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Algorithmic inclusion: Shaping the predictive algorithms of artificial intelligence in hiring

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Abstract

Despite frequent claims that increased use of artificial intelligence (AI) in hiring will reduce the human bias that has long plagued recruitment and selection, AI may equally replicate and amplify such bias and embed it in technology. This article explores exclusion and inclusion in AI-supported hiring, focusing on three interrelated areas: data, design and decisions. It is suggested that in terms of data, organisational fit, categorisations and intersectionality require consideration in relation to exclusion. As various stakeholders collaborate to create AI, it is essential to explore which groups are dominant and how subjective assessments are encoded in technology. Although AI-supported hiring should enhance recruitment decisions, evidence is lacking on how humans and machines interact in decision-making, and how algorithms can be audited and regulated effectively for inclusion. This article recommends areas for interrogation through further research, and contributes to understanding how algorithmic inclusion can be achieved in AI-supported hiring.

KEYWORDS
artificial intelligence, bias, hiring, inclusion, inequality, recruitment, selection, technology

Abbreviations: AI, artificial intelligence; ATS, applicant tracking system; CV, curriculum vitae; GDPR, general data protection regulation; HR, human resources; KSAOs, knowledge, skills, abilities and other characteristics; LGBTQ, lesbian, gay, bisexual, transgender, queer or questioning; STEM, science, technology, engineering, and mathematics.

Practitioner notes

What is currently known?

- Hiring is central to creating diversity and inclusion in organisations.
- Artificial intelligence (AI) is presumed to be more objective than humans in the hiring process.

What this article adds?

- AI may replicate and amplify existing biases in hiring.
- AI needs to be designed for inclusion.

Implications for practitioners

- Practitioners must develop an understanding of the tensions that exist in creating algorithmic inclusion.

1 | INTRODUCTION

Ensuring inclusivity in the hiring process is an obvious starting point toward making organisations more diverse and inclusive (Jonsen et al., 2021; Özbilgin et al., 2015). Owing to its potential to remove human bias in hiring (Eubanks, 2018; Raisch & Krakowski, 2021; Strange, 2018), AI is heralded as a way to improve diversity and inclusion (Daugherty et al., 2018; Feloni, 2017; McIlvaine, 2018; Riley, 2018); yet research has shown that AI suffers from algorithmic bias, whereby human biases are repeated and amplified (Benjamin, 2019; Noble, 2018). Rather than bypassing bias, discrimination is embedded in and perpetuated through AI (Benjamin, 2019; Pasquale, 2015). However, as society and technology are mutually constitutive (MacKenzie & Wajcman, 1999), technology has the potential to function as a means of inclusion as well as exclusion. The use of AI in hiring risks embedding existing societal relations in its design and use, while also promising to enable inclusion.

This article explores the tensions in making AI-supported hiring more inclusive by developing the notion of algorithmic inclusion. AI is itself a polysemous term with various interpretations. In this article, it is understood as a predictive technology that is shaped by and shapes society, ranging from simple automation to more complex machine learning (Joyce et al., 2021; Raisch & Krakowski, 2021). The use of AI to create algorithmic inclusion is theorised by reviewing the existing literature and suggesting future research directions. It is argued that use of AI for hiring risks amplifying existing biases, and that research should focus on how inclusion can be created through data, design and decisions.

2 | THE PREDICTIVE ALGORITHMS OF AI IN HIRING

The term AI requires careful definition insofar as it pertains to use in hiring. Russell and Norvig define AI as intelligent agents that ‘receive percepts from the environment and perform actions’ (2021, p. 7). AI thus refers to machines that appear to exhibit human-like intelligence (Russell & Norvig, 2021). Machine learning, a subset of AI, entails that ‘a computer observes some data, builds a model based on the data, and uses the model as both a hypothesis about the world and a piece of software that can solve problems’ (Russell & Norvig, 2021, p. 669). For machine learning training and testing, data are searched for patterns, on the basis of which models are built (Barocas & Selbst, 2016; Glikson & Woolley, 2020; Lum & Chowdhury, 2021; Tambe et al., 2019). These models function as a representation of reality. Algorithms are sets of rules that define sequences of instructions to perform tasks such as solving a problem

(Finn, 2017; Kearns & Roth, 2019; Lum & Chowdhury, 2021). The general definition of AI thus encompasses ways to analyse, learn from and make predictions based on data.

Algorithmic bias refers to errors in AI systems that lead to inequitable outcomes for different groups (Russell & Norvig, 2021). However, algorithmic bias can also be seen as a function of how technology and society are mutually constitutive; societal relations influence how technologies are shaped, while technologies in turn influence which societal interactions are possible (MacKenzie & Wajcman, 1999). AI is thus both shaped by and shapes society. In this article, the term 'predictive algorithms of AI' (Nowotny, 2021) is used to denote the future-shaping powers of AI technologies.

However, the same dynamic interplay between technology and society that produces algorithmic bias may also pave the way for algorithmic inclusion. While diversity describes the demographic composition of groups of the workforce that bring different approaches to organisations, inclusion refers to how those different individuals are integrated, can access resources, influence decision making and make meaningful contributions (Roberson, 2006). Most research on algorithmic bias seeks to eradicate bias to ensure that different groups are not disadvantaged, whereas algorithmic inclusion focuses on processes through which the design and use of AI can foster inclusion. This article reviews the literature to develop a research agenda that can create inclusion.

AI plays a role in a range of HR processes (Cheng & Hackett, 2021; Duggan et al., 2020; Tambe et al., 2019) including hiring (Eubanks, 2018) where it can broaden the candidate pool, increase efficiency and job tenure, and reduce hiring times and costs (Black & van Esch, 2020; Hoffman et al., 2015; Johnson et al., 2020; Tippins et al., 2021). The 'Uniform Guidelines On Employee Selection Procedures' (Biddle Consulting Group, 2018) apply to AI selection methods and decisions. They include criterion-related validity, which entails empirical data that shows that the selection procedure is predictive of job performance; content validity, which ensures that the content assessed in the selection is representative for doing the job well; and construct validity, which means that the data shows the degree to which applicants have the required characteristics to successfully perform the job (Biddle Consulting Group, 2018). Criterion-related, content, and construct validity are evaluated against the knowledge, skills, abilities and other characteristics (KSAOs) identified through job analysis. This ensures that the KSAOs are relevant to the job, models that predict those competencies are selected, and that the data collected with the KSAOs is linked to assessment by expert evaluators (Charlwood & Guenole, 2022; Johnson et al., 2020; Tippins et al., 2021). Those who best meet the job requirements based on job analysis should be the primary candidates hired (Biddle Consulting Group, 2018). Job analysis reduces the risk of suggesting candidates who are relatively similar to the current job incumbent, but it does not guarantee that the process will be discrimination-free (Charlwood & Guenole, 2022). Selection methods should be fair to all candidates by avoiding adverse (or disparate) impacts on members of protected groups (Biddle Consulting Group, 2018; Charlwood & Guenole, 2022; Stone & Dulebohn, 2013; Tippins, 2015; Tippins et al., 2021).

AI can be employed in every step of the hiring funnel (Sánchez-Monedero & Dencik, 2019; Sánchez-Monedero et al., 2020) but is currently used mainly in relation to chatbots, screening software and task-automation tools (Albert, 2019), simulations and games (Tippins, 2015), video interviews and social media (Davison et al., 2012; Tippins et al., 2021; Vosen, 2021). Companies like Unilever and General Electric ask candidates for high-volume roles such as graduate positions to record answers to pre-set questions on their mobile phones, and their word choice and tonality are used to infer certain qualities (Albert, 2019; Hoffman et al., 2015; Knight, 2021; Köchling & Wehner, 2020; Metz, 2020; Withers, 2020). However, the validity of data generated through such means in predicting employment-related outcomes has been questioned, as '[f] or business reasons and legal defensibility reasons, validity is a *sine qua non* of selection research' (Tippins et al., 2021, p. 14, italics in original). Camera angles, accents and other potential diversity-related factors, such as culturally-contingent facial expressions, can impact on the validity of such data (Tippins, 2015). Similarly, data 'scraped' from social media may violate candidates' privacy, by revealing their membership of protected groups in relation to race, age or disability (Black et al., 2015; Jeske et al., 2019). It is also questionable how such data can be linked to job requirements in a standardised, reliable and valid way (Davison et al., 2012; Tippins et al., 2021; Vosen, 2021). Criterion-related, content, and construct validity in relation to job analysis should thus remain central for AI-supported hiring.

AI-supported hiring can screen out candidates without much human intervention (Bogen & Rieke, 2018; Withers, 2020). Applicant tracking systems (ATS) are used by 98% of Fortune 500 companies to screen CVs based on keywords and reject 75% of candidates (Bartleby, 2018; Sánchez-Monedero et al., 2020). Such keywords should be derived from job analysis and show criterion-related, content, and construct validity to ensure consistency and fairness (Johnson et al., 2020; Stone & Dulebohn, 2013; Tippins, 2015). Chatbots screen candidates based on ideal answers (Charlwood & Guenole, 2022; Johnson et al., 2020); but if these reflect typical ways in which men express themselves, this may disadvantage women. Online tests used to screen candidates (Johnson et al., 2020; Tippins, 2015) often include branching, meaning that the difficulty of answers increases if a correct answer is presented which may disadvantage groups of candidates leading to adverse impacts (Johnson et al., 2020; Tippins, 2015).

Since human bias has long created exclusion in hiring processes (Noon, 2012), AI-supported hiring presents the opportunity to make decision making on hiring more inclusive (Daugherty et al., 2018; Johnson et al., 2020). Criteria for hiring including the avoidance of discrimination are well-established (Biddle Consulting Group, 2018; Tippins et al., 2021) yet the use of algorithms in hiring may replicate and amplify existing biases and introduce new ones (Dalenberg, 2018; Vassilopoulou et al., 2022). HR thus plays a central role in creating greater inclusion through the use of AI in hiring (Vassilopoulou et al., 2022). The purpose of this article is to review the literature on issues of inclusion in AI-supported hiring, focusing on data, design and decisions which is then used as a basis for recommendations on further research. Thus, the notion of algorithmic inclusion developed in this article is used to analyse how hiring can use AI that is shaped by and shapes society to *make predictions that create inclusion*.

3 | TOWARDS ALGORITHMIC INCLUSION IN HIRING

In examining the development of algorithmic inclusion in AI-supported hiring, this section focuses on three areas: data, design and decisions. Although these are intertwined, by focusing on each area in turn, the following subsections illuminate emerging issues and tensions. Emerging research questions are featured in Table 1.

3.1 | Data

Algorithms for selection draw on data such as education and work experience extracted from CVs, online tests, games and recorded interviews to assess aptitude and personality. These data feed into algorithms, and are weighed and statistically analysed to make predictions about job performance. A key concern is that such data may be biased, and thus disadvantage groups of people in the selection process. Although protected characteristics are commonly not allowed to be used in hiring, data may provide clues about differences that may lead to discrimination; race and age may be presumed from social media photos (Black et al., 2015), and video recordings may lack reliability due to accents (Tippins et al., 2021). The definition of the ideal candidate either consciously through job analysis or subconsciously through unspoken assumptions that end up in the model, will also impact inclusion (Table 1—A).

Datasets used for machine learning may contain historical biases, unrepresentative data and collection bias (Caliskan et al., 2017; Hao, 2019; Lee et al., 2019; Tambe et al., 2019). The often-referenced Amazon recruitment algorithm illustrates historical bias, because the ideal employee was defined based on historical CVs that came largely from men. Since men were defined as ideal, CVs mentioning 'women', such as having studied women's studies, were filtered out (Lee et al., 2019). Racial bias is also likely to be present (Benjamin, 2019), which is why applicants often conceal their race to avoid discrimination (Kang et al., 2016). Similarly, candidates may include 'Cambridge' or 'Oxford' in invisible white text on their CVs to pass the screening process (Buranyi, 2018). Historical recruitment datasets may affect candidates' rankings. If an organisation has not hired many queer individuals in the past, its candidate prioritisation systems are likely to assign lower scores to those who for instance indicate on their CV that they are part of an employee LGBTQ network (Tomasev et al., 2021). Datasets may include gender-stereotypical associations, such

TABLE 1 A research agenda for algorithmic inclusion in hiring.

Areas	Key issues	Research questions
Data	A. Underlying data	• How can the impact of data that may lead to discrimination be reduced in the selection process?
	B. Historical bias	• How can historical bias in HR datasets be mitigated? • How can stereotypical associations in datasets be eliminated?
	C. Unrepresentative data	• How can HR data be made more representative? • What considerations relating to inclusion must be examined with regard to video interviews?
	D. Collection bias	• How can HR ensure high-quality data, for instance by including those who are rejected? • How can in-built bias with regard to performance evaluation be corrected?
	E. Data labelling	• How can subjective assessments in data labelling used for selection be made visible to reduce bias?
	F. Formation of categorisation	• Is the likelihood of the exclusion of non-dominant groups higher when binaries for gender and narrow classifications for race are used than when more inclusive classifications are employed in AI-supported hiring? • How can AI-supported hiring consider that some categorisations are more discrediting than others? • Does self-classification with regard to LGBTQ identities reduce bias? • How can non-binary categories be established and utilised in HR data? • How are the categories used in AI-supported hiring established, defined and operationalised? • How can redundant encoding be avoided? • How can categories used in data labelling become more inclusive?
	G. Fit	• How can unusual hires be used to improve AI-supported hiring? • How can HR data be improved by tracking rejections, promotions and leavers? • Are those who differ from the norm more likely to be given lower fit scores? • Is it possible to develop inclusionary conceptions of fit?
	H. Intersectionality	• Under what conditions does it make sense to include intersectionality in data used in AI-supported hiring? • Does AI-supported hiring rank black women lower than white women, and all women lower than white men?
Design	I. Designers	• How are subjective categories transformed into objective ones through machine learning processes? • How can diversity be encouraged amongst information scientists working on AI for use in hiring? • How can collaboration be fostered between different stakeholders, such as data scientists and industrial/organisational psychologists, HR professionals and hiring managers?
	J. Bias in machine learning	• In what contexts does machine learning amplify bias and create exclusionary associations in AI-supported hiring?

(Continues)

TABLE 1 (Continued)

Areas	Key issues	Research questions
	K. Protected characteristics	• How can legal responsibilities not to use protected characteristics be reconciled with using protected characteristics to ensure that machine learning is fair? • How can HR researchers develop evidence-based guidelines for AI-supported hiring?
	L. Methodologies	• How can ethnographies of AI-supported hiring technologies illuminate their socially embedded design and use with regard to inclusion? • How can technology walkthroughs shed light on inclusion in hiring?
	M. Candidates' experiences	• Do different candidates experience AI-supporting hiring in different ways? • Do hiring platforms that aim to increase diversity and inclusion deter candidates particularly from non-dominant groups?
Decisions	N. Decision making	• How does AI-supported hiring reduce or increase human and machine bias respectively? • Under what conditions do AI-supported hiring decisions improve inclusion?
	O. Impact assessments and audits	• How are human decision makers involved in evaluating the predictions of AI-supported hiring? • What needs to be included in impact assessments and audit studies to ensure that they foster inclusion? • How do different ways of assessing impact compare with regard to inclusion?
	P. Regulation	• What regulations are effective in creating inclusion?
	Q. Hiring managers	• How do hiring managers and AI in hiring interact in the decision-making process? • Are hiring decisions by managers more biased than AI-supported hiring decisions? • How can HR professionals' AI literacy with regard to inclusion be developed?
	R. Candidate feedback	• How do candidates from a variety of backgrounds respond to AI-supported hiring and feedback mechanisms?

as picturing women as nurses, meaning that machines may learn that nurses must be women (Bass & Huet, 2017). Inputting information on working patterns to predict the likelihood that individuals will stay may also amplify bias, since women are more likely to take career breaks and work part-time (Table 1—B).

Underlying data may be unrepresentative of the wider population. For video interviews, reliance on facial recognition may mean that black women's faces are less well recognised (Buolamwini & Gebru, 2018) and their facial expressions poorly analysed. Similarly, it has been shown that wearing glasses or headscarves affect individual rankings (Harlan & Schnuck, 2021). If video interviews are analysed based on language (Knight, 2021; Murgia, 2021), then voice tone, accents and gender- or race-specific language patterns may influence assessments (Tippins, 2015). AI-supported hiring may thus give rise to biases owing to the domination of underlying datasets by specific groups (Table 1—C).

Datasets may also exhibit collection bias. Use of AI in HR is limited by the quality of the data collected, as HR may not collect data on those who have not been recruited (Tambe et al., 2019). However, such data might improve predictions based on these datasets. Similarly, many metrics used by HR have in-built bias. In performance evaluations, a manager who is biased against women may assign lower performance scores to women (Edwards & Edwards, 2019; Tambe et al., 2019). Such bias is then codified and influences future predictions (Table 1—D).

How data are labelled in machine-learning processes may be subjective, and thus introduce bias (Hao, 2019; Zou & Schiebinger, 2018). For example, when assessing candidate traits through images, those images must be labelled as displaying those traits, or a recorded video must be analysed based on rubrics to assess candidates (Kelan, 2023). Outcomes are affected by whether the assessors are recruited from a gig platform or are trained industrial/organisational psychologists. Such assessments are open to bias; how confidence presents in women and men may differ. Thus, data labelling may be a subjective process in which the background of the data labeller or assessor is important (Davani et al., 2021; Denton et al., 2021) (Table 1—E).

In order to frame a problem for AI, it must be defined by categories that are pre-established or newly created by either humans or machines (Hao, 2019). Although HR has introduced a range of inclusive categories such as moving beyond the gender binary (male/female) through non-binary classifications (Smith, 2018), AI tends to rely on binaries (Foulds et al., 2020; Friedler et al., 2018). Where gender is operationalised as a static binary associated with biological sex, transgender or fluid gender identities are excluded (Buolamwini & Gebru, 2018; Keyes, 2018; Scheuerman et al., 2019); if non-gender binary individuals apply for positions, they may be mislabelled. Protected characteristics may also be inferred from data through 'redundant encoding' (Dwork et al., 2012). For instance, social media 'likes' can be used to infer a person's characteristics, such as sexual orientation or class (Black et al., 2015; Derous & Ryan, 2019; Johnson et al., 2020; Wachter, 2020), and presumed identities may influence who sees an advert (Lambrecht & Tucker, 2019). Even if potentially exclusionary labels are avoided, they may still emerge through machine learning. For instance, AI may learn that people named 'Mark' do better than people named 'Mary' (Lee et al., 2019), leading to people named 'Mary' being less likely to be considered in AI-supported hiring. Therefore, the process of assigning data labels turns categories into established truths (Alaimo & Kallinikos, 2021; Barocas & Selbst, 2016). However how more inclusive classifications for race and gender could be used in hiring decisions is unclear. Including demographic information in hiring decisions is illegal in many global locations and even if that were not to be the case stereotypes have a differential effect with some stereotypes about subgroups being positive and others negative (Stone-Romero et al., 2020). How this could be considered in AI-supported hiring is unclear and creates a central tension for HR (Table 1—F).

Although careful job analysis should focus on the KSAOs required to perform the job well (Black et al., 2015; Derous & Ryan, 2019; Johnson et al., 2020), the notion of 'fit' may be exacerbated by AI (Vassilopoulou et al., 2022). For example, Google and McKinsey use algorithms to measure individuals' fit during the hiring process (Carey & Smith, 2016), Goldman Sachs uses a CV analysis tool to find a good match between a candidate's skills and the position (Dastin, 2018), and LinkedIn offers prospective employers candidate rankings based on algorithmic comparisons of individuals' CV information with job postings (Dastin, 2018). Using AI to support such matching is attractive because it saves time and allows recruiters to focus on candidates who are most likely to be successful. This also means that companies risk hiring the same types of people repeatedly decreasing diversity (Strange, 2018; Vassilopoulou et al., 2022). How an ideal candidate is defined is likely to entail exclusionary elements. Similarly, those who work part-time, have non-linear CVs or have not attended the right institutions may also receive lower fit scores. In order to disrupt this logic, it is necessary to go beyond fit. For instance, it may be beneficial to hire 'wildcards' or non-traditional candidates with low fit scores, because algorithmic decisions can only be improved through more diversity in hiring (Tambe et al., 2019). Most hiring processes should fulfil the criterion-related validity that shows how well those who are hired are performing (Biddle Consulting Group, 2018). Through AI-supported hiring, there might be an opportunity to expand the data that is being used to actual rather than predicted job performance. Adverse impact, for instance by building attrition models (Speer, 2021), should also be tested for to avoid underlying data bias (Table 1—G).

Another tension is intersectionality. Intersectionality is an analytical framework to show how different forms of inequalities interact such as how being a black woman is different to be a white woman (Crenshaw, 1989, 1991; Kelan, 2014; McCall, 2005). The effects of how intersectionality plays out is hard to predict in that for instance for some jobs Black women are rated as more suitable (Hosoda et al., 2003). In the field of AI, intersectional fairness is increasingly being discussed (Bogen & Rieke, 2018; Foulds et al., 2020; Friedler et al., 2018; Hao, 2019) but it is unclear how intersectionality can be considered in hiring as demographic characteristics should not be drawn upon in the hiring process (Table 1—H).

3.2 | Design

Data collected through means such as CV screening, online tests, recorded interviews or social media are evaluated against standards established through job analysis to forecast applicants' job performance (Black et al., 2015; Derous & Ryan, 2019; Johnson et al., 2020) but issues pivotal to inclusion require consideration in the design of AI-supported hiring.

Data scientists, programmers, HR professionals, recruiters, industrial/organisational psychologists and hiring managers act as stakeholders in the process of designing AI-supported hiring technologies (Tippins et al., 2021; Vassilopoulou et al., 2022). Data scientists may trust AI-guided decisions more than decisions by domain experts (Charlwood & Guenole, 2022), which may influence design considerations. Data scientists might aim to advance the top 20% of candidates following video interviews, whereas an industrial/organisational psychology perspective might suggest that this would result in insufficient numbers of candidates for the next selection step (Kelan, 2023). Data scientists are also predominantly white men under 40 (Simonite, 2018; Wajcman, 2018). This may influence how AI problems are framed, as coders may subconsciously define these problems by making subjective assessments of measurable outcomes that can be used in the algorithm, such as job tenure or higher sales, that disadvantage particular groups (Barocas & Selbst, 2016; Hao, 2019; Tippins et al., 2021). This can be addressed through rigorous coding protocols, job analysis and regular auditing of algorithms (Charlwood & Guenole, 2022; IBM, 2020; Johnson et al., 2020; Tippins et al., 2021) (Table 1—I).

Bias may arise through machine learning itself (Chamorro-Premuzic, 2019; Zhao et al., 2017). Unexpected and irrelevant parameters, such as frequenting Japanese cartoon websites (Dalenberg, 2018), may be used to build models that amplify stereotypes in machine learning (Bolukbasi et al., 2016; Zhao et al., 2017). Similarly, job ad delivery is often based on machine-derived perceptions of gender and race rather than qualifications (Datta et al., 2014; Imana et al., 2021; Sweeney, 2013). The black box of machine learning (Pasquale, 2015) means that there is a risk of unexpected and irrelevant parameters entering AI-supported hiring (Table 1—J).

While it is illegal to consider protected characteristics in hiring, machine learning may create proxies for protected characteristics or infer forbidden information that is then used in hiring, without the designers of AI knowing that this is occurring (Kearns & Roth, 2019). If a protected characteristic is correlated with being a good employee without this being flagged by the system, this may lead to exclusion. The technical fix is for protected characteristics to be included in the model and the system to be optimised, not only to minimise error but also to avoid violating fairness (Kearns & Roth, 2019). One might use inverse weight propensity scores to re-balance groups for instance by taking into account how many black women older than 30 are in the dataset and then balance results internally. Similarly, if more women should see adverts for STEM positions, the campaign must be targeted at women (Maron, 2018); and if the aim is to recruit more women, an algorithm must be created that compares women with other women, rather than with the overall population (Bass & Huet, 2017; Dwork et al., 2012). Such approaches are used in regard to affirmative action but would be illegal in many global locations. This means that the options for optimising for fairness are currently restricted by the very anti-discrimination regulations designed to prevent this from happening. This paradox will need to be addressed by HR in collaboration with other stakeholders (Table 1—K).

In order to explore design decisions, it would be important to use a broader methodological toolkit. Ethnographic approaches used in science and technology studies (Hess, 2002; Woolgar, 1991) could be employed to shed light on the hiring process (Charlwood & Guenole, 2022). In particular the technology walkthrough methodology might be used where interactions with hiring technologies are recorded and analysed (Ritter, 2021) (Table 1—L).

Job candidates' experiences of using AI in hiring are another important area of study. It has been shown that prospective applicants are more likely to apply for jobs using human rather than AI-aided evaluation (Mirowska, 2020);

they see AI-aided interviews as more objective, yet prefer to maintain a human element (Mirowska & Mesnet, 2021). AI-based interview processes are viewed less favourably overall, although there is no difference in perceived fairness (Suen et al., 2019). It has been shown that many candidates fear that revealing, for instance, their racial background will have detrimental effects in the hiring process (Kang et al., 2016). Yet hiring platforms that seek to increase diversity and inclusion often require such information (Table 1—M).

3.3 | Decisions

In AI-supported hiring, algorithmic inputs are used to enhance human decision making (Johnson et al., 2020) by reducing human bias (Johnson et al., 2020). Yet algorithmic bias may disadvantage certain groups (Benjamin, 2019; Noble, 2018). Although the issue of algorithmic bias may ultimately be solvable (Charlwood & Guenole, 2022), little research has yet investigated different forms of human and machine bias in hiring (Table 1—N).

Since AI is a black box, with limited information on how it arrives at predictions (Bass & Huet, 2017), it is essential to conduct impact assessments and audit AI carefully and regularly for potentially discriminatory effects (Burt, 2021; Lee et al., 2019; Lum & Chowdhury, 2021), and to refresh the algorithms accordingly (Tippins et al., 2021). Thus, the algorithms must be audited to ensure that they predict job performance without relying on explicit or inferred data from protected groups (Charlwood & Guenole, 2022). For example, HR professionals and an AI might rank a subset of CVs independently to then compare if both arrive at similar results and use this insight to fine-tune and refresh the results. Pymetrics has developed an auditing tool to check outcomes against protected characteristics; HireVue measures demographic parity to ensure unbiased hiring; and Applied monitors for discrimination by identifying masculine and feminine words (Sánchez-Monedero et al., 2020). Applied also uses classification, anti-classification and calibration to ensure that outcomes are independent of group category, which not only requires group definitions based on gender and ethnicity binaries, but is also selective in that it does not include other classifications, like disability and social class (Sánchez-Monedero et al., 2020). Human decision makers may also provide feedback on whether AI-supported hiring increases or reduces diversity (Table 1—O).

Regulation has a major impact on AI-supported hiring. In the US, considerations around adverse impacts are paramount in AI-supported hiring (Stone & Dulebohn, 2013; Tippins, 2015; Tippins et al., 2021). New York City Council has proposed a law that would require mandatory audits of automated assessment tools for bias (Givens et al., 2021; Lum & Chowdhury, 2021). The European Union's General Data Protection Regulation requires companies to disclose whether decisions that might significantly affect particular individuals, such as hiring, are automated and individuals can request an explanation as to why the system decided in such a way (Buranyi, 2018). The European Union's April 2021 proposed regulation on AI goes further in proposing an AI authorisation approval system (Fournier-Tombs, 2021) that will apply to hiring (Adams-Prassl, 2022). The United Nations are expected to develop similar conventions (Fournier-Tombs, 2021). HR researchers might explore what mechanisms are in place to audit and regulate AI-supported hiring and how these processes work to contribute to explainable AI (Table 1—P).

Hiring managers and HR professionals must also play a role in monitoring the predictions rendered by AI-supported hiring (Vassilopoulou et al., 2022) (Table 1—Q).

Future research should explore how candidates from diverse backgrounds experience AI-supported hiring (Table 1—R).

4 | DISCUSSION AND CONCLUSION

This article has developed the notion of algorithmic inclusion, which entails considering inclusion in relation to data, design and decisions in AI-supported hiring. For this purpose, the literature was reviewed and research questions developed. Although it is commonly assumed that AI is more objective than humans in hiring, this article has shown how use of AI in hiring may replicate and amplify bias, which may lead to exclusion. This is because society shapes AI, and vice versa. Conversely, the shaping process may also be used to embed inclusion in hiring.

Three key areas have been reviewed and a research agenda developed by posing specific questions that researchers might pursue. First, it has been shown that data may be exclusionary, and that this problem may be compounded by concerns around notions of fit, the establishment of fixed categories and the difficulties of including intersectionality. Second, as different stakeholders collaborate to create hiring AI, it is crucial to explore which groups are dominant in the process, and how subjective assessments are encoded in AI. Finally, research is required on how humans and machines interact in decision-making, and how algorithms can be audited and regulated for inclusion.

This article contributes to the literature by offering an understanding of how algorithmic bias in hiring emerges, and how this knowledge can be used to create algorithmic inclusion. The proposed research agenda focuses on the data, design and decisions relating to AI-supported hiring. This urgently needed future research on algorithmic inclusion might adopt quantitative (Köchling & Wehner, 2020) and qualitative approaches (Charlwood & Guenole, 2022).

This article helps HR practitioners in two ways. First, it provides HR practitioners with an understanding of how exclusion and inclusion may occur in relation to AI. Second, it outlines ways in which HR practitioners might become involved in building more inclusive AI. They might critically question AI providers on how diversity and inclusion are inscribed in the software, or work with these providers to develop more inclusive AI. This would help shift HR professionals from being solely customers to becoming actual co-designers of AI. HR practitioners should also be centrally involved in assessing the impact of AI and take corrective efforts. AI must also be included in training and professional standards for HR professionals.

Although this article focuses on hiring, the dynamics illustrated will also permeate other areas, such as promotions and employee engagement. Although using AI-supported hiring poses challenges for inclusion, if developed appropriately, AI can enable humans to ensure more inclusion in hiring.

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