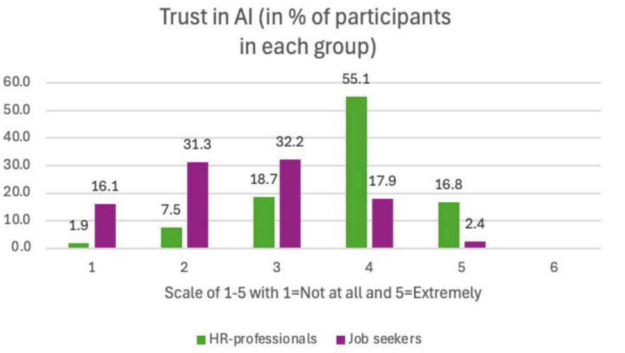


Figure 2: Trust in AI of different stakeholders



Job seekers seem to have much more distrust in AI than HR managers and recruiters. Job seekers echoed a bad feeling towards AI in some of their answers to text questions in the survey.

Some stated, "*I don't agree with using AI at all*", "*AI is a tool that is going to ruin our world*", or "*AI is too new to be trusted*". Another job seeker described in more detail:

> *I haven't been that impressed with AI. I've only seen it when I've asked questions on Google and the answers it generates are very generic. I don't find it particularly helpful. I imagine the same would carry over into human resource AI tools. For example, I applied to a job and was rejected in the same time it took me to create the application. I have to assume it was screened by AI. Some machine just decided based on arbitrary information that I wasn't qualified without considering my overall application. I tend to stay away from these systems if I can.*

HR professionals did not add any additional general comments about AI in the open-ended questions.

Overall, HR professionals have much more trust in AI in general than job seekers. While more than 70% of HR trust AI in general, only about 21% of job seekers do, while 47% have little or no trust in AI. This is a remarkable difference in the attitude towards AI. The average value for HR professionals regarding their overall experience using HR-AI tools on a scale of 1–5 was 3.77 and only 2.58 for job seekers. A t-test for figure 2 was performed, showing a 2-tailed significance of $p<0.001$.

Trust in HR-AI Tools

Knowledge of Job Seekers About Use of AI in Human Resources

The following graphs (figure 3 and figure 4) show how much knowledge job seekers have about the use of AI in the application and hiring process and whether they would like to know when AI is used in the process.

Figure 3: Knowledge of the use of HR-AI tool (job seekers)

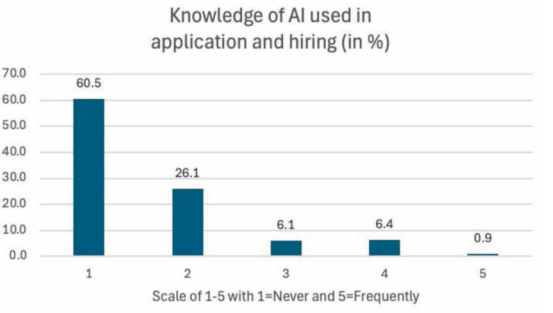
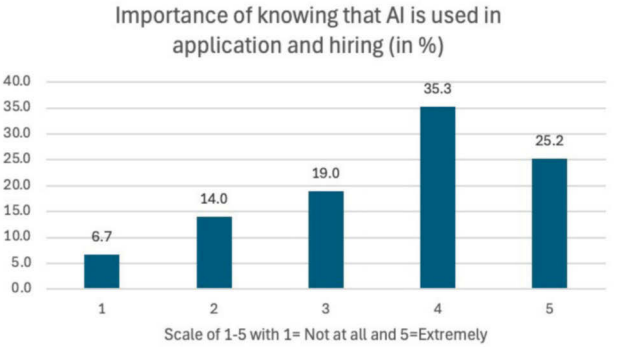


Figure 4: Desire to know when AI is used (job seekers)



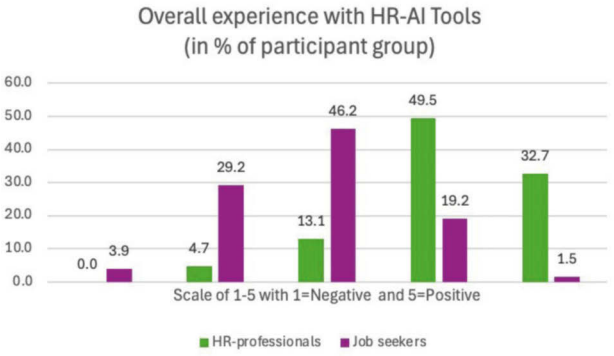
The responses of the job seekers in figures 3 and 4 show that most job seekers do not know or have very little knowledge about when and to what extent AI is used in the application and hiring process but would very much like to know when it is used. Around 60% found it important or extremely important. This shows a large gap between the current situation and the desired information job seekers would like to have.

Overall Experience Using HR-AI Tools

To understand the following graph (figure 5), it must be noted that, as explained above, it was a requirement for HR professionals to participate in the survey to have used AI tools for HR, so the responses reflect the answers from all participating HR professionals. Most job seekers had no knowledge of whether AI tools were used or not, as shown above. The results shown in figure 5 reflect the proportion of job seekers who have used AI tools or having knowingly been subjected to them, which was about 40% of the participating job seekers (130 of 329 job seekers).

The average value for HR professionals regarding their overall experience using HR-AI tools on a scale of 1–5 was 4.1 and only 2.85 for job seekers. A t-test was performed for figure 5, showing a 2-tailed significance of $p<0.001$.

Figure 5: Experience of stakeholders with HR-AI tools (HR professionals: n=107, Job seekers with experience: n=199)



The experience of HR professionals was thus overall, much better than the experience of job seekers who had knowledge about the use of AI tools in the hiring process, with around 82% having a good or very good experience as opposed to only around 21% of the job seekers with similar good or very good experiences. Job seekers who have used HR-AI tools are mostly neutral (46%) with a tendency to a negative experience, though not an extremely bad one.

Trust of HR Managers and Recruiters and Job Seekers in HR-AI Tools

The trust in HR-AI tools of all participants (figure 6) is overall lower than in AI in general (figure 1), with about half of the participants not trusting the tools or only trusting them a bit. There is again a big difference between the trust HR professionals place in HR-AI tools and the trust job seekers place in these tools. Looking at both, the experience of users with HR-AI tools and their responses on how much they trust these tools (figure 7), shows that there is a high mistrust among job seekers but not so among HR professionals. While HR professionals generally trust HR-AI tools with an average of 3.83 points on the scale of 1–5, the job seekers generally distrust the tools with an average of 2.27. A t-test was performed for figure 7, showing a 2-tailed significance of $p<0.001$.

Figure 6: Trust in HR-AI tools (all participants)

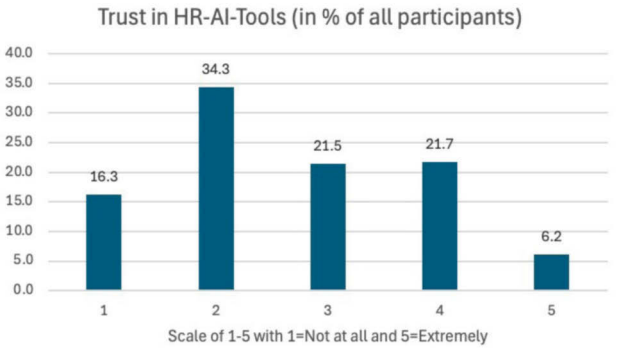
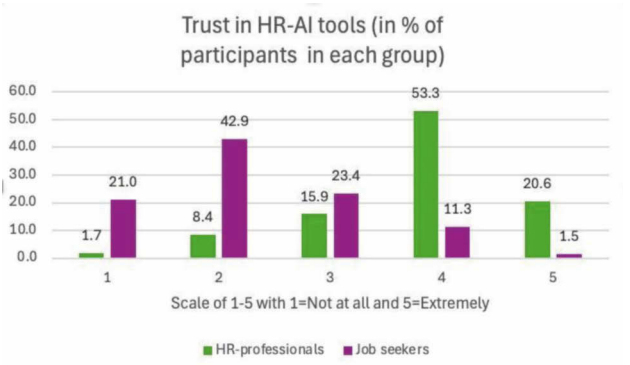


Figure 7: Trust in HR-AI tools of different stakeholders

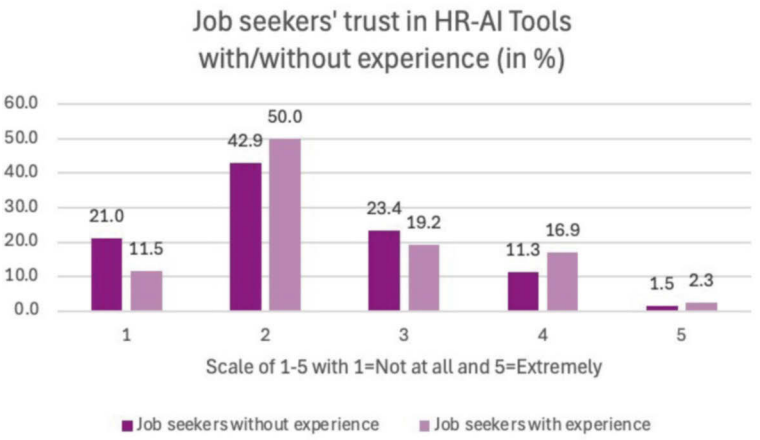


Comparing the trust of both stakeholder groups in AI in general versus the trust of AI in HR, there is an even more surprising difference notable. HR professionals trust HR-AI tools slightly more than AI in general, while job seekers trust it considerably less. Thus, the stakeholders using the tool consciously generally trust it, while the stakeholders who are not in control of using it but who are impacted by it tend to distrust it.

To find out whether the level of experience influences the level of trust, we also looked at the difference between job seekers who have been aware of the use of AI versus job seekers without such knowledge (figure 8). There is some

difference noticeable. Job seekers with experience tend to trust HR-AI tools more than the ones without. It is noteworthy though, that the percentage of job seekers not trusting the tools at all goes down significantly with increased experience. The average trust level of job seekers without experience is 2.29 and the average trust level of job seekers with experience is 2.48. The t-test with regard to figure 8 showed a 2-tailed significance of p=0.003.

Figure 8: Trust in HR-AI tools of job seekers



RQ 2: Knowledge about Algorithmic Audits, Experience with Audits

Knowledge about Algorithmic Audits and the New York City Law

Our survey shows that the participants of our survey overall know little about algorithmic auditing (figure 9) (69% have never heard of it) and even less about the New York City law bias audits (figure 10) (84% have never heard of it). There is, however, a significant difference between job seekers and HR professionals. While most job seekers have never heard of algorithmic audits (84%), most HR professionals who use AI tools are aware of algorithmic audits (87%). The difference regarding the NYC law 144 is even more distinct. Of the job seekers 98% have never heard of it, while 63% of the HR-mangers/recruiters have some or good knowledge of it. Chi-square tests of independence showed that there was a significant relation between stakeholder role and knowledge of algorithmic audits and of the NYC law. The p-value is <0.001 for both tests. For the NYC

Law results, the two columns indicating knowledge were aggregated, so the comparison was between Yes and No responses.

Figure 9: Have you ever heard of Algorithmic auditing?

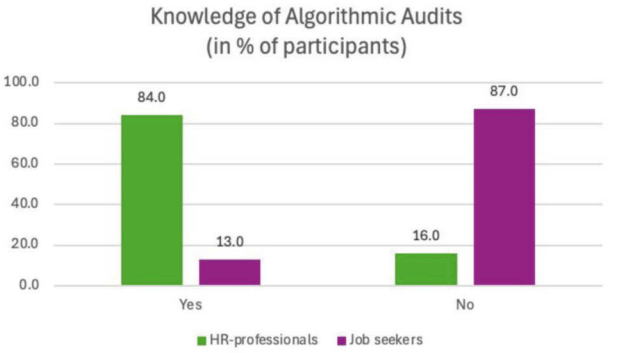
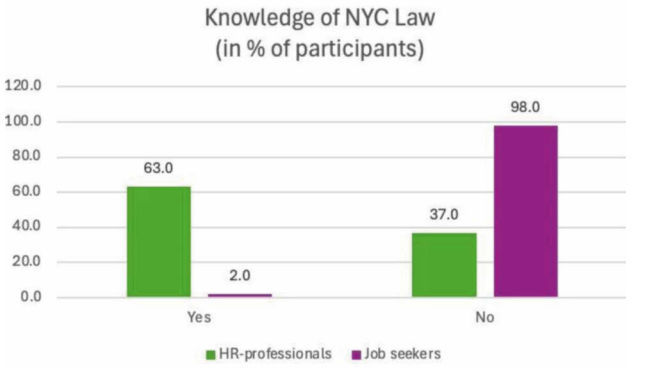


Figure 10: Have you ever heard of the New York City Law 144?



The results imply that there is a lack of information about algorithmic audits in the public but that most HR professionals who use AI have at least heard about such audits.

Experience with Algorithmic Audits

About half (51%) of the HR professionals indicated that they have worked with HR-AI tools that have been audited, while 24% were unsure and 24% indicated they had not. Of the HR professionals who have confirmed that they have experience with algorithmic audits about half (55%) answered our optional question about what kind of audit was performed. The rest did not explain what kind of audit was performed. The answers showed a full variety of audits (safety, security, privacy, bias, compliance, ethics, tax, accounting, functionality, accuracy and more) with no common definition. Many of them did not go into any detail ("*general run-of-the-mill audit*", algorithmic audit, general audit, "*a thorough one*") or said they were not sure what kind of audit it was, indicating some lack of understanding of what the audit conducted was about. Some concentrated on who conducted the audit (human, third party, naming a specific company). Few provided more detailed descriptions. One HR professionals described the audit in a vague way as:

> *We performed tasks and tests to see what the AI was scanning and basing its analyzation on, making sure it complies with legal compliance, and making sure it wasn't discriminating anyone based on different factors,*

Another provides more details but still lacks specifics:

> *We perform audits of our learning models, our datasets, and our results versus manual and more historic/traditional models.*

Only a couple of participants named classic algorithmic audits like bias audits (3 participants) or compliance audits (3 participants).

The results suggest that HR professionals notice the occurrence but not the type of audit. It also is confirming that there are a variety of audits out in the field. The concept of an algorithmic audit covers multiple aspects for our participants and can vary from one another substantially. Overall, the results indicate that there is no common understanding of what an algorithmic audit is among HR professionals. Our findings show that job seekers in general have almost no knowledge regarding algorithmic auditing, and HR professionals have a basic knowledge and some experience with them but mostly lack a deeper understanding.

RQ3: Stakeholders' Perspectives on Algorithmic Audits of HR-AI Tools

Importance of Algorithmic Audits

We asked the participants in question 19 how important they found it to audit AI. We expected that most respondents would find algorithmic audits important but were interested in what different nuances their answers would show. Several participants just echoed part of the definition, simply answered with 'Yes' or a similar answer, and did not come up with additional thoughts. Many answered very vague. Others just simply indicated that it is important. However, there was an overwhelming majority of job seekers and HR professionals who found audits very or extremely important.

Figure 11: Importance of Audits (n-261)

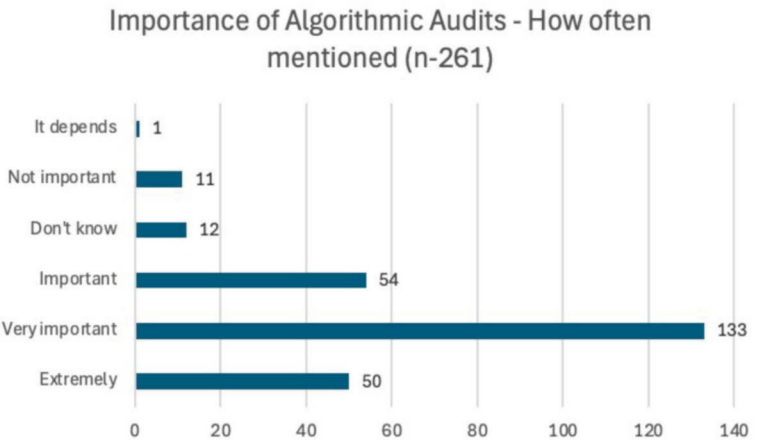
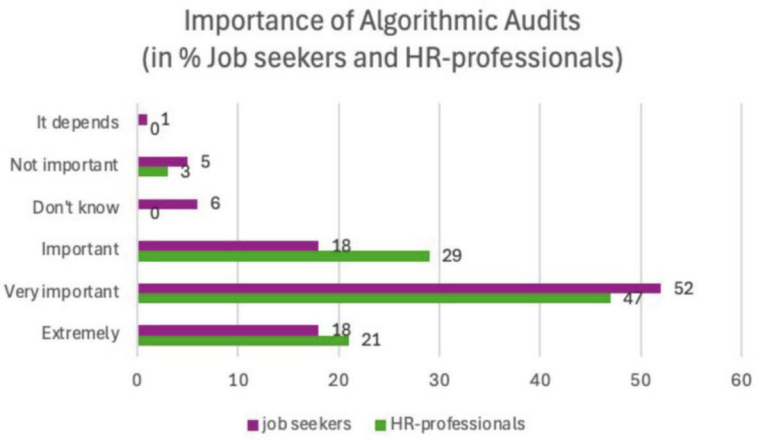


Figure 12: Importance of Audits for different stakeholders (in %)



Even though there are some slight differences in the degree of importance and there are more job seekers who do not know what to say, there is no remarkable difference between the job seekers and HR professionals. Both groups find the audits mostly very or extremely (including mentions like crucial, vital, essential etc.) important (job seekers 70%, HR professionals 68%).

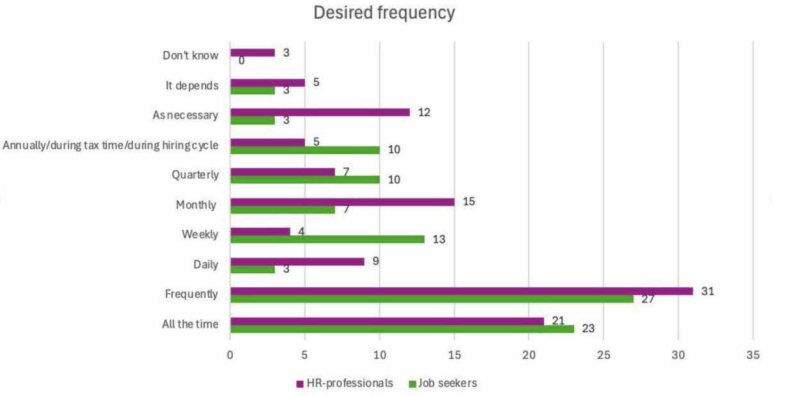
An additional comment emphasized the importance of audits in view of the novelty of AI.

> *It is extremely important, especially considering how early on we are with AI in the grand scheme of things. It being used for business, particularly with human interests in mind, it should be audited constantly. Used more as an assistant rather than a tool to use on its own. (jobseeker quote)*

Desired Frequency of Algorithmic Audits

In the same question, we asked how often they should be performed. The majority wanted them surprisingly frequently.

Figure 13: Desired frequency of audits (147 mentions)



Like the importance of algorithmic audits, there is no substantial difference regarding the frequency of algorithmic audits. About half of both groups want the audits all the time or frequently (Job seekers 52%, HR professionals 50%). The variations in the different categories are probably due to the low number of mentions and therefore less remarkable. The overall trend is similar.

A couple of participants suggested adapting the frequency over time and depending on needs.

> *With AI being a relatively new tool for HR, I think audits are very important and should be done at least once a hiring cycle. As the AI becomes more 'experienced' the audits probably need to be done less frequently but since each business has its own unique hiring practices and every position is different, audits should be required for every position for several hiring cycles before the company can choose to decrease to once or twice a year. (jobseeker quote)*

Other Thoughts about Algorithmic Auditing

Human-in-the-loop

It was striking that many participants particularly mentioned that it should be performed by humans, even though this was not included in the definition. It came up 17 times by job seekers and once by HR professionals. Having a human in the loop seems to be important.

Performance of Audits

In addition, there were some quite thoughtful suggestions on how they could be done. One jobseeker suggested that the AI decisions should be checked manually to allow for some more flexible decisions, indicating that a human touch is sometimes needed. Some suggest that people working in human resource should check whether they would reach the same output, and this should be done more frequently in the beginning and over time less frequently. One participant recommends doing this as a 'blind' test. HR professionals mentioned the independence of the auditor a bit more than job seekers. They also had some more concrete ideas in what phases of the AI lifecycle the audit should happen. One participant pointed out the auditing is particularly important for human resources. The responses indicate that the users asked in this survey find algorithmic audits in HR very to extremely important, would appreciate frequent checks of algorithms through audits and have some interesting ideas on how this could be done. Direct quotes underlining this can be found in the annex.

Independence of Auditor

Another striking difference in our survey between HR professionals and job seekers is the difference between the trust level in HR-AI tools depending on whether they have been not audited (figure 14), self-assessed (figure 15) or audited by an external auditor (figure 16).

HR professionals trust non-audited tools with an average of 2.68 while job seekers trust them with an average of only 1.55. Self-assessed tools are trusted with an average of 3.51 by HR professionals and with an average of only 2.39 by job seekers, and tools audited by an external auditor are trusted with an average of 4.9 by HR professionals and 3.78 by job seekers. T-tests performed for all three graphs showed a 2-tailed significance of $p<0.001$.

The trust HR professionals would have in self-assessment as opposed to job seekers is surprising. It is also noticeable that HR have more trust in non-audited tools than job seekers. Both groups have most trust in audits conducted by an external auditor.

The findings underline that most of the stakeholders deem algorithmic audits as quite important, stress values such as humans in the loop and independency of the auditor and have concrete and thoughtful suggestions on how audits could be conducted.

Figure 14: Trust with no audits

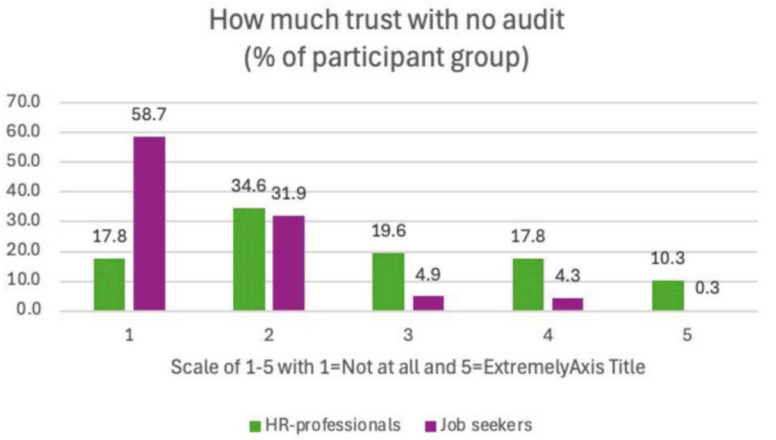
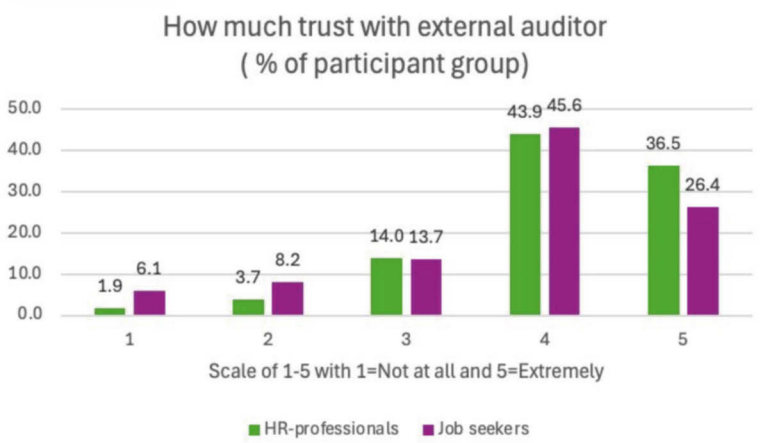


Figure 15: Trust with self-assessment

Figure 16: Trust with external auditor



Discussion

Trust of Stakeholders in AI and in HR-AI tools

Our findings demonstrate that HR professionals trust AI in general and HR-AI tools in particular substantially more than job seekers do. Job seekers show a high amount of distrust towards the tools. This attitude shows some connection to their knowledge of and experience with AI.

Trust requires knowledge and experience of the technology that should be trusted. While HR professionals are using the AI tools directly and therefore know when the tools are used, our survey shows that most job seekers do not know when and how these tools are used even though they are directly affected by the use. Current regulation like the New York City Law and the European AI Act aim to fill the knowledge gap by requiring that the use of AI in the hiring process should be made public, as detailed above. Such regulatory requirements seem to fill a need on the side of the stakeholders who would like to be more informed. Due to the limited scope of the NYC law these requirements will, however, not affect most job seekers in the US. The literature has also shown that currently the NYC law is rarely applied and that published audit reports lack accessibility and usability (Groves et al. 2024; Wright et al. 2024). It would be desirable to provide more and widespread

transparency for job seekers, similarly to the European AI Act. There were some movements towards more transparency following the Executive Order of the Biden administration 14110 regarding federal offices requiring them to be more transparent (DOL 2024). As a suggested Promising Practice, federal contractors should *"provide advance notice and appropriate disclosure to applicants, employees, and their representatives if the contractor intends to use AI in the hiring process or employment decisions that allows individuals to understand how they are being evaluated"* (DOL 2024). This Executive Order is, however, not in effect anymore.

More concrete and widespread regulation and standards expanding to the whole nation and including the private sector would help the desire of users of HR-AI tools to be better informed about the use of AI in employment decisions and help protect them from adverse impacts.

There is a striking difference between the trust level of job seekers and HR professionals regarding HR-AI tools. Of the two stakeholder groups job seekers are much more vulnerable than the HR professionals as they are affected on a more personal level. There is also a striking power imbalance in the relationships between job seekers and HR professionals which is exacerbated using advanced algorithms. While the workers are subjected to algorithmic management, the managers are implementing the decisions (Jarrahi et al. 2021). Furthermore, potential algorithmic discrimination can extend beyond traditional power imbalances and create new unprotected, vulnerable groups, such as single mothers, homeless people, or users who share a browser history (Rigotti & Fosch-Villaronga 2024). This power imbalance and the vulnerability could explain a higher level of mistrust by job seekers as they face a higher risk, such as the risk to be not hired or let go from their position.

As a first step, the use of AI should be made more transparent to allow all stakeholders a better understanding and more experience with the use of AI to allow for more calibrated trust in the future. As it is unlikely that there will be appropriate regulation requiring more transparency in the near future, the government, academia, and civil society should foster more education about the use of AI to improve AI literacy. Improved AI literacy could lead towards more calibrated trust.

Knowledge about Algorithmic Audits and in particular Algorithmic Audits in HR

The findings show that the knowledge about algorithmic audits is very sparse, even though audits are aimed to help inform the public. Job seekers have almost no knowledge about them, and even though many HR professionals claim to know what they are, they seem to have little actual knowledge about how they are conducted.

So far, not much research has been conducted regarding the communication of auditing results to users (Scharowski et al. 2023). As the literature points out, there are some significant issues in making the results of audits public. Wright et al. (2024) show the difficulties for users to find the publications of conducted bias audits in New York. Our study also found that the knowledge about the existing New York Law 144 is very limited. Regular job seekers have hardly heard about algorithmic audits and even less about the NYC law. Hiring managers and recruiters have some knowledge, but it is rudimentary. It seems that there is a significant lack of communication regarding algorithmic audits, even though job seekers and HR professionals expressed that they find them important. To have users and the public benefit from AI audits they need to be easily accessible and usable as Wright et al. (2024) point out. How this could be achieved has so far been understudied. A study by Scharowski et al. (2023) investigates the use of certification labels in an empirical mixed-method study and concludes that they could lead to increased trust and willingness to use AI, especially in high-risk scenarios. As shown above, employment decisions are considered high risk. The Responsible AI Institute has developed a model for certificates for responsible AI (Casovan 2022) using a comparable approach. Similar ideas have been around regarding the use of datasets, such as the research regarding data nutrition labels that provide information to dataset users to mitigate potential harm (Chmielinski 2022).

The ideas above can serve as raw models for the communication of AI audits. Further studies are needed to see how these could be implemented and how the acceptance would be.

Besides improving the way information about algorithmic audits is communicated, the government, academia, and civil society should also aim to improve general information about the nature of algorithmic audits. Once the general public has more knowledge about audits and what they can and cannot do, they can ask for more algorithmic audits, and they will also know better how to evaluate individual audits.

Perspectives of Stakeholders and Importance of Algorithmic Audits

The comments to our open text questions clearly showed that users across the board find algorithmic audits very if not extremely important and would support frequent audits conducted by humans.

So far, the perspective of HR professionals and job seekers regarding algorithmic audits in human resource has not been explored in more depth and has not been considered much. Some research regarding algorithmic audits introduces the idea of including users in audits. This is mostly suggested in AI content moderation and social media (Lam 2022, Shen 2021). A comparable direct input of users for the use of AI in employment decisions seems less applicable. The concerns and worries of users in such decisions should, however, be part of the discussion. As major stakeholders and the most vulnerable group, their opinion and ideas should be more included in designing proper algorithmic audits. This could happen in form of participatory design sessions where various stakeholders are actively included in the design process of audits. Another approach would be to use a value based design approach and inform the design of algorithmic audits by qualitative and quantitative research such as this study. Our research shows that our participants had very concrete and creative ideas. Furthermore, it seems that once users learn more about the concept of audits, they find them useful. Our survey demonstrated that job seekers have mixed experience with AI used in HR and would like to know more about the use. Established algorithmic audits communicated to them in a proper way could potentially improve their experience and increase trust. Many participants also stressed the importance of the human factor in the process. This should be another consideration for designing audits in the future.

Limitations and Future Work

A main limitation of our research is that users of HR-AI tool do not know much about algorithmic audits, and on the job seekers side they are not even always aware of the use of AI in HR. It is difficult to receive substantial and useful information about an area the respondent is unfamiliar with. This research is meant as a first step towards exploring what users might feel about algorithmic audits. It can so far only provide trends and first ideas to a very limited extent, as audits of HR-AI tools are not common yet.

Once algorithmic audits are more established and common, new studies should explore what stakeholders think about algorithmic audits, and what designs of such audits work, and which do not. Further studies could be done in the form of participatory design, including all stakeholders in the discussion. Future research should also extend beyond the field of HR to explore how different fields might need different approaches regarding algorithmic audits.

Conclusion

One key takeaway from our study is that job seekers have little to no knowledge about the use of AI during the application and hiring process or throughout their employment but would overwhelmingly like to know when AI is used. HR professionals who consciously use AI tools and have some experience with the tools have a higher trust overall in the tool. This could indicate that knowledge and experience with AI tools could increase trust in the tools. Current regulation aims to provide stakeholders with information about the use of AI in HR but so far is only very rarely applicable and not widely used in the field. We recommend further regulation, standards, and/or business best practices to make the use of AI in HR transparent for all stakeholders. Once job seekers have more information on the use of AI in HR and more experience with it, it should be further researched whether this helps them trust the tools and whether this trust is calibrated to the trustworthiness of the tool.

The surveyed stakeholders overall have a limited understanding of algorithmic audits and have not heard much about the New York City Law 144 requiring bias audits for automated employment decisions. While HR professionals have more knowledge about algorithmic audits, their understanding of the concept is rudimentary and there is no common understanding of what an algorithmic audit constitutes. More well communicated information about algorithmic audits and the results of conducted audits is needed to provide users with information that could influence their experience with and trust in AI. Our survey results indicate that further knowledge about what an audit is and how it is conducted is important to stakeholders and has the potential to affect their calibrated trust in the tools. Such information needs to be accessible, usable, and well communicated.

Once HR professionals and job seekers learn more about the concept of algorithmic audits, they find them very if not extremely important. While most are not sure how they should be conducted, they find that they should be per-

formed frequently and thoroughly and should have a human element. Our research shows that there is a wide interest in algorithmic audits once more information is available and that HR professionals and job seekers have creative and thoughtful opinions regarding algorithmic audits. The voices of the stakeholders should be heard to improve algorithmic audits in the future. It should be further explored how these stakeholders' opinions and concerns could be included in the design of algorithmic audits to give them a voice in the process.

Acknowledgements

The research was supported by a grant from the Notre Dame-IBM Technology Ethics Lab.

Annex

Complete questionnaire

	Question	**Kind of question**
Q1	Do you have prior experience working as a Human-Resource manager or as a recruiter?	Multiple choice
Q2	How many years of experience do you have as a Human-Resource manager and/or as a recruiter?	Multiple choice
Q3	In our study we are examining Artificial Intelligence tools used in Human Resources. We understand Human Resource AI Tools (HR-AI tools) as AI tools managing any part of an employee's life-cycle (including recruiting, hiring, onboarding, training, or promotional decisions). Have you in your professional life used HR-AI tools?	Yes – No
Q4	Are you actively seeking a job, or have you recently been on the job market as a job seeker?	Multiple choice
Q5	What is your age?	Multiple choice
Q6	What is your gender?	Multiple choice

	Question	Kind of question
Q7	What is your race/ethnicity? Please select as many as apply!	Multiple choice
Q8	What is the highest level of degree or school that you have completed?	Multiple choice
Q9	In this survey we understand Artificial Intelligence (AI) as ... How much do you trust Artificial Intelligence in general?	Slider question (scale of 1–5)
Q10	How often have you used HR-AI tools in your position as a Human Resource Manager or a recruiter?	Slider question (scale of 1–5)
Q11	In our study we are examining AI tools used in Human Resources. We understand Human Resource AI Tools (HR-AI tools) as AI tools managing any part of an employee's life cycle (including recruiting and hiring). Were you told that AI was used in the application and hiring process when you applied for jobs?	Only for job seekers Slider question (scale of 1–5)
Q12	How important is it for you to know if AI is used in the application or hiring process?	Only job seekers Slider question (scale of 1–5
Q13	How was your overall experience using HR-AI tools as a Human Resource Manager or recruiter?	Only HR Slider question (scale of 1–5)
Q14	How was your overall experience with HR-AI tools as a jobseeker	Only job seekers Slider question (scale of 1–5)
Q15	How much do you trust Human resource AI tools?	Slider question (scale of 1–5)
Q16	Please mark position four with the slider!	Slider question (scale of 1–5)
Q17	Have you ever heard of Algorithmic auditing?	Yes – No
Q18	Have you heard of the New York City Law 144?	Multiple Choice
Q19	Since AI does not always work as expected or intended, in some cases, organizations audit AI, which checks to ensure that they comply with legal and ethical standards. How important is it to audit AI, and when and how should this be done?	Open text
Q20	Have you ever worked with an HR-AI tool that has been audited?	Only HR Yes – Unsure – No

	Question	Kind of question
Q21	What kind of audit was performed?	Open text
Q22	How important are each of these aspects of audits of AI for you? (Safety and reliability of the AI tool, Legal compliance, Discovering of bias, Potential harm to the public)	Slider question for each (scale of 1–5)
Q23	Are there other important aspects of audits of AI for you that were not mentioned above? (Please explain)	Open text
Q24	What level of trust would you have in HR-AI tolls in these different situations (HR-AI tool is not audited, HR-AI tool is self-assessed by the company, HR-AI tool is audited by an external auditor)	Slider question for each (scale of 1–5)
Q25	How important is it to you that audits are mandatory?	Slider question for each (scale of 1–5)
Q26	How important is it to you that audits of AI are conducted by organizations that are required to meet established standards?	Slider question for each (scale of 1–5)
Q27	What is most important for you regarding the AI auditor?	Multiple choice
Q28	How important is it for you to understand how the audit of AI is conducted?	Slider question for each (scale of 1–5)
Q29	How important is it for you that the audit explains the AI and its consequences?	Slider question for each (scale of 1–5)
Q30	What do audits of AI evaluate?	Multiple choice
Q31	How would you like to see the results of an audit/certification? (You can choose more than one)	Multiple choice
Q32	How do you think the audit report should be shared with the public?	Multiple choice
Q33	How important is it to you that it will be required that the audit results are shared?	Slider question for each (scale of 1–5)
Q34	How important is it for you to know what actions the company took in response to the audit?	Slider question for each (scale of 1–5)
Q35	Please share any additional comments you have regarding audits of AI of Human Resource AI tools	Open text

Quotes regarding the performance of audits

Quote 1
It should be checked for reasonableness at least 50% of the time, by reviewing the same material manually and see if the answers are the same as those arrived at by AI. There could be some points that may have a "gray area" that should not be interpreted strictly by the book. AI cannot determine these "iffy" points. (jobseeker quote)

Quote 2
It is extremely important to audit AI, Computer(s) can and do fail and oftentimes need to be slightly reprogrammed for the original intent. This should be done by a person who is looking to have the same output the AI is intended for. As an example, if AI is working for HR, then someone who works in HR should check frequently to ensure the AI is working as intended. I would see this should be done around 50% of the time at the beginning, and then less frequently if the AI appears to be working as intended. (jobseeker quote)

Quote 3
I think it is very important because the decisions or advice given may not comply with standards. I believe this should be done every time AI is used to ensure its efficacy and areas of weakness. This will help evolve the technology until it is up to par with standard both legal and ethical. This should be done with a group of individuals who do not know they are analyzing the work of AI. A blind examination such as this can help prevent bias towards technology of this kind. (jobseeker quote)

Quote 4
It needs to be constantly audited and by third party sources. AI can be extremely dangerous, especially if it is connected to external sources like the internet or if it is taught coding. When these influences are introduced it's imperative that assessments be made as often as possible to verify input and output from the system as well as internal monitoring for processes being done. (HR professional quote)

Quote 5
Auditing artificial intelligence is of great importance because as AI is widely applied, reasonable regulations are needed to ensure its compliance. Auditing should be conducted during the development stage of AI, and an in-

dependent auditing team should be established to maintain independence from the developers and carry out objective audits. (HR professional quote)

Quote 6
I think it is incredibly important to audit AI, especially when it has to do with HR. Human resources can carry vital information for individuals and if AI is not frequently audited and kept working properly, important data could be lost or leaked, and people can be put in danger. (jobseeker quote)

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