WHEN THE CURRICULUM VITAE MEETS THE ALGORITHM

ALISON LUI

10.53478/TUBA.978-625-6110-66-3.ch01

WHEN THE CURRICULUM VITAE MEETS THE ALGORITHM

Alison LUI
Liverpool John Moores University

Abstract

UK employers increasingly use algorithmic hiring systems. These systems are often more complex than algorithmic credit-scoring systems. The hiring process involves a wider range of data types (structured and deeply unstructured, including video and text) and requires sophisticated multimodal tools. Further, the process must account for nuanced ethical, social, and legal variables, and often blends human and artificial intelligence (AI) decision-making in a multi-layered workflow. This is complicated by the fact that some algorithmic scores are so influential that the boundary between scoring and automated decisionmaking is hard to establish. It is well known that the 'black box' opacity phenomenon can reinforce and perpetuate algorithmic challenges such as bias, discrimination, and unfairness. The "black box" phenomenon in algorithmic hiring systems exacerbates biases even when protected characteristics such as age and race are excluded from the input data. Data which appear 'neutral', such as educational background or postcodes, may lead to bias and discriminatory outcomes. Certain postcodes may be associated with large populations of immigrants or ethnic minorities (European Union Agency for Human Rights, 2022). As a result, algorithms may unintentionally produce biased outcomes, particularly if the data used for training are not representative. This can cause harmful or unfair effects, such as bias or discrimination against certain job applicants, especially those from vulnerable groups, when making automated hiring decisions. This chapter critically reviews the challenges associated with automated hiring systems, especially at the screening and interview stages. It critically analyses recent U.S. court decisions on automated hiring systems and associated problems such as algorithmic bias and discrimination. The issue of third-party liability of AI software vendors will also be evaluated, in light of U.S. and European Union (EU) cases and legislation. The chapter argues that employers must provide a transparency notice when using automated hiring systems to job applicants at the outset, increasing transparency and trust between humans and automated hiring systems. The concept of an attractive virtual agent or avatar is also recognised as a means to increase affective trust in AI technology. Finally, third-party AI software vendors should be mindful of their potential liability when automated AI decisions play a significant role in the recruitment process.

Keywords

AI software vendors' liability in discrimination, automated hiring systems, algorithmic bias and discrimination, black-box problem, trust in AI, transparency in AI, algorithmic decision-making

1. INTRODUCTION

Approximately 30% of UK employers now use AI recruitment tools such as keyword matching and algorithmic hiring systems in recruiting talent in 2025 (Fennell, 2025). This figure has tripled since 2022, and such adoption is from both large and small to medium sized companies. 43% of big companies are using AI to interview candidates and 70% of recruiters say that AI is improving their hiring decisions (Castle Employment Group, 2025; Fennell, 2025). From an employer's perspective, using AI reduces the average cost of hiring a candidate by 71%. This saves significant costs given the rise in national insurance contributions by employers and increase in the national living wage in the UK (Partington, 2025). Recruitment is the core activity of professional recruiters, so it is no surprise that 48% of them use some form of algorithmic hiring system (Beveridge, 2025). HireVue, a company offering an algorithmic hiring system, claims that the pre-hiring assessment market is worth £2.2 billion a year (Buranyi, 2018). Multiple studies (McColl & Michelotti, 2019; McDonald et al., 2017; Woods et al., 2020) reveal that algorithmic hiring minimise risks, improves productivity and increases certainty in decision-making. Will et al (2023) posit that AI is largely better than humans in improving diversity. There is thus an upward trajectory in the use of algorithmic hiring systems in the UK, especially amongst large companies and recruitment agents.

The picture is not as rosy on the supply side of the job market. Job seekers are finding these algorithmic hiring systems deeply alienating, dehumanising and discouraging (Buranyi, 2018). For many job seekers, they do not have the opportunity to interact with any humans in the application process at all. The UK comedian and writer Richard Stott turned down an interview with artificial intelligence in May 2025. He said that it is 'disrespectful' and that 'personal interactions' with humans are important in hiring decisions (Daniel, 2025). Stott's opinion aligns with Buranyi's research in 2018, where many job seekers believe that human interaction is important in hiring decisions.

48% of unsuccessful job seekers find that the most frustrating aspect of the job hunt is to receive no feedback at all (Stefanowicz, 2025). Even if they reach the pre-hiring assessment stage of online videos or psychometric tests, these are all conducted online and then algorithms analyse their performances. If candidates are unsuccessful, many are not given their assessment scores or explanations, although HireVue offers an explainability statement. Their website states that every candidate receives a personalised Candidate Insights Report with the assessment scores (HireVue, 2025). If the employer that uses HireVue wants more data, then HireVue will provide the underlying data for each candidate.

Automated discrimination has existed for some time and does not only arise from black box models. For example, in the 1970s and 1980s, St. George's Hospital Medical School in London used a computer programme to screen job applicants. Although the system did not explicitly

consider ethnicity, it still unfairly discriminated against ethnic minorities and women. The programme inferred sensitive information from applicants' surnames and places of birth, which resulted in these groups having reduced chances of being invited for interviews (Guidotti et al., 2018). This can cause harmful or unfair effects, such as bias or discrimination against certain job applicants, especially those from vulnerable groups, when making automated hiring decisions.

Two studies (Chen et al., 2018; Su hr et al., 2020) confirm that search engine algorithms can lead to gender discrimination in candidate ranking. In Chen et al's study, data was gathered from three curriculum vitae (CV) search platforms, focusing on job titles across 20 U.S. cities. The specific algorithms powering these search engines were not disclosed, so Chen et al (2018) could only evaluate the resulting rankings. On these sites, candidates ranked higher are considered more desirable and are viewed first by recruiters. Even though sensitive personal information was removed from the candidate profiles, mixed linear model regressions showed that female applicants received slightly lower rankings than their male counterparts. It is important to note that this difference was minimal, making the gender gap barely noticeable among the top ten candidates for each job.

The study also explored variations across different job titles. The authors found that many job categories showed significant gender bias, consistently favouring men. Since the algorithms behind these search engines are opaque, the authors can only speculate about the causes of this bias. They suggest it might result from an undisclosed variable that correlates with gender, or from recruiter behaviours, such as a tendency to click more on male candidates, which could influence the rankings. Chen et al (2018) thus showed that female job candidates scored slightly lower in rankings based on job titles and were therefore discriminated even though sensitive information was removed.

Suhr et al (2020) demonstrated that changing how job candidates are ranked can reduce gender bias in hiring. They asked volunteers to participate in a fake job selection process where they chose four candidates from ranked lists. The candidates were ranked using three different methods: (1) by a relevance score from a search engine, (2) in a random order, or (3) by a fairness-focused algorithm designed to give more balanced representation of underrepresented groups (i.e. women). The fairness algorithm led to significantly more women being selected—sometimes increasing female selection by over 17% compared to the relevance ranking. The random ranking also helped increase female selection but less so than the fairness algorithm. This means that the way candidates are ordered by hiring search engines affects how much gender diversity appears in actual hiring choices.

Algorithmic hiring systems bring up concerns about fairness, and its automated nature worsens these concerns because the process is opaque. This lack of clarity makes it very difficult to identify the sources of bias or discrimination. This opaqueness can erode confidence in

algorithmic systems (Kuziemski & Misuraca, 2020). The concern becomes particularly acute in recruitment decision-making, because algorithmic hiring models are often more complex than credit scoring models due to the diversity of input data, variable target definitions, and operational requirements for fairness and adaptability (Jacobs, 2024). The 'black box' phenomenon makes it difficult for humans to explain the logic of machine learning algorithms in arriving its decision (Guidotti et al., 2018). Providing job applicants with the right to an explanation, along with clear information about the criteria and weightings used in recruitment assessments, enables them to receive useful feedback to improve their performances. According to Pavlidis (2024), increasing access to explanations supports informed decision-making, enhances the transparency and accountability of AI systems.

The chapter makes four contributions to the emerging area of algorithmic hiring systems. First, it critically evaluates the legal and ethical challenges of algorithmic hiring systems and associated problems of algorithmic bias and discrimination. Secondly, the chapter critically analyses recent U.S. cases on disparate impact and disparate treatment cases when employers used automated hiring systems. Gaps in the law will be revealed. Thirdly, the chapter highlights a possibility that third party AI software vendor can be held liable for algorithmic bias and discrimination, courtesy to the case of Derek Mobley v Workday Incorporation.[1] Finally, the chapter suggests measures as to how transparency and trust can be improved when automated hiring systems are utilised.

This chapter is structured as follows. In the next section, I will critically evaluate the use of algorithms in automated hiring systems. Section 2 details the legislative protection against algorithmic bias and discrimination in UK and US law. Sections 3 and 4 will critically analyse some U.S. cases in relation to automated hiring systems. Section 3 will focus on algorithmic bias and discrimination at the screening stage and section 4 will focus on algorithmic bias and discrimination in automated interview software. I provide some recommendations to improve trust and transparency in automated hiring systems. Section 6 concludes.

2. THE USE OF ALGORITHMS IN AUTOMATED HIRING SYSTEMS

Determining whom to hire is not necessarily a single decision. Rather, it can involve several decisions since the recruitment process can be conducted in several stages. From sourcing potential candidates to the selection stage, a plethora of algorithmic models can be used in the different stages of the automated hiring process. Bogen & Rieke (2018) do not attempt to specify which employers or sectors use what AI recruitment tools at what stage, as they believe that some employers use several AI recruitment tools which integrate with each other. Further, some employers can utilise different tools for different job roles within the same company. This would

[1] Derek Mobley v Workday (2024) Case No. 23-cv-00770-RFL

only be noticeable if a job applicant applies for various roles within the same company (Bogen & Rieke, 2018). The purpose of this section is not to provide a comprehensive analysis of what AI recruitment tools are used by what industries. Rather, I provide an overview of the main AI technologies used in automated hiring systems.

Sourcing algorithms use predictive analytics to see which candidates are likely to click on and apply to the advertisements which employers post on algorithmic advertising platforms or job boards. It is a proactive method which enables recruiters to use models such as graph-based algorithms, collaborative filtering and Boolean search algorithms to source potential candidates. Amazon's algorithm which displayed bias against women in applying for technical jobs is an example of sourcing algorithm. The Amazon algorithm also failed to rank candidates accurately according to their skills and qualifications, whereby unqualified candidates were recommended for jobs (Aumu ller-Wagner, 2019).

With screening algorithms, natural language processing model is used to analyse text-based data such as CV and cover letters. The model extracts keywords, skills, and experience from resumes and matches candidates to job descriptions using semantic similarity (Rojas-Galeano et al., 2022). Certain models leverage machine learning to predict a candidate's potential job performance by analysing indicators linked to length of service or efficiency, as well as the lack of signs associated with lateness or disciplinary issues (Bogen, 2019). Next, machine learning models such as logistic regression and decision trees predict candidate suitability by learning from historical hiring data (Maree & Shehada, 2024). Finally, ranking algorithms assign scores to candidates based on their suitability for the position. The top ranked candidates are judged to be the most suitable candidates (Nair et al., 2025). Screening algorithms consist of two algorithms. The first one is the 'screener', where the algorithm produces an evaluative score on for example, the future performance for each applicant. The second algorithm is the 'trainer', which uses data to help the screener produce an evaluative score for an objective function (Kleinberg et al., 2017).

Gadzinski & Castello (2022) note that within machine learning, rules-based systems are more interpretable and explainable than neural networks, which lack rule-based structures. The issue with neural networks is their opacity—since they do not rely on predefined rules, it is unclear how they process unexpected data. In contrast, rules-based systems, though complex, operate transparently by examining causal relationships without allowing machine reinterpretation, making them easier to understand. Discriminant models, for instance, objectively distinguish between strong and weak qualifications. However, they may struggle to assess soft skills such as teamwork and leadership skills accurately (Goretzko & Israel, 2021).

Neural networks, inspired by the architecture of the human brain, function by mapping independent variables to their corresponding dependent variables. They can be found in

recommender systems which recommend positions to candidates and vice versa by analysing skills, experience, and job requirements. Owing to the presence of multiple hidden layers within these networks, scholars have frequently critiqued neural networks for their lack of transparency (Wang et al., 2005). This opacity is particularly consequential in domains such as employment recruitment and access to finance, where the deployment of highly complex and minimally interpretable machine learning models has significant implications (Waa et al., 2020). Additionally, numerous machine learning models based on neural network architectures are often characterised as 'black boxes' due to their limited interpretability. Although such models may achieve high predictive accuracy, many scholars argue that their internal mechanisms are exceedingly difficult to comprehend or explain, even for domain experts (Pinetlas et al., 2020). Consequently, this lack of interpretability may result in recruitment decisions that are biased, discriminatory, or unfair to certain groups of job applicants.

Bias and discrimination in recruitment can take place for example, in giving 'employability' scores to job seekers. Algorithms rely on 'competence models' trained on data collected from existing employees, past interviews and assessments (Larsen, 2018). They then provide an 'employability score' for each candidate. An example is HireVue's platform which uses both natural language processing and machine learning. The algorithm can, according to HireVue, predict how likely a job seeker will be successful in the job based on the training data, which is collected from existing employees and prospective job candidates. The algorithm will consider intricate details in both verbal and non-verbal characteristics such as speech styles, tones and choice of words (Zhou, 2024). Emerging case law to date focuses on the use of AI algorithms in the screening and interviewing stages. This chapter therefore focuses on these two stages of the hiring process.

3. LEGISLATIVE PROTECTION FROM ALGORITHMIC BIAS AND DISCRIMINATION

The UK Equality Act 2010 protects job applicants from various forms of discrimination such as direct and indirect discrimination. The Equality Act also applies to discrimination caused by algorithmic hiring decisions. Most algorithms do not intend to discriminate. They do not have intrinsic preferences or motives to discriminate (Kleinberg et al., 2017). Direct discrimination claims under section 13 of the Equality Act 2010 are thus rare, although not impossible. As far as I am aware at the time of writing this chapter, there is no decided case on direct discrimination due to algorithmic hiring decisions in the UK. In the U.S, there is one settled case so far.

This case concerns EEOC v. iTutorGroup (2023)[2] using a recruitment software to hire tutors in the U.S. to provide online lessons to students in China. The allegation is that the recruitment

[2] EEOC v. iTutorGroup, Inc., et al., Civil Action No. 1:22-cv-02565

software rejected female applicants above the age of 55 and male applicants over the age of 60 (Boudjalis, 2023). Whilst not admitting liability, the U.S. Equal Employment Opportunity Commission found that the software contravened the U.S. Age Discrimination in Employment Act 1967, because older applicants were rejected based on the date of birth entered on the application form (Boudjalis, 2023). This Act prohibits employment related discrimination against applicants and employees over the age of 40. iTutorGroup had to pay damages of $365,000 to affected job applicants and to invite all those affected to reapply. iTutorGroup used a simple algorithm in this case, which rejected applicants based on age and sex criteria. It is clear from this settled case that employers should comply with U.S. employment law even though the tutoring services are conducted online for students in China.

Since direct discrimination is rare, most of the case law on automated hiring decisions are indirect discrimination claims under the Equality Act 2010 or disparate impact under U.S. legislation. Title VII of the U.S. Civil Rights Act 1964 prohibits employers from discriminating job applicants from sex, religion, race, colour and national origin. It prohibits employers from disparate treatment (overt, direct discrimination) and disparate impact (indirect discrimination). Section 19 of the UK Equality Act 2010 prohibits indirect discrimination. This is when an employer applies a prima facie neutral provision, criterion or practice (PCP) in its recruitment that puts people with a protected characteristic at a 'particular disadvantage', and the use of that PCP is not a proportionate means of achieving a legitimate aim.

If a job advertisement specifies that applicants need to be between the age group of 17-28, this criterion is potentially discriminatory against women, who will find it more difficult to comply than men due to childcare. This is likely to be indirect discrimination, unless the employer succeeds in the defence of a PCP.[3] If the employer succeeds in showing that the biased algorithm enables it to achieve a legitimate aim, it must then demonstrate that the use of the algorithm is a proportionate means of achieving that aim. If there are less discriminatory and equally satisfactory alternatives available, then using a biased algorithm will be disproportionate.[4] Using an algorithm which displays reasonably litigable bias will fail the proportionality principle (Kelly-Lyth, 2021). Otherwise, it is up to an employment tribunal to determine what is considered as acceptable bias. This is dependent on the facts and context, whereby a tribunal will decide whether the use of a specific algorithm in the specific context is legitimate. Sections 3 and 4 will critically analyse some recent U.S. disparate impact cases in relation to automated hiring systems. Section 3 will focus on algorithmic bias and discrimination at the screening stage and section 4 will focus on algorithmic bias and discrimination in automated interview software.

[3] Price v Civil Service Commissioner [1978] 1 All ER 1228

[4] Case C-83/14 CHEZ Razpredelenie Bulgaria AD v Komisia za zashtita ot diskriminatsia [2015] ECR I-00

4. ALGORITHMIC BIAS AND DISCRIMINATION IN AUTOMATED SCREENING TOOLS

The U.S. District Court in California set new precedent in the case of Derek Mobley v Workday Incorporation[5] by holding that third party automated screening software vendors can be held directly liable as agents of the employer company under Title VII of the Civil Rights Act of 1964 and other federal civil-rights laws. This is a significant development, since up till now, there is a gap in the law as to who should be liable for AI enabled discrimination. Mr Mobley's claims are that Workday Incorporation's automated screening software discriminated him on grounds of race, disability and age. Specific breaches of U.S. employment legislation include a disparate treatment claim based on race and age, disparate impact claim based on race, age and disability under Title VII of the Civil Rights Act of 1964; the Civil Rights Act of 1866; the Age Discrimination in Employment Act of 1967 and the Americans with Disabilities Amendments Act of 2008 (Derek Mobley v Workday Incorporation, 2024).

The Equal Employment Opportunity Commission (EEOC) enforces federal law against discrimination in employment. However, as resources are stretched in the EEOC, they typically investigate employment matters only if a claimant makes a specific complaint. The problem with AI automated screening tools is that many job applicants do not know that AI algorithms have assessed them (Bogen & Rieke, 2018). Even if they know, they often lack the resources or technical expertise to investigate and contest them (Kim, 2017).

Claimants face serious obstacles in proving statistical bias in algorithms. The first hurdle is obtaining access to the training data and the algorithm model. Claimants then have to find out how the data was collected, what sample populations were used and check for any errors (Kim, 2017). This is a very technical and time-consuming task, often beyond the remit of most claimants. It is very difficult to prove when and how the algorithm produced an adverse outcome.

To date, third party AI software vendors in credit scoring and employment hiring have avoided direct liability for discrimination because they argue that the training data, personnel records and algorithms are trade secrets (Kim, 2017). The balance between transparency and trade secrets was examined in the Court of the European Union in the SCHUFA Holding and Others (Scoring) Case C-634/21 in 2023 (SCHUFA, 2023).[6] Although the opinion of Attorney General Pritt Pikamae is not binding in the UK or the U.S, it can be a useful reference point. In the SCHUFA

case, the claimant was rejected a loan by SCHUFA, a German credit referencing agency. The claimant exercised her right under Article 15 (1)(h) GDPR for information about the automated credit making process which used her personal data. On the point about trade secrets, AG Pikamae said that this is a legitimate reason for non-disclosure of the algorithm, but it cannot justify an absolute refusal of information. Companies should facilitate 'meaningful information'

[5] Ibid (n 1). Mr Mobley, an over 40-year-old African American man applied for more than one hundred jobs with companies which used the Workday Incorporation online platform. He was rejected by all the companies. Mr Mobley claims that the Workday assessments and personality tests are likely to reveal mental health problems, of which he suffers from anxiety and depression. As a result, he alleged that job applicants with mental health problems are more likely to be rejected.

[6] Judgment of 7 December 2023, Case C-634/21 SCHUFA Holding and Others (Scoring)

and explanation to data subjects using appropriate communication methods, whilst ensuring a degree of confidentiality (SCHUFA, 2023).

The EU's Artificial Intelligence Act (EU AI Act) 2024 provides some compromise between the right to information/explanation and protecting trade secrets. The EU AI Act adopts a risk-based approach. The rules are more onerous if the risk of harm to society an AI use case poses high risks. According to Article 4 of Annex III of the EU AI Act, AI systems used in employment and recruitment are high risks. These systems must assess and reduce risks, maintain use logs, be transparent and accurate, and ensure human oversight. Under Article 11 of Annex 4, high-risk AI product developers must provide technical documents to national authorities and bodies to comply with the principles of explainability and transparency. Citizens will have a right to submit complaints about AI systems and receive explanations about decisions based on high-risk AI systems that affect their rights under Article 13 of Annex 4.

By holding third party AI software vendors directly liable, the ratio of this case fills an important gap where such software vendors act as agents of the employers. Using an interpretative approach, the U.S. District Court stated that Workday Incorporation is an agent of the employer under Title VII of the Civil Rights Act 1964, the Age Discrimination in Employment Act of 1967 and the Americans with Disabilities Amendments Act of 2008. Workday Incorporation's automated hiring system performed major recruitment functions such as rejecting candidates and recommending which candidates will proceed to the next stage. These are traditionally performed by human recruiters, but the substitution of AI makes no difference.

Indeed, the U.S. District Court stated that there is nothing in the language of the federal legislation or case law which distinguishes between delegating recruitment tasks to a human recruiter or an AI software acting as an agent (Derek Mobley v Workday Incorporation, 2024). Relying on the principal-agency theory, the U.S. District Court said that Courts have always focused on the 'function' that the principal (the employer) has delegated to the agent (Workday Incorporation) under the agency theory. The way how the agent performs the delegated task is irrelevant. The District Court further added that the inclusion of the term 'agent' in the definition of 'employer', which is separate from the term 'employment agency', suggests that the U.S. Congress anticipated that third party organisations acting as agents can be liable for hiring decisions when such tasks are delegated by the employers (Derek Mobley v Workday Incorporation, 2024).

The judicial interpretation of this case is entirely sensible and logical in automated AI recruitment decisions. Third party AI software companies cannot deny responsibility and shift liability to the employer just because it is AI, and not humans, acting as recruiters. The AI algorithm steps in as the human recruiter and makes significant decisions which impact upon candidates' lives. Bogen and Rieke's study (2018) reveals that AI recruitment software which produces scores for candidates and rankings may influence human recruiters more than we think. Further, there is not enough known about human recruiters act on the guidance provided by AI (Bogen & Rieke, 2018). Therefore, AI hiring software plays an important role in current recruitment practices. It makes sense that AI recruitment software vendors can be liable for any potential discriminatory outcomes.

In the UK, section 109 (2) of the Equality Act 2010 stipulates that anything done by an agent for a principal or with the principal's authority will be considered as done by the principal. If we adopt a similar interpretative approach as the U.S. District Court did in the Derek Mobley v

Workday Incorporation case, then I anticipate that UK courts would reach a similar decision in that an AI recruitment software vendor can be liable for any potential discriminatory outcomes. I am not aware of any UK case law in this area at the time of writing, but much depends on the final decision of Derek Mobley v Workday Incorporation case.

Even if the U.S. Court's final decision on Derek Mobley v Workday Incorporation does not hold the third-party AI software vendor liable, I believe that the CJEU's decision in SCHUFA can assist in holding third party AI software vendors liable. The impact of the CJEU decision is that third party credit scoring companies are caught by Article 22 of the GDPR because they make automated decisions on credit based on the scores they provide (SCHUFA, 2023). These are decisions of significant legal effects, since they assess an applicant's trustworthiness and ability to repay credit. Therefore, credit scoring companies can only assess applicant's creditworthiness using AI will need the applicant's express consent. Applicants as data subjects must also have the right to challenge the decision and be provided with 'meaningful information' about the data process methods so that they can make informed decisions (SCHUFA, 2023).

The consequences are far-reaching in that they are not limited to credit scoring companies. Any third-party company which uses automated decision-making processes that play a significant role in the ultimate decision, be it employment, insurance or healthcare, and impacting individuals on a significant level may be caught by Article 22(1) of the GDPR (Nonkovic, 2023). Such businesses need to ensure that they comply with the SCHUFA decision. The UK retained the GDPR in the UK Data Protection Act 1998. Therefore, Article 22 of the GDPR still applies, and it is possible that UK Courts will take a similar approach to the CJEU in the SCHUFA case in the future when interpretating Article 22 of the GDPR (Nonkovic, 2023). From both the U.S and EU judicial approaches, third party automated software vendors should be mindful of these new requirements relating to use of personal data and potential liability for discrimination.

5. ALGORITHMIC BIAS AND DISCRIMINATION IN AUTOMATED INTERVIEWS

Automated interviews range from candidates talking to the screens under the HireVue system to being interviewed by an AI avatar named Robot Vera (Umoh, 2018). The HireVue system lacks transparency because they are talking to a screen (Suen et al., 2019). HireVue is subject to at least two known cases regarding their automated AI video interview software used in hiring. First, in the class action case of Brendan Baker and Others v CVS Health Corporation and CVS Pharmacy Incorporation[7], CVS Health Corporation and CVS Pharmacy Corporation used HireVue's AI video interviews to score job applicants on their 'employability' based on their facial expressions. The software utilises speech recognition and facial recognition technology to evaluate job applicants from their appearances, expressions and speech (Uhunoma, 2023). The HireVue software asked candidates some questions concerning honesty and integrity, but without informing the candidates that this was essentially a lie detector test (Brendan Baker v CVS Health Corporation and CVS Pharmacy Incorporation 2024). The Massachusetts Lie Detector Statute requires employers to inform the candidates the notice of their statutory rights, which HireVue failed to comply in this instance.

HireVue claimed that their video interview algorithm can select candidates of the 'right cultural fit'; whether candidates have 'an innate sense of integrity and honour' and sift out candidates

[7] Brendan Baker v CVS Health Corporation and CVS Pharmacy Incorporation, Civil Action No. 23-11483

who exaggerate their accomplishments (Brendan Baker v CVS Health Corporation and CVS Pharmacy Incorporation 2024). Mr Baker was not aware that the questions formed the lie detector test, and the U.S. District Court of Massachusetts held that although the notice of his rights under the Lie Detector Statute would not have informed him that the interview included a lie detector test, the notice would have prepared Mr Baker better by being more critical of the HireVue interview (Brendan Baker v CVS Health Corporation and CVS Pharmacy Incorporation 2024). The Court gave standing to Mr Baker, so he can proceed to sue CVS Health Corporation and CVS Pharmacy Incorporation for breaching the Lie Detector Statute and failing to provide him with a notice of his rights. The case has since settled (Crist, 2024).

This case is primarily a matter of procedural deficiency by the employer, but it begs the question as to whether the AI video interview algorithm is effective or legitimate in determining the 'integrity' or 'right cultural fit' of a job applicant with a company. This is mainly because individual facial features are distinct, which makes it difficult for algorithms to make meaningful inferences from facial expressions. Research by Bogen and Rieke reveals that facial recognition technology is bad at recognising women's faces of darker tones (Bogen & Rieke, 2018). For job seekers with strong regional (such as Scottish) or non-native accents, the algorithm finds it challenging and does not perform as well as recognising mainstream accents (Tatman, 2017).

Other scholars have found that AI video interviews save time and money, as well as making the recruitment process more seamless (LinkedIn, 2018; Uhunoma, 2023). The legitimacy of using AI video interviews is a more pressing concern, since there is no evidence to date that I am aware of, which establishes a clear causative relationship between facial expressions at interviews and becoming a successful employee.

Not only is this an example of prioritising costs and efficiency over a candidate's experience, but it is ethically questionable. Bogen & Rieke (2018) opine that even if the test is conducted legally, the impact of AI video interviews would involve considering someone's 'immutable characteristics', which may breach their dignity and justice. 'Immutable characteristics' are traits which are integral to someone's identity, such as accents or political affiliation, and it would be fundamentally wrong to penalise someone for refusing to change, regardless how easy it is to change it (Watkins v. U.S. Army).[8]

Section 4 of the UK Equality Act 2010 protects individuals from being discriminated on nine characteristics such as sex, race and disability. Some candidates are worried about how their scores will be negatively affected because of their speech impediments or visual disability such as blindness (Riley, 2018). Various studies (Guo et al., 2020; Zhou, 2024) reveal that biases can stem from the training data if the data from under-represented groups is not added to the input. This is because many speech recognition technologies cannot understand atypical speech, which disadvantages deaf people. Further, personal traits such as low mood or low self-esteem detected by the algorithm can discriminate job seekers with mental health disorders (Zhou, 2024). The UK has seen a sharp rise in mental health disorders since the Covid pandemic. The percentage of 16–65-year-old adults with mental health disorders has increased from 17.6% in 2007 to 22.6% in 2023-24. The increase is particularly acute in young people of 17-19 years old (British Medical

[8] Watkins v. U.S. Army 875 F.2d 699, 726 (9th Cir. 1988) (Norris, J., concurring).

Association, 2025). In 2007, 10% of this age group had a mental health disorder. In 2023-24, this has increased to 25% (British Medical Association, 2025). Therefore, failing to include data from job seekers with disabilities such as mental health disorders in the algorithm can indirectly discriminate against young job seekers.

UK graduates are already facing one of the toughest job markets since 2018, with 33% fewer jobs advertised for graduates (Almeida, 2025). Young employees in the financial sector also have a higher degree of perceived discrimination based on age. Butler's (2024) empirical survey of 168 financial services employees in 2024 revealed that perceived discrimination is not an overt type of discrimination, and young employees in the financial sector have the highest degree of perceived age discrimination. Yet, this is a sector where many investment banks such as Citi, Morgan Stanley and Bank of America use HireVue in the recruitment process (TheirStack, 2025).

HireVue rebuts these ethical and legal concerns by submitting two points. First, they do not use the scores from the video interviews to make decisions (HireVue, 2025). The scores merely provide helpful information to employers about the candidates. HireVue submits that they are only a 'processor' of personal data, whereas the employers using the HireVue platform are the 'controller"'of data (HireVue, 2025). This is because the employers take the ultimate decisions on the purposes and means of processing (HireVue, 2025). HireVue's platform only provides a score and does not make recruitment decisions, so if a candidate wishes to query the decisionmaking in the recruitment process, then the website said the candidates should contact the employer which uses the HireVue's platform, who ultimately makes the final recruitment decision.

Interestingly, a study in Poland revealed that the automated interview and scoring system used by the Polish Ministry of Labour and Social Policy turned out to be the ultimate decision-maker in most cases (Kuziemski & Misuraca, 2020). This automated interview system scored the unemployed using several characteristics. The system would then allocate the jobseekers to a suitable programme such as a placement, apprenticeship or vocational training. The system was meant to help and supplement humans. Nevertheless, only 1 in 100 decisions made by the system was questioned by the officers (Kuziemski & Misuraca, 2020). The officers were reluctant to challenge the decisions for several reasons. First, they thought the automated system is objective. Secondly, the officers were worried about repercussion from their line managers. Finally, they were under time pressure and did not have time to challenge the decisions.

Even if humans are still selecting the candidates, automatic rejections of candidates by the HireVue software is still alarming (Bogen & Rieke, 2018). It is also unfair. Evidence shows that when decision makers explain their decisions to the recipients of information, the recipients are more likely to accept the outcome, even if it is negative. This is because they perceive that the decision making process is fair when there is an explanation (Shaw et al., 2003). Automatic rejections thus deprive subjective fairness in the decision-making process.

Further, HireVue's is not supported by recent Court of Justice of the European Union (CJEU) decisions in SCHUFA case and Case C-203/22 of Dun & Bradstreet Austria GmBH in 2025.[9] The CJEU in the SCHUFA case said that if the automated scoring of an individual's creditworthiness

[9] Judgement of 27 February 2025, Case C-203/22 Dun & Bradstreet Austria GmbH

plays a crucial role in the establishment, implementation or termination of a contractual relationship, it is then an automated decision-making process, which falls within the scope of Article 22 of the General Data Protection Regulations (GDPR). The CJEU appears to confirm in the Dun & Bradstreet Austria case that credit scoring agencies such as SCHUFA or Dun & Bradstreet can fall under Article 22 of the GDPR if their scores decisively influence the final decision. The situation will depend on a case-by-case basis.

The second defence made by HireVue regarding the ethical and legal issues is that their software allows employers to hide the scores from other reviewers, so the latter should not rely on the scores (Bogen & Rieke, 2018). According to their explainability statement, they reduce bias by complying with legal requirements in developing and monitoring AI assessments. They also check for group differences and adverse impact on particular groups. They can adjust the weightings and algorithm if for example, a disproportionate number of men perform better than women in the assessments, they will find out what are the reasons to rectify the difference (HireVue, 2025). Although there are attempts to reduce bias by HireVue, the next case illustrates the discriminatory and insensitive feedback that automated video algorithms made towards candidates with disabilities.

3.2 Association of Civil Liberties Union v. Intuit Incorporation and HireVue 2025

The claimant is a deaf, indigenous woman and speaks with a deaf accent. She applied for a promotion as a Seasonal Manager at Intuit but was rejected, despite having the qualifications, skills and experience. Prior to the application for promotion, the claimant had very positive feedback from Intuit Incorporation (Association of Civil Liberties Union, 2025). In the application process, Intuit Incorporation used HireVue's video and assessment software to assess the claimant. During the assessment, the software would produce questions from a recording of someone speaking. However, there were no subtitles of the recording during the claimant's assessment. The claimant asked for captions so that she can understand the questions, but Intuit Incorporation denied the reasonable adjustment request (Association of Civil Liberties Union, 2025). Further, there is evidence that Intuit Incorporation are aware the HireVue software had an adverse effect on deaf employees. This is because the claimant has previously raised her concerns about the AI video software, and her manager knew that the software was not accurately capturing the claimant's speech due to her disability. However, Intuit changed the claimant's job duties rather than fixing the technological issue. HireVue's feedback was that the claimant needs to improve her communication style, needs to be more concise when speaking and also 'practise active listening' (Association of Civil Liberties Union, 2025).

This case clearly reinforces that algorithms can discriminate job applicants with disabilities. The feedback is insensitive and undignified to a deaf applicant. Intuit Incorporation failed to make reasonable adjustments when it knew of the technical problem and failed to inform HireVue of the problem. Intuit Incorporation as an employer did not ensure that the assessments comply with anti-discrimination laws. The claimant alleges that there are breaches of several U.S. pieces of employment legislation such as the Colorado Ani-Discrimination Act, the Americans with Disabilities Act and Title VII of the Civil Rights Act 1964. This case is still under investigation at the time of writing.

6. RECOMMENDATIONS

To date, it is unclear whether humans or algorithms make fewer discriminatory decisions. On the one hand, it is sometimes hard to determine how and why someone reached a decision, and whether or to what extent, protected characteristics such as race or age played a role. On the other hand, Will et al (2023) posit that AI is mostly better than humans in improving diversity. Complete absence of bias is almost impossible in either human or algorithmic decisions, since bias in algorithms can occur in three stages in an algorithm: input, training and programming. The data input can be potentially biased or the information is insufficient for the algorithms to make fair decisions (Lui & Lamb, 2018). However, it is possible that an algorithm is less discriminatory than a human deciding whom to shortlist for an interview (Brione, 2020). Bringing a claim for discrimination, especially indirect discrimination due to an employer's use of an algorithm is thus dependent on facts and difficult to predict.

It would be better for job applicants if employers provide as much transparency as possible about the use of AI hiring software as an ex-ante measure. I submit that UK employers should adopt a similar approach to sections 6-1-1703, 4(a)(II) and 5(a) of the U.S. Colorado AI Act 2024 and produce a transparency notice as to how the automated hiring software works. The notice will include, amongst other things, details such as what factors the AI software consider; what information is used by the employer; how the employer manages 'known or reasonably foreseeable risks' arising from the AI software and appeal details.[10] This should be given to job applicants before they apply for the positions. There is no requirement now in the UK for employers to implement this. However, considering the CJEU decisions in SCHUFA and Dun & Bradstreet Austria, this recommendation very much aligns with judicial interpretation in the EU.

It would also build trust with the job applicants. Studies show that whether job applicants trust the automated video interview software is down to cognitive trust and affective trust (Basch et al., 2020; Hoff & Bashir, 2015). The former is about trust based on rational thinking, the latter is about trust based on emotions (Glikson & Woolley, 2020). Basch et al's research shows that applicants with less trust in interview technology might perceive the interview process as unfair, whilst the reverse is also true. Applicants who have more trust in interview technology will have greater faith in the interview process and perceive it with greater fairness. Blacksmith et al (2016) submit that applicants who have less trust in the interview technology may withdraw from the assessment or even reject the offer.

Some applicants find the idea of being interviewed by AI to be strange and alarming. This can negatively impact on their affective trust due to their irrational fear. Applicants' cognitive trust towards automated video interviews can increase if they believe that the employer will assess them fairly (Suen et al., 2019). Automated interview software is new to many applicants. This

can create unfamiliarity and anxiety amongst applicants (Meuter et al., 2003), especially if they do not know what the AI algorithms are assessing. This uncertainty is exacerbated by the 'black box' problem and the lack of explanations (Tambe et al., 2019). The uncertainty and anxiety can decrease applicants' affective trust in automated video technology. The lack of trust and

[10] Section 5(a) Colorado AI Act 2024

transparency are also grounds of dissatisfaction amongst the unemployed and users of automated interview software by the Polish Ministry of Labour and Social Policy (Kuziemski & Misuraca, 2020). The public criticised the algorithm used in the automated interview and scoring system because it was opaque. The job seekers do not know their score, nor do they know how the system determined which employment programme they were allocated. It was only after a successful legal challenge by a non-profit organisation that the Polish Ministry of Labour and Social Policy published the algorithmic guidelines.

The evidence above builds upon my argument that employers should provide a transparency notice when using automated hiring software. The software should not be the ultimate decision maker. Human recruiters should always review the automated decisions and encourage rigorous reviews and challenge the automated decisions. As Suen et al (2019) posit, such actions will increase objectivity of the interview process and increase applicants' cognitive trust. Details about what AI is used and how the automated software will make its decisions will increase transparency. Finally, to increase affective trust, they suggest that having an attractive virtual avatar or agent will increase affective trust due to the interactive element.

7. CONCLUSION

Recruitment is a time-consuming and expensive process. Yet, it is very important to ensure that the right candidates are hired. Selecting the right candidates has been an ongoing challenge with limited resources, time and increasing amount of applications. It is understandable why 90% of employers now use automated hiring software in interviews (Jaser et al., 2022). It is well-known that algorithmic bias and discrimination take place in automated hiring software, in both the screening and interview stages. Vulnerable groups such as individuals with disabilities, women and ethnic minorities are more likely to encounter discrimination by this AI technology. This chapter critically evaluated recent U.S. cases and legislation on algorithmic bias and discrimination in automated hiring systems from the U.S and UK. EU cases and legislation surrounding the balance of right to information and trade secrets were also scrutinised. Aligning with both judicial interpretation and social psychology literature, I recommend that employers must provide a transparency notice when using automated hiring software to job applicants at the onset, increasing transparency and trust between humans and AI technology. The concept of an attractive virtual agent or avatar is also recognised as to increase affective trust in AI technology. Finally, third party AI software vendors should be mindful of their potential liability when automated AI decisions which play a significant role in the recruitment process.

REFERENCES

Almeida, L. (2025). UK graduates facing worst job market since 2018 amid rise of AI, says Indeed. *The Guardian*. https://www.theguardian.com/money/2025/jun/25/uk-university-graduates-toughestjob-market-rise-of-ai

Association of Civil Liberties Union. (2025). *Redacted Complaint of Discrimination* (pp. 1–12). https://assets.aclu.org/live/uploads/2025/03/Redacted-HireVue_Intuit-Complaint-ofDiscrimination_Redacted.pdf

Aumu ller-Wagner, S. (2019). *Encoded Bias in Recruitment Algorithms*.

Basch, J., Melchers, K., Kurz, A., Krieger, M., & Miller, L. (2020). It takes more than a good camera: Which factors contribute to differences between face-to-face interviews and videoconference interviews

regarding performance ratings and interviewee perceptions? *Journal of Business and Psychology*, *36*(5), 921–940.

Beveridge, C. (2025). *Are you using AI for recruitment?* BDO Blog. https://www.bdo.co.uk/engb/insights/advisory/risk-and-advisory-services/are-you-using-artificial-intelligence-ai-forrecruitment

Blacksmith, N., Willford, J., & Behrend, T. (2016). Technology in the employment interview: A meta-analysis and future research agenda. *Personnel Assessment and Decisions*, *2*(1), 12–20.

Bogen, M. (2019). *All the ways hiring algorithms can introduce bias*. Harvard Business Review. https://hbr.org/2019/05/all-the-ways-hiring-algorithms-can-introduce-bias

Bogen, M., & Rieke, A. (2018). *Help wanted: an examination of hiring algorithms, equity, and bias*. Upturn. https://doi.org/https://www.upturn.org/work/help-wanted/

Boudjalis, G. (2023). *EEOC Settles First AI Hiring Bias Lawsuit*. JD Supra. https://www.jdsupra.com/legalnews/eeoc-settles-first-ai-hiring-bias-6261293/

Brione, P. (2020). *My Boss the Algorithm: An Ethical Look at Algorithms in the Workplace*. Acas. https://www.acas.org.uk/research-and-commentary/my-boss-the-algorithm-an-ethical-look-atalgorithms-in-the-workplace/paper

British Medical Association. (2025). *Mental Health Pressures in England*. British Medical Association Blog. https://www.bma.org.uk/advice-and-support/nhs-delivery-and-workforce/pressures/mentalhealth-pressures-data-analysis

Buranyi, S. (2018). How to persuade a robot that you should get the job. *The Guardian*. https://www.theguardian.com/technology/2018/mar/04/robots-screen-candidates-for-jobsartificial-intelligence?CMP=Share_iOSApp_Other

Butler, S. (2024). Perceived age discrimination: what is the workplace experience? *Strategic HR Review*, *24*(1), 42–46. https://doi.org/10.1108/SHR-08-2024-0060

Castle Employment Group. (2025). *How AI Is Changing Recruitment – What Candidates Need to Know*. AI Recruitment. https://www.castle-employment.co.uk/blog/2025/06/how-ai-is-changingrecruitment-what-candidates-need-to-know?source=perplexity.ai

Chen, L., Ma, R., Hanna k, A., & Wilson, C. (2018). Investigating the impact of gender on rank in resume search engines. *Proceedings of the 2018 Chi Conference on Human Factors in Computing Systems*, 1–14.

Crist, C. (2024). *CVS settles lawsuit alleging it used AI 'lie detector' in interviews*. HR Dive.

Daniel, A. (2025). *"Having AI interview me for a job felt wrong."* BBC News. https://www.bbc.co.uk/news/articles/c4gwwlj8dd3o.amp

European Union Agency For Human Rights. (2022). *Bias in Algorithms Artificial Intelligence and Discrimination Report*. https://www.redlinegroup.com/uploads/bias-in-algorithms-artificialintelligence-and-discrimination

Fennell, A. (2025). *AI Recruitment in Statistics*. StandOut CV. https://standout-cv.com/stats/ai-inrecruitment-statistics-uk

Gadzinski, G., & Castello, A. (2022). Combining white box models, black box machines and human interventions for interpretable decision strategies. *Judgement and Decision-Making*, *17*(3), 598–627.

Glikson, E., & Woolley, A. (2020). Human trust in artificial intelligence: Review of empirical research. *The Academy of Management Annals*, *14*(2), 627–660.

Goretzko, D., & Israel, L. (2021). Pitfalls of machine learning-based Personnel Selection. *Journal of Personnel Psycholology*, *21*(1), 1–22.

Guidotti, R., Monreale, A., Turini, F., Pedreschi, D., & Giannotti, F. (2018). A Survey Of Methods For Explaining Black Box Models. *ACM Computing Surveys*, *51*(5), 1–45.

Guo, A., Kamar, E., Vaughan, J., Wallach, H., & Morris, M. (2020). Toward fairness in AI for people with disabilities SBG@ a research roadma. *ACM SIGACCESS Accessibility and Computing*, *125*(1), 1–9.

HireVue. (2025). *HireVue Explainability Statement*. https://webapi.hirevue.com/wpcontent/uploads/2022/04/HV_AI_Short-Form_Explainability_1pager.pdf

Hoff, K., & Bashir, M. (2015). Trust in automation: Integrating empirical evidence on factors that influence trust. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *57*(3), 407–434.

Jacobs, R. (2024). *Algorithms and AI Can Make Hiring More Diverse*. Chicago Booth Review. https://www.chicagobooth.edu/review/algorithms-ai-can-make-hiring-more-diverse

Jaser, Z., Petrakaki, D., Starr, R., & Oyarbide-Magan a, E. (2022). *Where automated job interviews fall short*. Harvard Business Review. https://hbr.org/2022/01/where-automated-job-interviews-fall-short

Kelly-Lyth, A. (2021). Challenging Biased Hiring Algorithms. *Oxford Journal of Legal Studies*, *41*(4), 899–928. https://doi.org/10.1093/ojls/gqab006

Kim, P. (2017). Data-Driven Discrimination at Work. *William & Mary Law Review*, *58*, 857.

Kleinberg, J., MullainathanS, & Raghavan, M. (2017). Inherent Trade-Offs in the Fair Determination of Risk Scores. *In 8th Innovations in Theoretical Computer Science Conference (ITCS 2017). Leibniz International Proceedings in Informatics (LIPIcs), Volume 67*, 1–43.

Kuziemski, M., & Misuraca, G. (2020). AI governance in the public sector: Three tales from the frontiers of automated decision-making in democratic settings. *Telecommunications Policy*, *44*(6), 101976. https://doi.org/https://doi.org/10.1016/j.telpol.2020.101976

Larsen, L. (2018). *Train, Validate, Re-train: How We Build HireVue Assessments Models*. HireVue Blog. https://www.hirevue.com/blog/hiring/train-validate-re-train-how-we-build-hirevueassessments-models

LinkedIn. (2018). *Global Recruiting Trends 2018*.

Lui, A., & Lamb, G. (2018). Artificial intelligence and augmented intelligence collaboration: regaining trust and confidence in the financial sector. *Information and Communications Technology Law*, *27*(3), 267–283.

Maree, M., & Shehada, W. (2024). Optimizing Curriculum Vitae Concordance: A Comparative Examination of Classical Machine Learning Algorithms and Large Language Model Architectures. In *AI* (Vol. 5, Issue 3, pp. 1377–1390). https://doi.org/10.3390/ai5030066

McColl, R., & Michelotti, M. (2019). Sorry, could you repeat the question? Exploring videointerview recruitment practice in HRM. *Human Resource Management Journal*, *29*(4), 637–656.

McDonald, K., Fisher, S., & Connelly, C. (2017). e-HRM systems in support of '"smart"' workforce management: an exploratory case study of system success. In Bondarouk, T; Rue l, H; Parry, E (Ed.), *Electronic HRM in the Smart Era* (pp. 87–108). Emerald Publishing Ltd.

Meuter, M., Ostrom, A., Bitner, M., & Roundtree, R. (2003). The influence of technology anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research*, *56*(11), 899–906.

Nair, R., Vejsbjerg, I., Daly, E., & Varytimidis, C. (2025). Humble AI in the real-world: the case of algorithmic hiring. *In Proceedings of Symposium on Human-Computer Interaction for Work (CHIWORK '25). ACM, New York, NY, USA, 7 Pages. Https://Doi.Org/XXXXXXX. XXXXXXX*. https://arxiv.org/html/2505.20918v1

Nonkovic, M. (2023). *SCHUFA: What does the landmark CJEU ruling on Automated Decision-Making mean for businesses?* Kemp IT Law Blog. https://kempitlaw.com/insights/schufa-what-does-thelandmark-cjeu-ruling-on-automated-decision-making-mean-for-businesses/

Partington, R. (2025). Could AI be accelerating slowdown in the UK job market? *The Guardian*. https://www.theguardian.com/business/2025/jul/13/could-ai-be-accelerating-slowdown-in-theuk-job-market

Pavlidis, G. (2024). Unlocking the black box: analysing the EU artificial intelligence act's framework for explainability in AI. *Law, Innovation and Technology*, *16*(1), 293–308. https://doi.org/10.1080/17579961.2024.2313795

Pinetlas, E., Livieris, I., & Pintelas, P. (2020). A grey-box ensemble model exploiting black-box accuracy and white-box intrinsic interpretability. *Algorithms*, *13*(1), 17.

Riley, T. (2018). *Get ready, this year your next job interview may be with an A.I. robot*. CNBC.

Rojas-Galeano, S., Posada, J., & Ordon ez, E. (2022). A Bibliometric Perspective on AI Research for Job-Re sume Matching. *The Scientific World Journal*, *2022*(1), 8002363. https://doi.org/https://doi.org/10.1155/2022/8002363

Shaw, J. ., Wild, E., & Colquitt, J. . (2003). To justify or excuse?: A meta-analytic review of the effects of explanations. *Journal of Applied Psychology*, *88*(3), 444–458.

Stefanowicz, B. (2025). *AI Recruitment Statistics: What Is the Future of Hiring?* Tidio Blog. https://www.tidio.com/blog/ai-recruitment/

Suen, H., Chen, M., & Lu, S. (2019). Does the use of synchrony and artificial intelligence in video interviews affect interview ratings and applicant attitudes? *Computers in Human Behavior*, *98*, 93–101.

Su hr, T., Hilgard, S., & Lakkaraju, H. (2020). Does Fair Ranking Improve Minority Outcomes? Understanding the Interplay of Human and Algorithmic Biases in Online Hiring. *ArXiv Preprint ArXiv:2012.00423.*

Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial intelligence in human resources management: Challenges and a path forward. *California Management Review*, *61*(4), 15–42.

Tatman, R. (2017). Gender and Dialect Bias in YouTube's Automatic Captions. *Proceedings of the First Workshop on Ethics in Natural Language Processing*.

TheirStack. (2025). *Companies that use Hirevue*. https://theirstack.com/en/technology/hirevue

Uhunoma, E. (2023). Facial Recognition Technology and Racial Discrimination a Study on the Design of On-Demand-Asynchronous Video Interview Solutions Used in Recruitment. *International Journal of Multidisciplinary Research and Analysis*, *6*(7), 3240–3259.

Umoh, R. (2018). *Meet the robot that's hiring humans for some of the world's biggest corporations*. CBNC News. https://www.cnbc.com/2018/04/20/this-robot-hires-humans-for-some-majorcorporations.html

Waa, J., Schoonderwoerd Van de, T., Diggelen, J, V., & Neerinex, M. (2020). Interpretable confidence measures for decision support systems. *International Journal of Human Computer Studies*, *144*, 1–11.

Wang, Y., Wang, S., & Lai, K. (2005). A New Fuzzy Support Vector Machine to Evaluate Credit Risk. *IEEE Transactions on Fuzzy Systems*, *13*(6), 820–832.

Will, P., Krpan, D., & Lordan, G. (2023). People versus machines: introducing the HIRE framework. *Artificial Intelligence Review*, *56*(2), 1071–1100. https://doi.org/10.1007/s10462-022-10193-6

Woods, S., Ahmed, S., Nikolaou, I., Costa, A., & Anderson, N. (2020). Personnel selection in the digital age: a review of validity and applicant reactions, and future research challenges. *European Journal of Work and Organizational Psychology*, *29*(1), 64–77.

Zhou, F. (2024). AI System Report: Hirevue's AI-Driven Assessment Tool. *Innovation in Science and Technology*, *3*(4), 109–113.

ABOUT AUTHOR

Dr. Alison LUI | Liverpool John Moores University |
A.Lui[at]ljmu.ac.uk | ORCID: 0000-0003-2463-5177

Dr Alison Lui is an Associate Professor of Corporate and Financial Law at Liverpool John Moores University, UK.. Dr Lui is Max Planck Fellow; Inner Temple Associate Academic Fellow; Churchill Fellow. She has won research awards from the British Academy, Research England, the British Council, Society of Legal Scholars, the Honourable Society of Inner Temple, Association of Commonwealth Universities. Dr Lui has published a monograph and an edited book with Routledge, various book chapters and many peer reviewed articles in top journals such as the Law, Innovation and Technology, Northern Ireland Legal Quarterly, Information and Communications Technology Law, Journal of Banking Regulation and Journal of Financial Regulation and Compliance.